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Circling the Wagons: Middle Class Whites and the Election of Rudolph Giuliani

by

Melissa Levitt

A dissertation submitted to the Graduate Faculty in Political Science in
partial fulfillment of the requirements for the degree of Doctor of
Philosophy, the City University of New York

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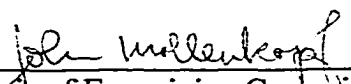
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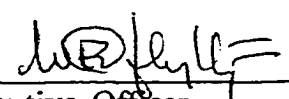
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This manuscript has been read and accepted for the Graduate Faculty in Political Science in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy

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Dr. Philip Thompson
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Dr. Kenneth Sherrill

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THE CITY UNIVERSITY OF NEW YORK

Abstract

Circling the Wagons: Middle Class Whites and the Election of Rudolph Giuliani

By

Melissa Levitt

Chair: John Hull Mollenkopf, Graduate Center of the City University of New York

The 1989 and 1993 New York City mayoral elections were decided by only 97,000 votes—an extremely small margin. Both elections pitted David Dinkins and Rudolph Giuliani against each other; approximately the same proportion of New Yorkers came to the polls. This dissertation attempts to show that pessimistic outlook of middle class white New Yorkers swung the election toward Giuliani. He was able to tap into the pessimism of this key group, motivating them to come to the polls and vote for change. This dissertation will analyze Census data, cross-sectional survey data and election district data in an effort to prove that members of a single race or class did not determine Giuliani's victory. Instead, his victory was determined by the effect of pessimism on race- and class- based factors. In the end, although much scholarly research appeared to support the original hypothesis of the dissertation, thorough analysis of all three datasets instead proved the opposite true. In the final analysis, the shift in white votes from all income classes toward Giuliani had a markedly smaller impact on the 1993 election than originally predicted. Surprisingly, the movement of Asian and Hispanic voters toward Giuliani had a far greater impact; these voters constituted the small but vital force which

swung the election in Giuliani's favor, thus ushering in a new era in New York City politics.

Acknowledgements

A dissertation cannot be completed without the support of family and friends. I would like to dedicate this dissertation to my mother and grandmother, now departed. Their lives as strong, confident and intelligent women gave me the inspiration to complete this project. I would also like to thank my father for his continual support throughout my education. Without his constant love, support and guidance, I am sure I would have given up long ago. Additional thanks go to my two advisors, John Mollenkopf and Richard DeLeon. Both are more than advisors, they have become mentors and I will strive to keep up with their level of scholarship and teaching throughout my career.

Table of Contents

<u>Introduction</u>	1
<u>Chapter 1 Laying the Groundwork</u>	10
<u>The Articulation of Race and Class Perspectives</u>	10
<u>The Articulation of Race</u>	11
<u>Articulating Class</u>	15
<u>Mobilization</u>	17
<u>Race and Mobilization</u>	17
<u>Class and Mobilization</u>	20
<u>Turnout</u>	21
<u>Race and Turnout</u>	22
<u>Class and Turnout</u>	23
<u>The Middle Class?</u>	26
<u>Middle Class in Recent New York City History</u>	34
<u>Theory, Hypotheses and Definitions</u>	37
<u>Definitions</u>	39
<u>Chapter 2 Setting the Stage: An Analysis of Census Data</u>	44
<u>Focus on The Late 1960s to Mid 1970s – a Period of Turmoil and Despair</u>	47
<u>Mayor Koch Sets the Stage</u>	48
<u>Dinkins Arrives on the Scene</u>	52
<u>The Effect of the Recession</u>	55
<u>Data and Methods</u>	57
<u>Basic Demographics of New York City</u>	59
<u>New York City from 1978 to 1987</u>	59
<u>New York City During the 1990s</u>	65
<u>Conclusion</u>	74
<u>Chapter 3 How New Yorkers Feel</u>	75
<u>The State of Mind in New York City</u>	78
<u>Attitudes on Crime</u>	79
<u>Attitudes on Race Relations</u>	83
<u>Attitudes on Quality of Life</u>	87
<u>Liberalism and Conservatism in New York City</u>	91
<u>Conclusion</u>	92
<u>Introduction to Chapters 4 to 6</u>	94
<u>Chapter 4 Round One</u>	110

<u>Pessimism in 1989</u>	114
<u>The 1989 Election</u>	128
<u>Model B</u>	135
<u>Conclusions</u>	150
<u>Chapter 5 Round Two</u>	152
 <u>Pessimism in 1993</u>	 157
<u>1993 Equation</u>	169
<u>Conclusion</u>	194
<u>Chapter 6 A Post-Fight Analysis: A Comparison of the 1989 and 1993 Elections</u>	195
 <u>Pessimism in 1989 and 1993</u>	 197
<u>Comparison Between 1989 and 1993 New York Times/CBS News Polls</u>	203
<u>Comparison with Exit Polls</u>	213
<u>Conclusion</u>	223
<u>Chapter 7 Election District Analysis</u>	226
 <u>The Dataset</u>	 228
<u>The Method</u>	230
<u>Preliminary Results</u>	233
<u>Mobilization Model</u>	248
<u>Shift in Support?</u>	251
<u>Conclusion</u>	254
<u>Chapter 8 Concluding Thoughts About the Research Question</u>	256
 <u>Appendix A</u>	 263
 <u>Dataset descriptions</u>	 263
 <u>Appendix 4.1</u>	 266
 <u>Appendix 4.2</u>	 287
 <u>Appendix 5.1</u>	 307
 <u>Appendix 5.2</u>	 314

<u><i>Appendix 5.3</i></u>	338
<u><i>Appendix 6.1</i></u>	341
<u><i>Appendix 6.2</i></u>	345
<u><i>Data from the Exit Polls</i></u>	355
<u><i>Appendix 7.1</i></u>	365
<u><i>Bibliography</i></u>	420

List of Tables

<u>TABLE 1.1 HUD 1997 DEFINITIONS OF MIDDLE CLASS HOUSEHOLDS</u>	42
<u>TABLE 2.1 INCOME BREAKDOWNS FOR THE MIDDLE CLASS IN 1997</u>	
<u>DOLLARS</u>	57
<u>TABLE 2.2 BASIC DEMOGRAPHICS FOR NEW YORK CITY</u>	60
<u>TABLE 2.3 SELECTED HOUSEHOLD INCOME FIGURES FOR NEW YORK CITY</u>	
<u>IN 1997 DOLLARS</u>	62
<u>TABLE 2.4 MEAN HOUSEHOLD INCOME IN 1997 DOLLARS BY CLASS</u>	62
<u>TABLE 2.5 PERCENT OF INCOME CLASS HOUSEHOLDS BY RACE OF</u>	
<u>HOUSEHOLDER OVER TIME</u>	64
<u>TABLE 2.6 BASIC DEMOGRAPHICS FOR NEW YORK CITY DURING THE 1990S</u>	67
<u>TABLE 2.6 CONTINUED</u>	68
<u>TABLE 2.7 SELECTED HOUSEHOLD INCOME FIGURES IN 1997 DOLLARS</u>	
<u>OVER TIME</u>	68
<u>TABLE 2.8 MEAN INCOME BY CLASS OVER TIME IN 1997 DOLLARS.</u>	70
<u>TABLE 2.9 PERCENT OF INCOME CLASS BY RACE OF HOUSEHOLDER OVER</u>	
<u>TIME</u>	71
<u>TABLE 2.11 PERCENTAGE OF ALL ADULTS AGED 18 AND OVER BY</u>	
<u>SELECTED OCCUPATION</u>	72
<u>TABLE 2.12 – MEAN MIDDLE CLASS PERSONAL INCOME BY RACE IN 1997</u>	
<u>DOLLARS</u>	73
<u>TABLE 3.1 AFRICAN AMERICAN AND JEWISH RELATIONS</u>	85
<u>TABLE 3.2 TOP EIGHT NUMBER ONE PROBLEMS FOR NEW YORK CITY</u>	90
<u>TABLE 3.3 PERCEPTIONS OF THE CANDIDATES</u>	93
<u>TABLE 4.1 — ODDS RATIOS FOR TWO MODELS OF PESSIMISM IN 1989</u>	120
<u>TABLE 4.2— UNADJUSTED AND ADJUSTED PREDICTORS FOR PESSMISM IN</u>	
<u>1989</u>	126
<u>TABLE 4.3 ODDS RATIOS FOR THE RESULTS COMPARING ““NEITHER/NO</u>	
<u>VOTE”” TO GIULIANI IN 1989</u>	134
<u>TABLE 4.4— ODDS RATIOS FOR THE DINKINS VERSUS GIULIANI</u>	
<u>COMPARISON IN 1989</u>	135
<u>TABLE 4.5 RECYCLED PREDICTORS OF CANDIDATE SUPPORT IN 1989</u>	145
<u>TABLE 4.6 RECYCLED PREDICTOR TABLE CONTINUED FROM TABLE 4.5</u>	148
<u>TABLE 5.1 ODDS RATIOS FOR THE CAUSES OF LONG TERM PESSIMISTIC</u>	
<u>OUTLOOK, SATURATED AND PARSIMONIOUS MODEL</u>	163
<u>TABLE 5.2 PESSIMISTIC LONG-TERM OUTLOOK FOR NEW YORK CITY 1993:</u>	
<u>UNADJUSTED ESTIMATES AND ADJUSTED ESTIMATES</u>	166
<u>TABLE 5.3 ODDS RATIOS FROM THE MULTINOMIAL LOGISTIC REGRESSION</u>	
<u>FOR CANDIDATE SUPPORT – “NEITHER/NO VOTE” SECTION</u>	174
<u>TABLE 5.4 ODDS RATIOS FROM THE MULTINOMIAL LOGISTIC REGRESSION</u>	
<u>MODELS FOR CANDIDATE PREFERENCE IN 1993 BETWEEN DINKINS</u>	
<u>AND GIULIANI</u>	177

<u>TABLE 5.5 — UNADJUSTED AND ADJUSTED PREDICTORS FOR THE MULTINOMIAL LOGISTIC REGRESSION 1993</u>	186
<u>TABLE 5.6 — CONTINUATION OF TABLE 5.5, RECYCLED PREDICTOR TABL</u>	190
<u>TABLE 6.1 – ADJUSTED PROBABILITIES FOR PESSIMISM FOR 1989 AND 1993</u>	198
<u>TABLE 6.2 ADJUSTED PROBABILITIES FOR CANDIDATE SUPPORT FOR 1989 AND 1993</u>	205
<u>TABLE 6.3 COMPARISON OF RECYCLED PREDICTORS WITH EXIT POLLS 1989 AND 1993</u>	215
<u>TABLE 6.4 LONG-TERM OUTLOOK COMPARED</u>	216
<u>TABLE 6.5 COMPARISON OF 1993 RECYCLED PROBABILITIES AND 1993 EXIT POLLS FOR INCOME CLASS AND RACE RELATIONS</u>	217
<u>TABLE 6.6 PROBABILITIES AND RESULTS FOR VOTING IN 1993 BASED ON 1989 VOTING BEHAVIOR</u>	220
<u>TABLE 6.7 "SWITCHER" PROFILE FROM MAY 1993 POLL AND NOVEMBER 1993 EXIT POLL</u>	223
<u>TABLE 7.1 — MYTHICAL PRECINCT OUTCOME</u>	231
<u>TABLE 7.3 MEAN ESTIMATED TURNOUT FIGURES BY BOROUGH AND FOR NEW YORK CITY</u>	234
<u>TABLE 7.4 -- TURNOUT CHANGE FROM 1989 TO 1993 BY NEIGHBORHOOD</u>	236
<u>TABLE 7.4 EZI ESTIMATED VOTES BY RACE AND BOROUGH IN 1989</u>	238
<u>TABLE 7.5 BREAKDOWN OF NONWHITE ESTIMATED VOTES</u>	239
<u>TABLE 7.6 EZI ESTIMATED VOTES FOR CANDIDATE BY RACE AND BOROUGH IN 1993</u>	240
<u>TABLE 7.7 BREAKDOWN OF ESTIMATED NONWHITE SUPPORT FOR THE CANDIDATES</u>	241
<u>TABLE 7.8 -- CHANGE IN EZI ESTIMATED SUPPORT FOR DINKINS BY NEIGHBORHOOD</u>	242
<u>TABLE 7.9 CHANGE IN EZI ESTIMATES FOR GIULIANI SUPPORT BY NEIGHBORHOOD</u>	246
<u>TABLE 7.10 REGRESSION MODELS FOR RACE-BASED EZI ESTIMATED TURNOUT</u>	249
<u>TABLE 7.11 OLS REGRESSION COEFFICIENTS FROM ESTIMATED SUPPORT FOR GIULIANI MODELS BY RACE AND YEAR</u>	252
<u>TABLE A2 BASIC DEMOGRAPHICS FROM THE 1989 <i>NEW YORK TIMES</i>/CBS NEWS SURVEY AND THE 1993 <i>NEW YORK TIMES</i>/CBS NEWS SURVEY</u>	265

List of Illustrations

<u>Figure 3.1 Graphical Display of Basic Theory</u>	76
<u>Figure 4.1 Graphical Representation of Selected Relative Risk Ratios from the Multinomial Logistic Regression on Candidate Choice</u>	140
<u>Figure 4.2 Graphical Representation of Selected Odds Ratios from Multinomial Logistic Regression on Candidate Choice</u>	142
<u>Figure 5.1 Odds Ratio Plot for Multinomial Logistic Regression on Candidate Choice</u>	182
<u>Figure 5.2 Odds Ratio Plot of Multinomial Logistic Regression on Candidate Choice</u>	184
<u>Figure 6.1 Chart of Pessimism Broken Down by Race and Income Class</u>	202
<u>Figure 6.2 1989 Graphical Representations of Primary Theoretical Variables</u>	210
<u>Figure 6.3 1993 Graphical Representations of Primary Theoretical Variables</u>	212

Introduction

The American urban scene changed dramatically during the latter half of the 1980s. Many cities changed their overall political orientations to a more conservative viewpoint after decades of liberalism. Other cities saw their first African American mayors, while others reached new levels of prosperity during a shift to a postindustrial economy. The nationwide recession and the election of a Democratic president after 12 years of Republican rule ushered in a new need for “getting down to business” on all levels of government. New York City was not immune to these phenomena as they influenced the result of the 1993 New York City mayoral election.

This dissertation explores the changes that occurred within the city to bring the first Republican mayor to power in over twenty years. It shows that in individual voters’ perceptions of life in New York City in 1993, the negative outweighed the positive, contributing to an increase in long-term pessimism. This dissertation theorizes that the increase in long-term pessimistic outlook, particularly when combined with the influence of race and class, was a determining factor in Giuliani’s victory in 1993 over incumbent mayor David Dinkins. It was not a factor in the 1989 contest between Giuliani and Dinkins.

The 1989 and 1993 New York City mayoral elections appear to be mirror images. In each, the candidates were the same, and a similar proportion of votes decided both outcomes. In 1989, Rudolph Giuliani faced David Dinkins and lost by fewer than 50,000 votes. In 1993, the same candidates faced each another again, and this time Rudolph Giuliani won by 47,000 votes, a difference of 97,000 on a base of nearly 4 million

potential voters. The motivations and reasons behind an individual's vote are complex, and with such small margins, one might conjecture that it was either chance or statistical noise that granted Giuliani his 1993 victory.

The hypothesis of this dissertation states that race, class, and long-term outlook influenced support for Giuliani such that middle class whites and those who were pessimistic about New York City's future would support Giuliani. Nonwhites, those who were not middle class, and those who were not pessimistic about New York City's future would support Dinkins. The key variable that is different between the two races is the voter's long-term outlook for the city, which made a difference in the 1993 election but not in the 1989 contest. The voter's long-term outlook for the city was critical in 1993 given that the city's first African American mayor was finishing his first term and looking to be re-elected. The theory of retrospective voting dictates that if one is satisfied with how the system is working for one's personal well being -- one will not act to change it (Downs 1965). Therefore, those respondents to the pre-election surveys who indicated satisfaction or indifference to the city's future should be inclined to support Dinkins, while those who were dissatisfied should support Giuliani.

Both Dinkins and Giuliani were supported in their contests by coalitions. Political coalitions are fragile entities; small shifts in support make a big difference. Dinkins' coalition consisted of African Americans and other communities of color paired with liberal whites and city employees, while Giuliani's coalition consisted mostly of outer borough whites and the business community. Giuliani's coalition appeared to be relatively stable during both contests, while Dinkins' coalition underwent some major

changes, primarily, a loss of support from various sectors of the African American community.

During his first term, Dinkins was often stuck between the proverbial rock and hard place. On the one hand, he was facing a high crime rate (Thompson 1996). To combat this, he hired five thousand new police officers, angering sections of the African American community because they saw this action as placating scared whites. What Dinkins should have done, and failed to do, according to these groups, was to treat the root cause of the problem, namely poverty (Thompson 1996). Additionally, Dinkins was facing a large budget deficit. To trim costs, Dinkins was forced to fire government employees, many of whom were African American. In New York City, as in other urban areas, one of the primary means of moving up the socio-economic ladder is through civil service. In cutting these jobs, Dinkins eliminated chances for some people to move up the social ladder. Therefore, the first alternative hypothesis states that African Americans, in particular African American males, stayed home instead of coming out to vote (rather than voting for Giuliani). Voter turnout for this group was down considerably from what it was in 1989 diminishing the pool of “natural” constituency that Dinkins had to draw from and providing some support for this hypothesis (Mollenkopf 1995).

In New York City, Jews and African Americans have a long history together. Much of the liberal Democratic establishment was Jewish, and as Dinkins gained political power he counted on them as a second crucial base of support. His reported mishandling of the Crown Heights incident, as well as alleged anti-Semitic remarks by some of his associates, led some liberal and moderate Jewish voters to question their ties to Dinkins. However, as the second alternative hypothesis states, many liberal and moderate Jews

also remained at home, feeling alienated from Dinkins and not wanting to support Giuliani thereby diminishing Dinkins' pool of support. This hypothesis is more difficult to test. Election district data do not contain religion as a variable so determining levels of Jewish turnout is difficult. However, the pre-election survey polls analyzed in Chapters 3 to 6 do ask a respondent's religion, providing a means to at least test the inclination of Jewish respondents to stay home or vote for either candidate.

It is possible to test a third alternative hypothesis, which states that the small change in the proportion of white voters that elected Giuliani was not the causative factor in his victory. Rather his victory largely resulted from the change in votes from Dinkins to Giuliani of a small portion of nonwhite voters who not only felt alienated by Dinkins but also who found Giuliani's message appealing. As it was only a small proportion of votes that elected Giuliani in 1993, this hypothesis is entirely plausible. However, this dissertation ascertains that it was the influence of middle class whites on the election that turned the tide towards Giuliani and away from Dinkins.

There is a fourth alternative hypothesis that is only beginning to be explored in the literature. The transformation of the black-white dynamic in major cities across the US into one that is multicultural including newer immigrant groups within the Asian and Hispanic communities. This alternative hypothesis is particularly critical when discussing New York City politics. Politics in urban areas is traditionally a black vs. white contest, and on the face of it, it seems that the Dinkins vs. Giuliani is a manifestation of this dynamic. African Americans supported Dinkins, while whites supported Giuliani by overwhelming margins. As the margin of victory between Giuliani and Dinkins was so small, the difference could have been made by the newer Asian or Hispanic voting blocs,

rather than movement along the traditional black-white dynamic. During the 1980s and early 1990s, white and African American populations remained relatively stable or decreased, while Asian and Hispanic populations grew due to increased immigration from these areas and subsequent citizenship. While it would be a mistake to state that these newer groups all behave politically in the same manner, their emerging influence on local-level politics should not be dismissed. It is difficult to test this hypothesis in this dissertation, as the datasets used in Chapters 3 to 6 do not differentiate between Asians and non-Asians, while Hispanic versus non-Hispanic is a variable included in the equations in these chapters. However, the dataset used in Chapter 7 does provide an opportunity to test this alternative hypothesis as election district data is paired using an ecological inference method with data from the 1990 Census on race.

Giuliani represented what many middle class voters across the country wanted: a chance at effective government. Dinkins was elected in 1989 in part as an example of racial harmony. His multiracial coalition symbolized for many the best of “rainbow politics.” Over the course of his term, Dinkins committed a series of mistakes that alienated major portions of his coalition, namely his difficulties battling crime, balancing the budget and the specific instances of Crown Heights and the Korean store boycott. Additionally, Dinkins lost middle class support primarily through a perceived failure to control crime. Many New Yorkers saw his personal failures as the failures of a “liberal” government paving the way for Giuliani’s more conservative, more ruthless method of governing (Thompson 1996).

Middle class dissatisfaction with the direction in which the city was headed did more than simply change the occupant of the mayor’s office; it changed city politics in a

conservative direction. In particular, middle class whites had a lot to be pessimistic about during the four years between 1989 and 1993. Their overall numbers shrank both as a share of total population and as a section of the middle class. Whites were no longer the majority racial group in New York City, and the middle class overall had been steadily losing economic ground to both the poor and the rich. As the single largest voting block, middle class whites had long held sway over New York City politics. No candidate could win an election without winning support from at least a substantial minority of these voters. As their numbers shrank, so did their political influence, so that the 1993 mayoral election could be seen as a kind of “last stand.”

This theorized “last stand” is similar to what some scholars stated was occurring within the middle class on a national level during the 1980s and 1990s (Greenberg 1995; Tolchin 1994; Ehrenreich 1990). According to Greenberg and Tolchin among others, the middle class was suffering from a major case of depression (Greenberg 1995; Tolchin 1994). By exploring the middle class in New York City, this dissertation analyzes the applicability of middle class depression and its influence on voting behavior in a local level election.

Candidates win elections when they articulate themes that the voters want to hear. This mobilizes the candidate’s key support groups, and theoretically, increases turnout (Przeworski and Sprague 1986). Articulation was crucial to New York City’s mayoral election. Giuliani was able to give voice to the dissatisfaction that had permeated New York City’s white middle class since 1989, as Clinton did during his 1992 presidential candidacy. New York City was in the midst of a recession, a rising crime rate and increased racial tension; its white middle class feared for its very existence. By

articulating dissatisfaction over the direction the city was taking and offering solutions to some of the major problems facing New York City, Giuliani motivated large numbers of his core constituency to come out and vote. The 1989 and 1993 elections seem a perfect foil to explore this issue, bracketing as they did the pivotal 1992 presidential election (Tolchin 1994; Teixeira 1996).

One cannot discuss class on an urban level without discussing the way race colors class within their specific social constructs. It should be noted that race in this dissertation operates primarily as a distinction between white and nonwhite. Whenever available in the data, further breakdowns of the nonwhite population were used. Additionally, “middle class” refers to the middle class whites unless otherwise noted. On the topic of how race influences class, Terry Nichols Clark states that “[R]ace in America, by promoting hierarchical cleavages, operates like class in Europe,” (Clark 1996: 368); Huckfeldt and Kohfeld (1989) make this same argument. Fiscal conditions and race, according to Brint, tend to eclipse class level discussions (1991). Is this always the case? When people of a certain class sense a dramatic shift in their situation based on economic and social changes, they may react in a unified manner. This can be based in part on their social networks that may have few members of other classes, or on a “neighborhood effect” based on where they live. For the middle class during this period, particularly middle class whites, a sense of diminished “life chances” was taking hold, causing a shift in their political attitudes and beliefs (Greenberg 1995; Tolchin 1996). Race has always served both as a fissure and as a catalyst for change in American politics (Huckfeldt and Kohfeld 1989; Edsall and Edsall 1992.) However, class has also been a powerful component

particularly when the middle class feels squeezed. At such points, class-based concerns may become paramount.¹

By examining the context in which these concerns arose, this dissertation contends that the 1993 election between Giuliani and Dinkins was very different from their 1989 contest. This dissertation first discusses the theoretical basis for discussing race and class's influence on elections. It then examines New York City's history through the 1989 mayoral race in an attempt to "set the stage" for the upcoming chapters (Chapter 1). Chapter 2 is an exploration of Census data from the year 1978 to 1996. This exploration is meant to both color the picture of New York City painted in Chapter 1, and to test if Greenberg's and other's theories about middle class depression can be applied to New York City. Chapters 3 through 6 detail the pre-election survey analysis both in regards to the reasoning behind a pessimistic outlook and for candidate support. Chapter 3 paints an ideological and attitudinal portrait of New York City using the pre-election surveys from the *New York Times*/CBS News organization dating from 1985 to 1994. Chapter 4 presents the result of a multinomial logistic regression analysis of the 1989 pre-election *New York Times*/CBS News survey to determine the causes of candidate support and of a pessimistic outlook in the 1989 election. Chapter 5 uses the same methods to determine the reasons behind pessimistic outlook and the causes of candidate support in the 1993 election. Chapter 6 compares the two elections with each other through the final resultant model based on exit polls from both elections. The actual results from each precinct are used in an ecological inference model in Chapter 7. This chapter details how

¹ I acknowledge that people must have class-consciousness to act as a class. However, none of the datasets used in this dissertation specifically address class-consciousness, so proxies must be used.

the estimated proportions of different racial groups voted. The final chapter presents conclusions on this dissertation and on its implications for scholarly research.

Individual motivations to vote are complex; one must often look to the context of the election in an attempt to discern a voter's reasoning behind his or her choice at the ballot box. The 1993 election between Rudolph Giuliani and David Dinkins occurred in a very different New York City than their first contest in 1989. This dissertation argues that the outcome of the rematch election between Rudolph Giuliani and David Dinkins was not decided on racial lines alone—but that middle class mobilization played a decisive role. Additionally, race and class were filtered through a prism of long-term outlook. In other words, people's views of the long-term prospects for the city substantially affected their voting behavior in 1993. Therefore, the combination of race, class and long-term outlook determined the outcome of the 1993 election.

Chapter 1 Laying the Groundwork

A candidate who presents an identifiable persona to the voters is more likely to be elected. To do so, a candidate must articulate what the potential voter wishes to hear, and then work to mobilize the voter to come to the polls. The voter, in this scenario, also has a task – to vote for the candidate who articulated and mobilized the best. The following review of the empirical and theoretical literature has five main sections. It first discusses how race and class issues have been articulated in the US and in New York City politics. The second section focuses on how candidates have articulated views in order to mobilize constituencies. The third section details the effect of articulation and mobilization on turnout in the past and present. To provide context for examining the elections, a discussion of New York City history will be followed by the theoretical model and definitions of its variables.

The Articulation of Race and Class Perspectives

Articulating the views of a majority of the voters is the first step towards winning an election. To win, rational candidates seek to appeal to the middle ground of voter opinions (Downs 1965). They will not swing too far to the left or the right of the median, to maximize the number of potential voters that they receive (Downs 1965). In turn, the voter uses the information that he or she learns from the candidates' messages to arrive at a decision in the voting booth (Popkin 1991). This method of deciding on a candidate is termed retrospective voting. Voters take into account the candidates' messages and

personas. They then decide if that candidate will improve their personal lot in life. If the candidate is determined to have a possible positive effect on the voter's future, then the candidate will likely obtain that voter's vote (Popkin 1991). On the national level, the major concerns are deemed to be financial (Popkin 1991, MacKuean, Erikson and Stimson 1995). The voters in this scenario are termed "peasants" or "bankers" depending on their financial outlook. Those who view the election as influencing the long-term economic picture are termed "bankers," while those who focus on the short-term are "peasants" (MacKuean, Erikson, and Stimson 1995).

In New York City elections and in other local elections, voters have traditionally looked for a mayor who can "fix" whatever they see as wrong with the city rather than taking the national level focus of "peasant" or "banker." During boom times, this may include such issues as improving service delivery from city employees. However, during bust periods, the voter looks to mayoral candidates to improve the basic standard of living. In New York City, the candidate who seems most able to reduce crime, increase racial harmony and improve the schools (or any combination of the above factors) is more likely to be elected. The articulation of race as a motivating factor or class is not as common on the local level as it is on the national level; therefore, mostly national level sources will be discussed in the following section.

The Articulation of Race

A voluminous literature discusses large and well-documented racial cleavages in American politics. Key's work on racial politics in the Southern states ushered in an

examination of this topic (1949).² Carmines and Stimson postulate that race has an evolutionary effect on national-level politics. At key moments in American history, race has punctuated the national psyche, serving as a catalyst for dramatic political change (Carmines and Stimson 1989). Huckfeldt and Kohfeld counter that since World War Two, race has supplanted class as the mobilization mechanism that draws individuals to their respective political parties (Huckfeldt and Kohfeld 1989). Edsall and Edsall elaborate on Huckfeldt and Kohfeld's view by arguing that racial polarization moved large numbers of working and middle class whites away from the Democratic Party during the 1970s and 1980s (Edsall and Edsall 1992).

Carmines and Stimson categorize three models of change: the critical election realignment model, the secular realignment model and the punctuated equilibrium model. In the latter model, the system moves from a steady state to a rapid pace of change. This shift is caused by a critical moment. Change does not stop with this moment, but continues at a quicker pace than before (Carmines and Stimson 1989, 13). Carmines and Stimson (1989) point to race as an evolutionary issue (14); a candidate's or critical actor's ability to act at the critical moment to bring around a large portion of the electorate determines the success of the transition. Race is a force behind such a punctuated equilibrium because it encourages a bifurcation of views. In the 1960s, race was arguably the dominant cleavage in American politics. Politicians either articulated for integration or exploited racial polarization. Critical actors at the time were able to step in and

² Key (1949) and Converse (1965) are two prominent early scholars. Key focused on what happened to turnout. At the time, the South voted for only one political party, and African Americans were effectively excluded from voting. Thus, turnout was suppressed through lack of choice for the populace (Key 1949).
Footnote continued on next page

persuade the American populace that integration was a necessary and useful step. Subsequently, the system returned to equilibrium (Carmines and Stimson 1989), ushering in a new group of politicians for whom the popular split on race was not a central question, thereby slowing the effect of race on the national political agenda.

Huckfeldt and Kohfeld contend that when the Democratic Party gained the support of African Americans, it lost the support of lower middle class and working class whites, who would not share the party (Huckfeldt and Kohfeld 1989, 10). Race can threaten the party in power in one of several ways; one, numbers of African Americans increase so that they become the majority; or two, politicians manipulate white fears so that they vote along racial lines (Huckfeldt and Kohfeld 1989, 182). Huckfeldt and Kohfeld's argument has a significant empirical basis, but they fail to address the emergence of other racial groups into the political scene. While they predict either a "Balkanization" of parties along racial lines or their fusion (Huckfeldt and Kohfeld 1989, 185-186), neither has occurred.

Edsall and Edsall focus on Republican attempts to gain support from white voters alienated from the Democratic Party. The Republican Party was able to gain support by subtly implying that Democrats were giving special treatment to African Americans to whites' disadvantage (Edsall and Edsall 1992). The portrayal of civil rights as "special rights" or of "welfare programs as minority handouts" began as an effort by Republicans to harness racial fears felt by many working class and middle class whites who were competing for the first time against members of other racial groups for their jobs. Any

Schattschneider detailed how large groups of individuals have been alienated over time (1960). Converse sought to explain the drop-off in turnout by using survey data (1965).

program that gave someone else a “leg up” was deemed unfair and needed to be abolished, according to the Republicans. The GOP positioned itself as the party that could make this happen, and the Democratic Party was ineffective in stopping them, at least until Bill Clinton’s candidacy (Edsall and Edsall 1992, 271).

These three perspectives shed a good deal of light on the national political scene, but they fail to address specific racial concerns in New York City. All three assume an American society bifurcated into white and black. Each study fails to take into account the heterogeneity inherent in broad racial categorizations; in particular, the differences among different white ethnic groups and the changing face of communities of color since the immigration reform of 1965 were ignored. Both the heterogeneity of the white community and the changes within what can be broadly described as communities of color have had profound effects on New York City politics.

The white community in New York City has always contained a variety of ethnic groups. One hundred years after the founding of New Amsterdam, a visitor to New York City counted over 10 different white ethnic groups (Binder and Reimers 1995, 23). This trend continued as New York City became the entrance point for immigrants to the United States. During the 1850s alone, one million immigrants arrived in New York City (Binder and Reimers 1995). Not all the immigrants were white; some of the new arrivals were Asian or Hispanic in origin. When combined with newly arrived African Americans from the South, New York City became the most ethnically diverse city in the US.

However, until the 1920s, whites alone held political power. During the 1920s, African Americans in Harlem organized as part of the Democratic Party (Sleeper 1990). Since this time, shifts in political dominance took place not only in the “white”

community but among different communities of color as well. To summarize, the Dutch, British, Irish, Germans, Italians, and Jews dominated the New York political system, each in succession. In the 1960s, the Democratic Party that had ruled New York City for decades began to admit African Americans and Hispanics into its upper ranks (McNickle 1993). This signaled a change in the racial balance in New York City: no longer would a politician be able to win an election by articulating the concerns of white ethnic groups alone. Now, he or she would have to draw other groups into their inner sanctum and respond to their demands, as well as articulate their desires. Some scholars have stated that this was one of the problems with Dinkins as mayor; he could not respond to all the needs and desires emanating from the different factions within his coalition. This dissertation will argue instead that another force was at work, which was partially beyond his control: voters' increasing pessimism with the direction of New York City.

Articulating Class

Although the majority of Americans consider themselves middle class, a sizable minority consider themselves working class without ever being sure what that means. Portrayals of middle class life dominate television and film to the extent that working class or upper class characters are rare. Huckfeldt and Kohfeld and Edsall and Edsall both believe that the Democratic Party once articulated class-level concerns (primarily working class) as its primary basis of mobilization but pushed to the background class level issues as African Americans started to enter the party (Huckfeldt and Kohfeld 1989;

Edsall and Edsall 1992). This argument is problematic, since it assumes that class-based articulations cannot or will not appeal to members of all races.

Running contrary to this perspective is the literature on materialist versus postmaterialist values in politics.³ Inglehart among others argues that appeals made along traditional class lines will fall on deaf ears, due to the increased standard of living, which has generated a new sense of need. In a postmaterialist society, the market has generally met these basic needs; therefore, the concerns that people have are such that they address “higher order” needs such as the environment or educational quality (Inglehart 1977). However, even Inglehart acknowledges class cleavages have been in place a long time, and will not disappear overnight (Inglehart 1990). His emphasis on economic success as a predictor of postmaterialist values indicates that as a society’s economy improves, so should its predilection for postmaterialist values (Dutch and Taylor 1993). The United States, by all accounts, is a successful economic power. Therefore, successful politicians should no longer articulate working class concerns, but should instead focus on quality of life issues that will appeal to voters across racial boundaries (Pierce, Lovrich, Tsurutani, and Abe 1993).⁴

³ This argument is also known as the industrialist versus postindustrialist argument.

⁴ Wright identifies two themes within the literature. The first is the industrialist versus postindustrialist argument. The second posits that even though we are moving away from the industrial notions of class structure, we still enmeshed in capitalism. Therefore, we will continue to be driven by the “laws of motion within capitalism” (Wright 1997, 91). Within this Marxist conception, work under the post-industrial rubric is even more proletarian as technical expertise is confined to an even smaller section of the population (Wright 1997). Yet Wright admits that the changes brought about by the movement away from industrial capitalism have created a demand for labor with high degrees of technical training that are then divided from more “traditional” laborers lacking training (Wright 1997, 119).

What a candidate articulates matters only if the voters listen, so the message must be packaged so that they do not have to exert a lot of effort (Popkin 1991). However, it is not enough for a candidate to disseminate information and for the voters to listen. To be successful, a candidate must bring the voters to the voting booth; the candidate must mobilize the voters.

Mobilization

It is difficult to answer the question: what brings a voter to the polls? Voters will make the special effort to come to the polls if they feel that they have something to say which can be expressed through voting (Downs 1957). Making sure a voter has an opinion on a subject is one of the primary goals of articulation. Mobilization involves transforming that opinion into a decision to vote. In order to do this, candidates use symbols or symbolic messages that convey the candidate's stand on a particular issue (Edelman 1964). These symbols then resonate with voters and encourage them to vote.

Race and Mobilization

Overtly mobilizing voters by appealing to their race is rare in modern American politics. Aside from a few fringe candidates, politicians do not say "vote for me because I am white," or "vote for me because I am not white." Instead, one finds veiled allusions to race (Hagen 1995). A candidate might say that he or she is closer to the voters' interests, or might align him- or herself with community leaders of a particular racial or ethnic

group. This section will focus on two strands in the literature—mobilization strategies that unite and mobilization strategies that divide.

The literature on unity strategies focuses on people or communities of color. In many cities, candidates from a nonwhite racial group represent a minority population. Relying solely on members of their own community for support is not enough to win an election. The candidate can then opt for a “deracialized” campaign strategy to try to build a multiracial coalition to launch him or her into office.

In “deracialized” or race-neutral campaigns, the agendas of communities of color (most commonly African Americans) are de-emphasized in order to accommodate white voters (Albritton, Amedee, Grenell, and Veal 1996). This type of strategy plays toward issues everyone can agree upon (for example, better education or clean streets) and veer away from issues that can be deemed race-specific (Perry 1991). Race-neutral strategies have helped many public officials get elected—including David Dinkins (Sleeper 1990; Sonnenshein 1993). However, these strategies have also been criticized for abandoning a more progressive stance on issues that affect communities of color for one that “placates” white voters into voting for a nonwhite candidate (Perry 1991; Albritton, Amedee, Grenell and Veal 1996). Jesse Jackson was the first to try this on a national scale with his run for the presidency under the Rainbow Coalition banner. The most common coalition is between African Americans and white liberals (Browning Marshall and Tabb 1996; Sonnenshein 1993; Perry 1991). This strategy can often pull together enough disparate voting blocs on the local level to win an election, as in Los Angeles under Tom Bradley or New York City with Dinkins (Sonnenshein 1993). The coalition of African Americans and white liberals works because these groups have similar progressive agendas. This

shared agenda speaks to all progressive and moderate voters regardless of race and usually results in victory.

Aside from direct appeals to vote against a candidate due to his or her race, the main dividing strategy employs racial symbols or veiled racism to mobilize voters against a candidate of color. Society generally does not allow a public and open campaign against a candidate today due to his or her race. However, these campaigns do exist in a covert manner. According to Hagen, whites ascribe anti-African American references to all minority races (Hagen 1995, 61). White politicians speak this new language of race most often to a white electorate using references to “law and order,” “crime,” or “welfare.” Crime became a shorthand to some white voters touching on their fears of social unrest (Edsall and Edsall 1991; Hagen 1996; Gilens 1996). Candidate support for poverty programs and welfare also took on a racial dimension (Hagen 1995). White candidates who espoused support for these types of programs were seen as colluding with members of other racial groups, possibly alienating white voters (Hagen 1995).⁵ Republicans under Reagan and Bush became known for speaking to white voters in these terms (Huckfeldt and Kohfeld 1989; Edsall and Edsall 1991; Hagen 1995). Giuliani also spoke often of the need for law and order and cutting welfare in his campaigns. While some minority voters who responded to his divisive message, most saw it as an appeal to white voters to oust a mayor who was not working in “their” interests.

⁵ Gilens’ study based on the 1991 National Race and Politics Study illustrates how racial attitudes are significant indicators of whites’ opinions on welfare. When the respondents were given one of two descriptions of a welfare recipient—one African American and one white—white respondents given the portrayal of the African American mother were more likely to be hostile towards welfare policy (Gilean 1996: 600). “...negative beliefs about black welfare mothers were associated with significantly more negative views of welfare in general than were negative beliefs about white welfare mothers (600).”

Class and Mobilization

Some may ask why the U.S. lacks a working class political party when a sizable proportion of the citizenry states that they are indeed working class (Jackman and Jackman 1983). This seems strange; if a proportion of the population identifies with being working class then a party should emerge to speak to their issues. Huckfeldt and Kohfeld are not alone in stating that the U.S. did have a party that addressed working class issues (the Democratic Party) and when the Party began addressing the concerns of blacks, working class whites left in droves (Huckfeldt and Kohfeld 1989). They either went to the Republican Party or did not vote at all. Edsall and Edsall underscore the fact that whites did not join the Republican Party because it was addressing working class issues, but instead because it addressed their race-based fears (Edsall and Edsall 1992).

When the modern period is contrasted with the 19th century, it becomes apparent that when parties that once addressed lower class or working class issues, but later stopped doing so, turnout fell (Hill and Leighley 1992; Piven and Cloward 1988.) During the New Deal and post-New Deal era, working class issues again came to the foreground, only to be overshadowed by race in the 1960s (Huckfeldt and Kohfeld 1989). The consensus is that the power of class to mobilize voters is on the decline (Hout, Brooks and Manza 1995). Przeworski and Sprague trace the decline of class-based parties in Europe to the inclusion of middle class members (Przeworski and Sprague 1986.)

If one believes in class-based mobilization, what issues should be employed in a campaign? Hill and Leighley state that the more liberal and pluralistic the Democratic Party is, the more likely it is that working class people will vote Democrat (Hill and

Leighley 1992). This raises the question: why do middle class or upper class people not vote for them too? Traditionally, the working class has had its own issues and leaders knew that they needed to dilute their class message if they were to add middle class voters to their working class base (Przeworski and Sprague 1986). Instead, mobilizing from the middle from the outset would be a more rational way to gain a majority. This is what Clinton did in 1992 and what many postindustrialists argue is currently happening in Europe (Przeworski and Sprague 1986; Inglehart 1990). Political focus has shifted from working class to middle class.

Perhaps the best hope for mobilizing urban voters lies not along race or class lines, but in areas where they intersect. DiGaetano notes that in cities converting from an industrial to a postindustrial economy, the progressive pro-growth coalition is often the best way to address issues that concern all residents (regardless of class standing or racial background) (DiGaetano 1991). These coalitions are usually multiracial and multiclass. It was this type of coalition that mobilized voters to vote for David Dinkins in 1989. This type of coalition also appeared at the start of Koch's first term as mayor, although he dispensed with it soon afterwards (Mollenkopf 1993). However, as DiGaetano indicates, the polarization of population along race and class lines due to outside forces could topple the coalition (DiGaetano 1991).

Turnout

Turnout is defined as the percentage of the voting age population who vote. Turnout has declined dramatically since the late 1800s; scholars have arrived at two broad

reasons for the decline: institutional changes and lack of party competition. The institutional-level reasons for not voting are currently based in registration difficulties and short polling hours. Prior to the 1964 Voting Rights Act, voters were further hindered by poll taxes and literacy tests that were constructed to keep African Americans and poor whites from voting in the South. Northern cities had higher levels of African Americans voting (Niemi and Weisberg 1984). These higher levels in turn increased party competition. High levels of competition have a circular effect on voting behavior as they encourage more people to vote; the more people who vote, the greater the competition (Niemi and Weisberg 1984). Higher levels of competition combined with a decrease in institutional restrictions should have increased turnout. Instead, turnout on all levels of elections has continued to decline (Niemi and Weisberg 1984).

Race and Turnout

Before 1964, the main institutional barrier to voting was race. Poll taxes and literacy tests were instituted in the South primarily to keep African Americans from voting. Additionally, in the late 19th Century, ballot reforms such as printed ballots and secret ballots discouraged illiterate voters (Niemi and Weisberg 1984). Currently the interaction between race and turnout is due to individual candidate appeal rather than institutional barriers. Voting is, in many regards, based in irrationality. Citizens turn out to vote for myriad reasons, not the least of which is the feeling that they “have” to. As we live in a democracy, it is expected of us to vote. Yet, a voter may rationalize not voting because he or she knows that her vote is unlikely to determine the outcome (Olson 1965).

Therefore, a candidate's ability to differentially mobilize voters can often determine the results on Election Day. Both the candidacies of Jesse Jackson and David Dinkins elicited unprecedentedly high turnout levels in the African American community in New York City (Mollenkopf 1997). Yet the ability to sustain momentum depends on the candidate and the coalition backing them to continuously "Get Out the Vote" (Browning, Marshall and Tabb 1996).

Racial turnout levels are also influenced by the "newness" of the racial group.⁶ The relatively "new" status of many Asian Americans and Hispanics has limited their potential clout through low turnout. The low turnout in these groups inhibits politicians from "wasting" mobilization efforts on them such as registration drives. This becomes a circular pattern, as there are few efforts to include these groups, and the turnout rates for them during even critical elections remains low. In New York City, this is a particular burden due to the multiracial coalitions needed to win an election (Mollenkopf 1997).

Class and Turnout

One of the most important discussions of class deals with the relationship between social class and voting (including turnout and candidate choice). Most of these studies define class through measures of socioeconomic status. Income, education and occupation are the three most common operationalizing measures of class. Income demarcations are most common, due to readily available government statistics used to determine class-based programs. Education is also used to distinguish between different

classes, although perhaps this was more useful when few people had post-secondary education. Occupation is used, most specifically, in the distinction between blue- and white-collar workers. These socioeconomic factors are also used in combination. For example, blue-collar workers who did not attend college are one key voting group (Teixeira 1996).

However, these distinctions pose specific problems. Political scientists have long known that education and income predict the likelihood of voting. These individuals also tend to have high-status occupations. Leighley and Nagler (1992) indicate that, “the magnitude of the difference (in socioeconomic terms between voters and non-voters), and more importantly, its stability over time are disputed” (Leighley and Nagler 1992, 725).

Leighley and Nagler (1992) ask whether turnout for various socioeconomic groups has risen or declined over time, and review work by many scholars during the last 25 years. They find that the correlation between income and turnout has remained stable over the last twenty-five years. Comparing 1964 with 1984, the turnout rates of the two lowest income fifths had increased, the middle fifth decreased slightly and the upper two-fifths remained stable (Leighley and Nagler 1992, 728). Scholars who found an unstable or declining relationship used factors other than income to determine their groups (Leighley and Nagler 1992). Burnham argues, for example, that turnout has decreased faster among men whose jobs were classified as manual labor than for men whose jobs were classified as white-collar (Burnham 1987). Leighley and Nagler state that income is preferable to occupation for two main reasons: one, the government uses income to

⁶ “Newness” refers to the arrival of Latino and Asian residents in the US after the 1964 immigration reform.

determine policy; and two, there is a great deal of ambiguity inherent in occupational status (Leighley and Nagler 1992, 727). Some jobs can be either white-collar or blue-collar or both, calling for a more nuanced examination of the effect of occupation on political behavior.⁷ Education poses a similar problem. Since more and more people are obtaining at least a high school degree, and more and more jobs are informally requiring some schooling beyond college, it becomes more difficult to classify educational achievement.

The main reason behind the decrease in turnout when examined from an income class basis is the lack of class-based appeals arising from the Democratic Party. While this may be true to some degree—due either to the unreliable support of labor unions or to the acknowledgement that it is difficult for African Americans and working class whites to “live” under the same party roof—it is also true that the Democrats have not entirely given up on class-based appeals (Huckfeldt and Kohfeld 1989; Weakliem 1997). The Democratic Party has simply changed classes. The middle class in America (however one defines it) is the focus of the Democratic Party. President Clinton tailored his campaign to its concerns, knowing that middle class voters were not only the most disgruntled but also the largest group (Greenberg 1995; Teixeira 1996). The shrinkage of the working class, and its decline in support for the Democratic Party since World War Two, indicates that it has become a less important group. Politicians tend to be “rational;”

⁷ In his work *Classes* (1985), Wright describes the different modern class groupings as consisting of crosscutting cleavages, therefore, a group that can be both worker class and *petit bourgeois* at the same time.

they will focus on groups that hold the majority of votes, and during the 1990s, this was the middle class.

The economy remains relevant to voting behavior. Since New York City experienced a severe downturn between 1989 and 1993, the 1993 election offers an ideal venue for analyzing the effects of pocketbook voting on an urban election. If a voter's economic standing has decreased since the last election, it grows more likely that he or she will likely vote against the party in power as a means of redressing his or her economic grievances (Rosenstone 1982).⁸ In theory, the reverse should also be true: when an individual's economic standing improves, he or she should tend to support the incumbent (Welch and Hibbing 1992). However, scholarly evidence supporting these claims is relatively weak (see Welch and Hibbing 1992, pp. 198-200). It does appear that recessions depress turnout more than changing the direction of the vote (Rosenstone 1982).

The Middle Class?

Identifying members of the middle class in modern U.S. society is somewhat confusing, since studies have shown that nearly everyone considers himself or herself part of the middle class. Therefore, it is analytically important how one defines middle class. For Marx, the essential feature of class was the relationship of the worker to the means of production, an economic concept. Capitalists exploited workers. The two classes, workers

⁸ Some support for this line of reasoning is found in Thomas and Bass's work on Clinton's victory in 1992. Factor B, as they term it, is a defeat for Bush rather than a victory for Clinton due to the recession (Thomas and Bass 1996, 322).

and capitalists, existed in conflict with one another. Interestingly, Marx did not directly confront the problem of how to fit the middle class into his model; so, he never bothered to define it (Wright 1985, 2). Marx's middle class was the "petty bourgeoisie." Since they were not capitalists, they had to be workers, locked into an antagonistic relationship over the control of economic resources.

Weber offered a more fluid definition of class that is relational rather than antagonistic. While Weber does not define the middle class, he allows for its existence. Instead of using the relatively immobile relationship of the means of production, an economic measure, as Marx did, Weber relied on status hierarchies and the relationship to the means of consumption (Weber 1956). He sought to analyze how class interacts with other means of grouping people in a modern society such as race and ethnicity. These status hierarchies were residence-based than workplace-based, allowing for a middle class simply because more than two classes could compete with one another for control of the economic realm (Weber 1956). Weber was as concerned with consumption as he was with production. In Weber's world, one could move out of one class or status group and into another through education (Weber 1956).

Both Marx and Weber have modern followers. Neo-Marxists construct the middle class according to four primary theories. First, all those who are neither working class nor capitalist are really manifestations of the working class—the most traditional Marxist line of thinking. The middle class, i.e., managers, engineers and professionals, sell their labor to an employer and are therefore part of the working class in the same manner as a factory worker thereby extending Marx's original economic/workplace line of class demarcation (Jackman and Jackman 1983, 54). This line of reasoning is not particularly compelling

when discussing the modern class structure; as Jackson and Jackson state, “The frequent appearance of only two sides does not reflect the underlying structure of relationships, but rather results from the formation of transitory coalitions among multiple contenders for power” (Jackman and Jackman 1983, 5). In addition, this line of thinking best typifies situations where there are usually only two sides to the conflict (Vanneman and Cannon 1996, 39). This theory also does not adequately allow analysis hierarchies developed outside of the workplace.

The second theory treats the middle class as Marx’s “new petty bourgeoisie.” This is similar to Poulantzas’ way of thinking (Wright 1985). Poulantzas’ emphasis on productive versus unproductive labor places service workers in the unproductive labor category (Wright 1985, 154). Since service workers represent a large sector of today’s economy, this distinction limits Poulantzas’ applicability to modern urban class definitions. Poulantzas placed the middle class within the traditional Marxist framework by identifying three basic divisions between workers and capitalists. The economic division is primarily due to the capitalist nature of society (Vanneman and Cannon 1996, 56). The political division is maintained through the supervisory authority managers have over their workers. Finally, ideological division divides mental laborers (the managers, professionals, etc.) from manual laborers (Vanneman and Cannon 1996, 57).

All of these divisions occur within the workplace, and the workplace is Poulantzas, who focuses on power and exploitation. The middle class has the power to both exploit and be exploited, both of which have developed throughout modern history. The division between mental and manual labor is in some ways the most difficult concept for the modern scholar. Mental labor workers keep the ability to think and to maintain

control over their own thoughts. Poulantzas argues that although people who labor mentally retain some degree of freedom within their jobs, their labor is still subordinate to the interests of the capitalists (Wright 1985, 155). Interestingly, Poulantzas groups clerical workers in the mental labor category. Wright counters by saying that although clerical workers might use their brain, their work is inherently manual (Wright 1985, 155). Much of what clerical workers do consists of data processing. In this light, they are assembly line workers of the service sector (Wright 1985, 155).

In addition, Poulantzas' distinction between productive and unproductive labor is problematic because he includes within the unproductive sector industries such as finance, real estate and insurance (FIRE) as well as government employees (Wright 1985, 154). Poulantzas considers them unproductive because they do not "produce" surplus value. Instead, they are paid out of other workers' surplus value. However, these industries are an important part of the modern urban economy (Drennan 1991). Characterizing them as unproductive seems parochial.

A third Neo-Marxist view, typified by Vanneman and Cannon (1996), sees the middle class as a new class, both subordinate and rival to the capitalist class. This analysis "retains the concept of class as a social relationship between dominant and subordinate groups" (Vanneman and Cannon 1996, 40). They argue that class is useful for understanding conflict in American society while status hierarchies are useful for observing lifestyle (Vanneman and Cannon 1996, 46). This distinction seems arbitrary. Many people use lifestyle as the discerning factor between classes (Vanneman and Cannon 1996). Conflict is an inherent part of lifestyle. It infiltrates advertising and

consumption patterns. The phrase “keeping up with the Joneses” is meant literally; if we do not keep up with our peers, we will lose the battle and be left behind.

The fourth Neo-Marxist definition of the middle class places it outside the basic model of class relations (Wright 1985, 38-41). Wright attempts to place the middle class both within the workplace and within society, but he is unable to leave the workplace due to his central emphasis on class exploitation. Wright considers the middle class citizen a member of many classes simultaneously. As Wright contends, “contradictory locations are contradictory precisely in the sense that they partake of both sides of these inherently contradictory interests” (Wright 1985, 42). For example, a manager works for capitalists but also manages labor, making him or her both capitalist and working class. Distinctions such as gender, race and ethnicity have also united or divided people within or across their traditional class locations.

There have been a number of expansions on Weber’s ideas of status hierarchies. Many Weber-based theories are residence-based. Hierarchies of occupational status and income are more important in the neighborhood than they are at work. How much a person earns at his or her job contributes greatly to modern perceptions of social status. Some neo-Weberian scholars have argued that social relations in urban areas are based on ownership of domestic property. These scholars theorize that tenure-based divisions within neighborhoods are also likely to engender class-consciousness, albeit not along the lines of Marx (Davis 1992, 27). Therefore, neighborhoods might be designated as middle class by the virtue of having many homeowners. Saunders, in contrast, believed that housing was not the total of “achieved life chances,” but rather an entity that could affect those life chances (Davis 1992, 31). Using housing as a class division allows for the

creation of distinct residential housing classes, which can be very different from the Marxist view of classes based in the workplace.

One of the main ways in which people are placed, or place themselves within social hierarchies, is through status. Status ranks people according to their occupational, income-based, and consumption characteristics. Consumption patterns often determine how a person is perceived in society and how he or she perceives himself or herself. For example, Hochschild employs points along a continuum of stratification of status rather than a dichotomous distinction between owners and workers (Hochschild 1995, 276). This is more useful to this discussion of class, which does not explore class conflict but rather inquires about how the way a particular class has fared influences its political attitudes and behavior.

Other scholars have modified this model. Yet, taken as a whole, the literature often fails to address the specific nature of class differentiation within urban areas. In New York City, middle class whites have long held a privileged position. Until recently, they represented the majority of both residents and the electorate. Now, they are only the majority of the electorate.

Members of the American middle class today perceive others as having more, or at least more than they deserve (Greenberg 1995). Many middle class individuals see themselves as deserving something better. Growing up in an atmosphere where “everyone” seemingly had a single-family home, a steady job and two cars, creates an unintentional feeling of entitlement that can carry into the voting booth. Unfortunately, the literature about the distinctly urban middle class is scarce. For the most part, it discusses the suburban middle class, although their concerns may well be similar. For

many, statements such as “the American dream of the last half-century has been revoked for millions of people—a dream rooted in a secure job, a home in the suburbs, the option for families to live on one income rather than two, a better life than your parents had and a still-better life for your children,” typify middle class disillusionment (Bartlett and Steele 1996, 1). Hochschild uncovers four flaws in the American Dream. Not everyone can participate in it equally, as the dream assumes. She discusses this important point in her work, *Facing Up To the American Dream: Race, Class and the Soul of the Nation* (1995). The second flaw is that Americans, as individuals, have an unreasonable expectation of success. This, in turn, fosters envy and hatred between the haves and have-nots. “In short, the right to aspire to success works as an ideological substitute for a guarantee of success only if it begins to approach it” (Hochschild 1995, 27). The more people achieve the dream, the more those who have been left behind become bitter (Hochschild 1995). This is especially true for the urban white middle class; who see others (nonwhites) taking over “their” territory and “their” jobs. In addition, if they cannot afford to leave the city, their frustration is compounded by feeling trapped. The perception that failure to succeed is a personal downfall is the third flaw with the American Dream. One fails only because one did not work hard or long enough, or want the dream badly enough to achieve all that one deserves. This leads to the fourth flaw, “if success implies virtue, then failure implies sin” (Hochschild 1995, 30). President Reagan was able to capitalize on this notion during his restructuring of the welfare system (Katz 1995), as did Horatio Alger at the turn of the century. This notion of failure as sin is especially demoralizing, since so many Americans have extremely high expectations for success. In a recent survey directed at the middle class, 15 percent of the respondents

stated that to be middle class, one had to make over \$200,000 a year (Wolfe 1998). Earning that amount places a member of the middle class well in the top one percent of the nation's earners. At the same time from 1972 to 1992, only ten percent of the General Social Survey sample stated that they were either lower or upper class at any given time. In light of all this evidence, how can the middle class be shrinking? In a National Opinion Research Center Survey, only when a household's income exceeds 20 percent of the median income does a large majority of respondents label themselves middle class (Miller and Ferroggiaro 1995).⁹ Movement out of the middle class has increased in recent years (Duncan, Smeeding and Rodgers 1992). Taking a dynamic view, Duncan, Smeeding and Rodgers found that during the 1980s, middle class individuals were more likely to fall out of the middle class into a lower income class than to move into the upper classes (Duncan, Smeeding and Rodgers 1992, 14).¹⁰

If the American Dream were truly achievable for most people, these numbers would be reversed. While studies do not agree on a single definition of middle class, they all arrive at the same conclusion: the middle class has shrunk, in terms of its share of the

⁹ Miller and Ferroggiaro contrast this with the results of the General Social Survey where the majority said that they were middle class when presented with three possible answers (Lower, Middle and Upper). When they were presented with four possible answers (Lower, Working, Middle and Upper), the proportion that stated that they were middle class dropped to the same level who said that they were part of the working class. Reports that state that there is a huge middle class usually report the results of the three-answer question rather than the four-answer question (Miller and Ferroggiaro 1995).

¹⁰ Duncan, Smeeding and Rodgers (1992) arrived at this conclusion after analyzing 22 years of Panel Study of Income Dynamic's data. They used a definition of middle class as ranging from 20 to 90 percent of the income of prime age (25 to 54) adults. They found that especially during the 1980s, members of the middle class (without family size taken into account) were more likely to fall into a lower income bracket than to rise into the upper income bracket. The second measure was the income-to-needs ratio symbolizing the ratio of family income to the poverty level for the same size family. The proportion in the middle income-to-needs ratio category declined sharply after the 1970s (8). Slightly more than two-thirds of the population was in the middle-income category (11), as compared with 75 percent during the 1970s.

wealth and income of the United States. The current political tide reflects this; more people are voting against taxes and programs for the poor because they fear for their own financial security (Greenberg 1995).

Middle Class in Recent New York City History

Cities originated as market centers where individuals would come to sell wares and produce. Eventually, as these markets became institutionalized, cities became the economic and political centers of the emerging capitalist economy. As cities in the U.S. expanded and became more important, state and federal governments constricted their autonomous power (Peterson 1981). Cities became limited in their ability to control their own destinies. This is especially true in the case of New York City, making it hard for New York to try to keep itself middle-class-friendly. The alternating economic devastation and skyrocketing popularity of New York threatened the position of its middle class. The middle class found itself fearing for its communal survival either by being “forced” from their homes by neighborhood decline and racial succession, or being priced out by skyrocketing housing costs; neither one of these makes for a healthy city.

When one listens to middle class whites in New York City, one usually imagines hearing a thick outer borough accent, however, many white New Yorkers have stayed in Manhattan.¹¹ The three major ethnic groupings within the white middle class are Irish, Italians and Jewish. Each group has held influence at different times and each has come into conflict with the others. Members of all white ethnic groups scored steady economic

and political gains between 1945 and 1970. As quotas were dropped from universities and professional schools, the children of immigrants were able to move into the middle class. As they moved up the social ladder, many also moved to the suburbs. Binder and Reimers note that in the 1940s, more than four hundred thousand white New Yorkers moved out of the city, a figure which grew to 1.2 million in the 1950s (Binder and Reimers 1995, 206). Those who moved could commute back to the city by train or bus.

As New York City entered the 1960s, it seemed that its position at the top of the nation was invulnerable (Bellush and Netzer 1990). This period was also the height of a large-scale residential movement out of the city to the more affordable suburbs. The development of inexpensive housing developments and affordable transportation alternatives led both to a commuter nightmare and to shrunken tax coffers. The loss of a large residential tax base was to have unforeseen effects on the city's economy, however, just as new social services were being enacted to help the city's poor.

The movement of industry to cheaper locations also eroded the tax base. Before this period, business taxes and expensive real estate represented the high cost of doing business in New York (Bellush and Netzer 1990). During the 1960s, both manufacturing and corporate headquarters left New York in droves as other cities vied for the position as global headquarters. Mayor Lindsay was able to balance the budget while increasing services, but only by increasing taxes on businesses, further heightening the risk of corporate flight (Bellush and Netzer 1990).

¹¹ The Outer Boroughs of New York City are the Bronx, Brooklyn, Queens and Staten Island.

The out-migration of large sections of the white middle class left those who remained “vulnerable to the incursion on their territory by others.” Eight hundred thousand African Americans and Puerto Ricans moved in during the 1950s (Sleeper 1990, 76). It seemed, as Jim Sleeper stated, we were “integrated before we knew it” (Sleeper 1990, 68). Before the 1960s, African Americans and whites often shared the same neighborhood and schools without major incidents. Citywide institutions like mass transportation and the City University system united poor and middle class individuals into a broader civic culture (Sleeper 1990).

Yet, the feeling of vulnerability combined with entitlement was also pervasive during this period. Some working class whites needed to feel superior to someone (usually African Americans). New Yorkers had led the way in combating discrimination (Sleeper 1990). However, not everyone shared this sentiment. As Rieder indicates in his work on Canarsie, accepting a few “good” African Americans moving into the neighborhood gave way to widespread panic as their numbers increased (Rieder 1985). The influx of middle and lower middle class African Americans and Latinos into the white ethnic neighborhoods represented the demise of New York City to their residents. As one resident said, “[T]he element had unbridled appetites. Their culture, considered an anti-culture, devalued the respect and duties that convert natural beings into civilized people” (Rieder 1985, 66).

The white middle class also experienced economic distress during this period, as New York rapidly became a postindustrial economy. Between 1950 and 1990, New York saw a drop from 30% employment in manufacturing to about 10%. This was accompanied by a growth from 9.7% in 1950 to 14.7% employment in FIRE (Finance,

Insurance and Real Estate) (Mollenkopf 1992, 54). This shift eliminated many traditional employment sectors of the white middle class. Until this period, a high-paying union manufacturing job's salary could allow one and one's family to enter the middle class. The good jobs that remain after this transformation usually require a college degree at a minimum. In addition, the influx of immigrants and women into the labor force displaced many older members of the white middle class.

These economic and industrial changes resulted in a new division of labor. Overall, whites still tend to occupy management positions in corporate services, government and construction, while African Americans tend to be concentrated in the lower-paying health care and government sectors (Mollenkopf 1992). Hispanics have migrated to the few remaining manufacturing jobs as well as food service. These transformations of New York's social structure both increased the need for social services and decreased the tax base (Mollenkopf 1992).

Theory, Hypotheses and Definitions

This dissertation's theory is that middle class whites constitute the volatile element in New York City politics. Race and class intersect within the middle class white population of New York City, and it was the support of this group caused Giuliani to be elected. Giuliani did a better job than Dinkins in articulating the concerns of a large disgruntled group of New Yorkers. These middle class white New Yorkers responded by turning out to vote for Giuliani, either as they had already in 1989 or by abandoning their past (1989) support for Dinkins. This dissertation tells the story of these individuals. Chapter 2 sketches their economic background. Chapter 3 draws out salient voter

attitudes during each election period. Chapters 4 through 6 build on the evidence in Chapter 3. By examining how race and class are differently affected by long-term outlook, chapters 4 through 6 employ an analysis of *New York Times*/CBS News survey data, exploring attitudinal questions. The final research chapter, Chapter 7, analyzes election district data made available by John Mollenkopf. The hypothesis for this chapter is that the model from Chapters 4 through 6 will hold true.

In an effort to confirm these hypotheses, one contextual and two analytical data sources will be utilized. The first data source is contextual; the U.S. Census conducts the Housing and Vacancy Survey (HOUSING AND VACANCY SURVEY) every three to four years. It contains information on housing stock, demographics and residential movement patterns throughout the city to establish the socio-economic contexts for the two elections. Shifts in income, both personal and household, shifts in occupations and industries and other demographic information from 1978 to 1996 will be examined. The first analytical data source consists of sample surveys conducted by the *New York Times*/CBS News pollsters to measure the attitudes of New Yorkers around the mayoral elections. One survey from 1985 serves as a benchmark. The subsequent surveys were taken in 1988, 1989, 1993 and 1994. To depict who is pessimistic in New York City at the time of both elections, logistic regressions on a long-term outlook indicator for pessimism or non-pessimism will be run. Multinomial logistic regression will be used to analyze the causes of shifts in candidate support. John Mollenkopf created the second analytical dataset, linking election district data with Census data to make ecological analysis possible. An ecological regression technique developed by Gary King will be used to analyze this dataset.

Definitions

In this dissertation, race is operationally defined as an individual's self-reported ethnic group. This dissertation will use three data sources to triangulate and cross-support the conclusions. These data sources all rely on self-reported sources of information about the respondent's racial or ethnic group. The basic question asked across all three datasets is: "Do you consider yourself white, Black, Asian or Other?" The Census further breaks down the Asian and Other categories. Hispanic origin is classified by the Census as an ethnic group rather than a racial category. Wherever possible, Hispanic origin or its absence was combined with race to create non-Hispanic categories and a Hispanic category (regardless of race). This combination was not used in Chapters 3 through 6 because during some years, Hispanic origin was not identified in such a way that it could be cross-classified with other races (*New York Times*/CBS News poll 1985).

Defining class for this dissertation was much more problematic than defining race. As previously mentioned, Marx first postulated the notion of a class of individuals as defined by their economic status. Since then, many different theoretical definitions of class have emerged, and all have been used in various forms in social science research. This section will describe these definitions. There are three primary problems when discussing class in the modern American urban environment. First, many scholars do not think that there are class distinctions in the U.S. at all. Many people operate under the assumption that the class structure is static, so that the U.S., with its relatively fluid patterns of social mobility, cannot have a class structure. This dissertation, however,

assumes that there are classes in American society. While this is a major assumption, it has been successfully handled in previous research. The second problem is discerning class's primary location—is it in the workplace or in the residence, or both? Due to the concentration on place-based politics within cities (Katznelson 1981), this dissertation will concentrate on place-based status factors. The economic and social changes cause “class anxiety” because they threaten people’s lifestyles and their ability to consume and to enjoy this consumption. These levels of anxiety can result from what Greenberg terms “the middle class squeeze” and a stagnated sense of social mobility, due to a falling income and standard of living (Greenberg 1995). This is especially important when discussing the place or role of the middle class, since neither Marx nor Weber confronts the middle class directly.

The third problem is deciding which socio-economic factors are appropriate for studying class on the local level. Many scholars have used the term “professional/managerial class” to describe the modern middle class (Ehrenreich 1990, Brint 1991). The “professional/managerial class” consists of “[p]eople who earn at least a middling income from the application of a relatively complex body of knowledge. Professional services can involve teaching, healing, advocating in court, building, designing, accounting, researching, or any one of a number of other activities requiring advanced training in a field of learning and non-routine mental operations (Brint 1991, 3)”

These jobs, and the people who hold them, are becoming increasingly important in our postindustrial economy. The shift to the service sector has led these individuals to become at least 30% of the labor force in New York City (Brint 1991, 155). This class is

also particularly important in the urban economy because it is the fastest growing job sector. However, using these classifications, rather than income classifications, limits the scope of the middle-class. There are many members of the middle class whose jobs may not require an advanced degree (policemen, firemen, computer programmers or technicians etc.) but whose income places them firmly in the middle-income levels. Therefore, this dissertation's definition of class for New York City focuses on income levels.¹²

In Chapter 2, the income classes will be divided according to HUD's qualifications for housing assistance in Fiscal Year 1997.

¹² Ideally, I would have liked to analyze class-level issues based on class consciousness, which would allow me to explore how people's political attitudes directly relate to how they perceive themselves. Unfortunately, the data does not exist on the local level. Much of the data is incomplete on questions of class consciousness, if it is asked about at all. Therefore, a person's class must be inferred based on where he or she fits within a socioeconomic framework. Income-based definitions are useful for two main reasons. First is that income is the main means by which people measure themselves against their neighbors. A common question is "How much do you make?" and not "How many people do you supervise?" or "What sort of authority do you have over company policy?" It is assumed that people who make a lot of money have high-powered jobs. The other reason is that the government uses income when discussing class-based programs. Income breakdowns are the easiest and most consistent across datasets to accomplish this. I had hoped to use the same income divisions so that the individuals analyzed will be comparable across datasets. However, that was not possible. Therefore, my income breakdown for class will be specific to each dataset.

Table 1.1 HUD 1997 Definitions of Middle Class Households

# of People in Family{P RIVATE }	1	2	3	4	5	6	7	8
Middle Class Income	27,450- 68,600	31,350- 78,400	35,300- 88,200	39,200- 98,000	42,350- 105,800	45,450- 113,600	48,600- 121,600	51,750- 129,400

Those who earn less than 80 percent of the median income are considered low income, 80 percent of the median to the median comprises lower middle income, the median to two times the median is middle income and over two times the median is upper income. Income was divided in this manner, because in terms of demographic data and the ability to track the actual changes, this is the most detailed dataset. The HUD qualifications are also weighted by family size so it is much easier to get an accurate description of what was really happening to each family in each income class and how that translated to the class as a whole.

In Chapters 3 through 6, a dataset based on the *New York Times*/CBS News polls is used. As in most polls, pollsters ask about income rangers, not exact amounts. For example, a question might read: "Would you say your family income last year was less than \$15,000, between \$15,000 and \$30,000, between \$30,000 and \$60,000 or over \$60,000?" In asking the question in this manner, it is hoped that the respondent will give a more honest response than had the pollster asked for the actual dollar amount. Since many people are embarrassed or hesitant to give their actual income, this approach reduces the risk of respondent-based error. Low-income respondents are those who respond in the lowest two categories. Middle-income respondents are those with the

middle two income categories, and high-income respondents are those in the highest income categories.

The dataset in Chapter 7 matches election district data (votes and registered party affiliation and no demographics) with census tract demographic data. Since aggregate data is being analyzed, using the individual-level responses for income questions would not be appropriate. Instead, the population was broken down into three categories: low income (less than \$22,500 in household income), middle income (between \$22,500 and \$60,000 in household income) and upper income (\$60,000 or more).

This dissertation will try to determine through the use of a triangulation strategy, the determining factors behind Giuliani's victory in 1993. While the hypothesis states that it was the middle class white community that was the volatile element, there may have been other groups that were at least as volatile. Whenever possible, this dissertation will attempt to elucidate other factors that may have been responsible.

Chapter 2 Setting the Stage: An Analysis of Census Data

The middle class perceives its decline as due in large part to diminished economic opportunities. Members of the middle class were raised to believe that they could improve upon their parents' financial situation (Ehrenreich 1990, Newman 1993, Hochschild 1995, Greenberg 1995). The largest segment within the middle class is the baby boom generation. Their parents, buoyed by the GI Bill and other post-World War Two policies, were encouraged to pursue upward mobility and home ownership, leading to a much higher quality of life than their parents had enjoyed during the early part of this century. However, many current members of the middle class are finding this postwar standard hard if not impossible to achieve.

The American Dream, broadly conceived as homeownership, job security and an improvement in the standard of living from one's childhood, has eroded in large part due to four economic factors:

1. A tight housing market with exorbitant housing prices due to a decline in new home construction that has only begun to be reversed in the past few years (Census 1999).
2. Occupational insecurity caused by waves of downsizing that have gripped the American corporate scene since the early 1980s.
3. Limited job mobility due to an excess of overly qualified individuals competing for fewer jobs.
4. An increase in the cost required to maintain a "middle class lifestyle" (Newman 1993, 11).

New York City has been especially hard hit by the above four factors. “Middle classness” began as an urban phenomenon (City Council 1997). The urban middle class, especially the white urban middle class, has seen its position erode over the last 50 years as economic life in cities became more bifurcated. Rapid increases in the proportion of the population living in poverty as well as modest increases on the opposite end of the spectrum has left members of New York City’s middle class feeling stranded. Many members of the urban middle class chose to move to the suburbs rather than face the daily challenges of living in a major urban area. This has shrunk the city tax base, forcing it to make choices that make the city more unpopular for middle class residents of all races (City Council 1997). As the city diverts its attention away from programs and policies that favor the middle class, it becomes a less desirable place to live. This translates into a loss of well-paying jobs and a poorer quality of education and infrastructure, which hastens the city’s deterioration. Camden, New Jersey, and East St. Louis, Illinois, are examples of urban areas that once had a thriving middle class population and are now in serious decline.

This dissertation theorizes that middle class perception of its economic situation is a critical factor in its behavior and attitudes about life in general. If members of the middle class become increasingly anxious about economic standing, it would be fair to guess that they would try to “hold onto” what money they have through supporting candidates who advocate lowering taxes and reducing government services to the poor. In addition, as shown throughout history, when middle class whites perceive themselves to be under fire from other groups, they will either fight or flee. The massive out-migration

of the middle class from New York City began in the 1950s and continues today. The members of the middle class who remain in the city often “circle the wagons” to protect against outside intrusion. This can be seen by their focus on crime, private schools and neighborhood preservation—all code issues for anti-minority sentiment. Perceptions, however, are not always in line with reality.

This chapter will explore the economics and demographics of the middle class in New York City through a detailed analysis of Census data using the Housing and Vacancy Survey, a survey commissioned by the New York City Government and administered through the US Bureau of the Census from 1979 to 1996. This triennial survey is a quasi-panel survey with the sample changing every decade based on the decennial census. The sampling method, weighting characteristics and question wording will be discussed at length later in the chapter. The Housing and Vacancy Survey focuses on occupied housing characteristics, the demographic characteristics of the occupants, and on characteristics of vacant housing. It is entirely focused on New York City, and for that reason provides a more accurate picture of the city and its people than national-level surveys, such as the decennial census or the Current Population Survey.

The proposed decrease in overall economic standing acts as an influence on people's attitudes and behavior in New York City. This dissertation's argument is implicitly based on the assumption that if life is no longer satisfying in New York City, and people can afford to leave the City, they will leave as soon as possible. Therefore, either those who stay are happy with the way life is in the city, or they cannot afford to leave.

Focus on The Late 1960s to Mid 1970s – a Period of Turmoil and Despair

The 1969-1971 recession knocked New York City off its feet. The city had relied on four main areas to shore up its economy: the financial services industry, a boom in office construction, high rates of new apartment construction and the expansion of public sector employment (Bellush and Netzer 1990). The city had enacted short-term measures and had benefited from a lucky rise in inflation. The long-term outlook seemed rosy until the 1974 recession and subsequent financial crisis.

In 1974, the gas crisis and subsequent recession reduced New York City's tax base to a new low. Poor financial management combined with the cost of the extensive social service programs created during the Lindsay Administration created record budget shortfalls (Fuchs 1992). These programs were funded under the assumption of a relatively stable tax base. When this tax base was decimated, New York City was left with no way to make up for budget shortfalls. State and national funds were denied to New York City due to poor financial management of previous loans and outlays. The city's debt rating dropped dramatically as the city frantically tried to borrow from underwriters to keep from going bankrupt (Fuchs 1992). In response to the crisis, New York State stepped in and created the Municipal Assistance Corporation (MAC). MAC had two main functions: to replace short-term debt with long-term bonds; and to require the city to correct the shortsighted financial practices that had led to the crisis, including running city government under a deficit, using the capital budget for operations and following quick-fix borrowing plans (Netzer 1990). In addition, the Financial Emergency Act of 1975 was

enacted, creating the Financial Control Board, which was empowered to oversee the city's finances.

These measures demoralized the people of New York City. By 1977, the city had begun to recover financially, but emotionally the city was in tatters. The crisis had surprised members of the academic, political and public policy community (Fuchs 1992). Fuchs contends that a mayor can offer fiscal stability through limiting public demands, and controlling expenditures (Fuchs 1992, 3). A mayor's ability to do this should be constrained by both the fiscal realities of the city's situation and the institutional structure laid out by the charter, the state and past budget decisions. Before the 1975 crisis, the mayor had been in control of the budget. Mayor Lindsay had enacted programs based on increased public demand for services without any fiscal accountability (Fuchs 1992). To ensure that this would not happen again, MAC wrested control from the mayor, but the demands on the mayor's office remained. The emotional devastation after the fiscal crisis only increased movement out of and tension within the city (Fuchs 1992).

Mayor Koch Sets the Stage

The election of Mayor Edward Koch revitalized the city. Through his contacts with the business community and a lucky boom in the financial services industry, the city enjoyed a burst of economic activity, at least for its richer residents. The mid-1970s saw the culmination of the transition of New York City's economy from industrial to post-industrial (Mollenkopf 1996). During the period from the first recession in 1969 until the depth of the financial crisis in 1976, New York lost one-sixth of its jobs and income base,

decimating the local tax base (Mollenkopf 1992). This crisis was averted by a subsequent rise in public revenues and in federal and state aid directed towards the city. The growth in tax revenues accompanied a large growth in government services and employment. From 1978 to 1989, the city's public employment sector grew by 22.5%, one of the largest growth spurts ever (Mollenkopf 1992). This was accompanied by a rise in poverty to 23% in 1987 and low labor force participation for essential groups.

New York City elected Mayor Koch in 1977 as a response to the ineptitude of Mayor Beame during the fiscal crisis. Koch led the field as a reform-based liberal candidate by presenting himself as a "tough liberal" who was able to "get things done" (Mollenkopf 1992, 103). He sought support from all groups, including African Americans and Latinos as well as his more traditional white ethnic base. He was elected by a narrow margin in large part due to white liberal and African American support in the late days of his campaign. His traditional base, more conservative whites, actually decreased their support at the voting booth in his first election (Mollenkopf 1992, 107). Koch's 1977 coalition was divisive at best. White reformers and liberals, middle class Jews, African Americans and Latinos resembled Dinkins' coalition rather than Giuliani's.

By the 1981 election, Koch's coalition shifted to include outer-borough Jews, Catholics and downtown business interests. In doing so, Koch alienated liberals, African Americans and Latinos, and created a coalition similar to Giuliani's of today (Mollenkopf 1992). By the 1985 election, the formation of an African American-Latino coalition seemed likely. Yet, no candidate could be found who would beat Koch, who went on to win 63.3% of the primary vote, including a majority of the Latino vote.

Mayor Koch's coalition partners reflected both old and new. His reliance on white outer-borough voters represented the old, while his alliance with downtown business interests represented the new. While many previous mayors associated with and drew support from downtown business interests, the movement of many firms out of the city, combined with their refusal of help during the fiscal crisis, made the partnership of Koch and the business community unusual.

Koch's business supporters came mainly from the financial and real estate sectors of New York City's economy. To Koch, it was *quid pro quo*; he would support certain projects and in exchange, the selected firms would invest and stay in the city (Mollenkopf 1992). Throughout his tenure as Mayor, Koch was able to provide a reasonably positive environment for private investment (Mollenkopf 1992). He was able to promote projects and get them through the planning commission with relative ease, thereby providing jobs, and office and/or apartment space. In order to quell community protest, he would accompany many of these projects with funds for the surrounding areas, as in the Javits Center and the South Street Seaport. As Mollenkopf points out, however, Koch's support of real estate often pitted declining industries that supported his key white outer borough constituencies against the business sectors that also supported him. It also ultimately priced many members of the white middle class out of New York City altogether (Mollenkopf 1992).

In many ways, Mayor Koch's three terms illustrate the importance of the conservative white ethnic vote to New York City politics. Both Rieder and Sleeper describe the "closing ranks" of the white ethnic population (Rieder 1985; Sleeper 1990). Koch, because he could play on the fears of the outer-borough white ethnic groups, was a

natural candidate in these areas. He “restored a measure of moral legitimacy to the broad outer-borough white middle class which limousine liberals and radicals had so grandly disdained” (Sleeper 1990, 110). His ability to forge a coalition between outer-borough white ethnics and the board members of leading New York City corporations provides an interesting foil to Giuliani’s ability to appeal to white voters. With the support of the corporate elite, Mayor Koch could advance policies that would revitalize real estate development and municipal finance. In return, developers, bankers and other financial institutions would invest in the city and promise not to move their businesses (Mollenkopf 1992). The support of local financiers also furnished Koch with a large coffer from which to run his reelection campaigns. In the 1985 election, the top 200 contributors gave close to one-third of the money. Of these, 60% had business pending before the Board of Estimate (Mollenkopf 1992, 125).

The new coalition allowed Koch almost unparalleled power within the city. He managed to create a strong white alliance that, while tested under Dinkins, was able to re-coalesce with Giuliani’s second run. “By attacking corrupt African American politicians and advocating the death penalty, Mayor Koch tapped into, and helped to foster, white middle-class residents’ fear of the problems that might come with racial succession in the city” (Mollenkopf 1992, 126). His defense of “middle class” interests also allowed him to reach African American and Latino voters, although their community leaders did not support him. This alliance, combined with elite support, would later give Giuliani a building block from which to tap into in his two electoral battles against Dinkins.

Dinkins Arrives on the Scene

Dinkins was elected in part simply because he was not Giuliani and not Koch. Jesse Jackson's 1988 presidential campaign had revitalized African American and Latino political coalitions in the city (Thompson 1996). In addition, several of the major labor union leaders were now African American or Latino and wielded heavy amounts of control over their members (Mollenkopf 1992). These factors, combined with a renewed interest among white liberals in finding a candidate who could calm the growing racial discord in the city, encouraged Dinkins to run for mayor.

Dinkins represented the middle road between a white liberal Jewish candidate and a more entrenched group of African American politicians still fighting against the "white political establishment." Brooklyn Democrats represented the latter, while Dinkins represented Manhattan Democrats, among whom he had long enjoyed liberal (mostly white) support (Sleeper 1990). Before the 1950s, New York City's Democratic Party was a bastion of white ethnic pride; control of the party had gone from Irish to Italian to Jewish. During the 1950s and 1960s, however, areas of the city that were primarily African American began to demand a voice within the Democratic Party (Sleeper 1990). By the 1970s and 1980s, the combination of "white flight" from areas of the outer boroughs and the rise of the Black Power movement created a largely militant African American wing of New York City's Democratic Party. Only in areas like Manhattan, which remained white and reasonably liberal, could biracial coalitions be formed (Sleeper 1990).

It was in this environment that Dinkins won the Manhattan Borough presidency (Sleeper 1990). His ease in working with a biracial coalition made him a natural choice to run against Koch, whose racially divisive tactics had exhausted the city. Dinkins was able to seek and obtain support from the African American community, public sector unions (now a powerful force in the city), white liberals and Latino voters. In a city that had a nearly 4:1 ratio of registered Democrats to registered Republicans, Dinkins should have won easily; yet, he won by only a small margin of the vote. Carsey found a positive effect of precinct-level African American density on white votes in 1989; the higher the concentration of African Americans in the precinct, the more likely whites were to vote for Dinkins (Carsey 1995). In contrast, Sleeper argues that areas with perceived heavy racial threats, meaning that they were closer to African American neighborhoods, were more likely to vote for Giuliani (Sleeper 1990).

The battle between Dinkins and Giuliani was largely image-based. Giuliani sought to portray Dinkins as soft on crime and as heavily tied to the Democratic establishment in the city (Mollenkopf 1992). Dinkins, in contrast, sought to gain inroads in the Jewish community by pledging support for Israel and other traditionally Jewish concerns. The general election showed more polarization than the primary. African Americans, Latinos and white liberals voted strongly for Dinkins, with white ethnic outer-borough voters supporting Giuliani, albeit with significant proportions voting for Dinkins (Thompson 1996). The main swing vote among white voters occurred in areas where the perceived racial threat was low (i.e. the Upper West Side of Manhattan). In these areas, Dinkins did not seem threatening and won handily. However, in areas such as Canarsie, where the perceived racial threat was high, Giuliani won.

Crime and racial issues such as fairness to one race over another were the main dividing points during the election in 1989 (Mollenkopf 1992). Dinkins was perceived as being soft on crime, while Giuliani portrayed himself as the “bulldog” former prosecutor who would make fighting crime his main priority (Mollenkopf 1992). The “race card” was not played as openly as some might suggest, since racial tensions during Dinkins’ tenure worsened although he had been elected under a multiracial banner. Two factors contributed to the worsening of race relations. First, the recession of 1990-1991 left Dinkins and the city financially strapped. The budget had to be cut in order to avoid economic disaster (Thompson 1996). There were two options for Dinkins; either reduce services, which would anger one of his main constituency groups, African Americans; or cut public service jobs, which would anger one of his main constituency groups, African Americans. Since Mayor Lindsay’s era, working in public administration had become a main means of moving into the middle class for New York City’s African Americans. Cutting either jobs or services would inevitably set Dinkins up for the charge that he forgot where he came from. Not wanting to seem like a traitor to his own people, Dinkins neither cut services greatly nor cut jobs, leaving him open to the charge that he was both indecisive and captive to the “African American interest” (Mollenkopf 1997).

The other factor leading to the deterioration in race relations was the tragedy in Crown Heights, Brooklyn. A Hasidic man killed a young Guyanese immigrant during a traffic accident. The aftermath of this was a week of alternating between tense standoffs and rioting between Hasidic and African American residents. Dinkins was criticized by the white liberal (mostly Jewish) establishment for not doing enough to stop the rioting and not making an effort to tone down the anti-Semitic nature of many of the taunts

directed at the Hasidic community (McNickle 1993; Thompson 1996). African American leaders criticized Dinkins for not doing enough to quiet the taunts from the Hasidic community and for not “backing them up” on charges of racial bias by the police in the case. On the heels of this was an African American sponsored boycott of Korean-owned grocery stores to protest discrimination. Dinkins was slow to act in this incident as well, leaving him even more vulnerable to charges of being captive to African American interests and to betraying the multiracial coalition that elected him (McNickle 1993). Either way Dinkins left office having largely alienated his liberal constituency.

The Effect of the Recession

Dinkins came into office during a period of worldwide recession, having inherited a budget deficit. The recession of the early 1980s and the cutbacks on aid to urban areas caused the budget deficit during the 1980s. The 1987 stock market crash, which began the recession, directly affected many white-collar workers through downsizing and closures. Many scholars view the crash and the two 1980s recessions as the principle reason behind the “middle class revolt” during the late 1980s and early 1990s that culminated in the election of President Clinton. Additionally, under Presidents Reagan and Bush, the federal government cut aid to urban areas. This occurred during a period of uneven growth for New York City. It was uneven because until 1987, the booming stock market created a new class of well-to-do young people, who had come to New York City after college to make a living in the financial industry.

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Not everyone enjoyed the wealth of the booming market. The recession from 1981 to 1983 caused the bottom to drop out of the manufacturing sector in New York City, as much of the remaining industry left for cheaper locales (Mollenkopf 1993; Netzer 1997). In addition, the 1980s saw the shuttering of many state-run institutions, leaving many mentally ill people to fend for themselves in the streets. Mayor Koch enacted a number of programs to help poorer residents of New York City in large part due to the increase in tax revenues brought in by the stock market boom (Mollenkopf 1992). The 1987 stock market crash and subsequent recession had a devastating effect on the New York City economy. The few programs Koch had enacted to help poor residents and the homeless were overrun with applicants (Thompson 1996). The money to fund these initiatives had dried up, due to both national-level cutbacks and a decline in tax revenue. The city was running with a record deficit.

In 1989, Dinkins inherited these economic problems. Over the course of his term, Dinkins was seen as a financial failure because of his inability to balance the budget due in part to the continuation of the national-level recession, and his unwillingness to take drastic action by cutting the budget in ways that would have damaged his relationship with key supporters (Thompson 1996; McNickle 1993). Furthermore, the needs of the city's poor were growing rapidly. For example, the amount spent by the city on Medicaid between the years of 1989 and 1991 jumped from 6.2% to 7.7% of the city's budget (City Council 1997).¹³

¹³ New York City is a unique case when it comes to Medicaid because New York State requires it to pay a proportion of the Medicaid costs unlike other states and cities.

Data and Methods

Trying to measure changes both within and between classes over time is difficult primarily because most researchers have different measures for what they consider class. As stated in the previous chapter, this dissertation's definition of class is income based using the 1997 HUD qualifications for housing assistance. By allowing for family size, HUD qualifications as shown in Table 2.1 are a more accurate prediction of what a family needs to survive. A family's or household's well being depends not only on its resources, but also on how they are distributed (Duncan, Smeeding and Rodgers 1992).

Table 2.1 Income Breakdowns for the Middle Class in 1997 Dollars

# People in Family{PRIVATE }	1	2	3	4	5	6	7	8
Income for Middle Class in 1997 \$	27,450-68,600	31,350-78,400	35,300-88,200	39,200-98,000	42,350-105,800	45,450-113,600	48,600-121,600	51,750-129,400

Source: HUD qualifications for Public Housing 1997. See Bibliography for full citation.

The data for the following analysis comes from the Housing and Vacancy Survey for New York City collected by the US Bureau of the Census from 1978 to 1996.¹⁴ The

¹⁴ The description that follows of the Housing and Vacancy Survey is taken from the "Description of the Sample Design, Estimation Procedure, and Reliability" statement prepared by the Bureau of the Census periodically and distributed with the Housing and Vacancy Survey tapes. The basic description is the same for all of the Housing and Vacancy Surveys completed during the period of 1978 to 1996. When necessary, the specific year and appendix are cited. I had originally intended to use both the 1990 Public Use Microdata Sample, and the Current Population Surveys from 1993, 1995 and 1997. However, combining

Footnote continued on next page

purpose of these surveys was to measure vacancy rates, as well as a variety of household and personal characteristics. These surveys were conducted approximately every three years to determine how and whether rent control and rent stabilization measures should be continued. The sampling frame and survey itself has changed over the years to account for both shifts in the city's population and characteristics, and changes in the Census instrument itself. Appendix A provides a full description of the dataset.

The principle variables in the upcoming sections are family type, income, race, gender, tenure and, starting in 1991, occupation and industry. They will be analyzed by race and class, with a particular focus on the middle class. Occupation and industry are important variables to examine because of their connection to both perceptions of economic decline and New York City's shifting role in the global marketplace. Personal income is important because class is stratified by family income, so by looking at personal income across family income demarcations, one can get a sense of what it takes for each individual to maintain a certain family status. Family type is another key variable. Studies have shown that female-headed households are on the rise, while married couple households are on the decline (City Council 1997). Determining what types of families dominate the middle class can give indications of how many adults are needed to maintain a middle class lifestyle.

the two different datasets especially when the Current Population Surveys included the New York City Metro Area rather than just the five counties within New York City proved to be too cumbersome. It is hoped that concentrating instead on the Housing and Vacancy Survey will provide a more accurate picture of New York City residents and housing stock over time.

Basic Demographics of New York City

Due to the changes in the survey instrument itself, this section is divided into three parts. The first section will be an overview of the changes in New York City demographics from 1978 to 1987. The second and third sections will be more in-depth looks at the demographics during the 1990s on a household and person level. Occupation and income will be of special concern, as will a portrait of the middle class in 1993, the year when Giuliani became mayor.

New York City from 1978 to 1987

New York City underwent drastic changes during the period of 1978 to 1987. By 1987, the city had become majority nonwhite. There was an increase in female-headed households, as well as a decline in the number of poor and working class households. It is unfortunate that during this period, the Housing and Vacancy Survey did not ask questions about occupation, industry and wages in order to further explore this area.

Table 2.2 Basic Demographics For New York City¹⁵

Race of Householder¹⁶	1978	1981	1984	1987	% Change
Non-Puerto Rican White	57.43	56.02	54.08	49.64	-7.78
Non-Puerto Rican African American	19.71	19.76	21.17	20.31	0.60
Puerto Rican	9.36	9.27	9.32	9.13	-0.22
Other Race	3.95	5.19	7.20	7.50	3.55
Not Answered	9.56	9.75	8.22	13.42	3.86
Income Class of Household¹⁷	1978	1981	1984	1987	% Change
Not Reported	25.78	23.77	23.45	29.99	4.21
Working Class	30.74	32.93	32.48	26.29	-4.45
Lower Middle Class	15.91	15.84	13.86	12.64	-3.27
Middle Class	24.34	24.17	25.74	25.43	1.09
Upper Class	3.23	3.30	4.47	5.65	2.42
Gender of Householder	1978	1981	1984	1987	% Change
Male	63.00	57.78	54.32	54.77	-8.23
Female	36.63	41.49	44.71	44.41	7.77
Not Answered	0.36	0.73	0.97	0.82	0.45
Tenure	1978	1981	1984	1987	% Change
Own	27.37	27.84	29.49	30.26	2.89
Rent	72.63	72.16	70.51	69.74	-2.89

¹⁵ All the percentages were taken from the Housing and Vacancy Surveys conducted by the US Bureau of the Census during the period of 1978 to 1987. The responses that follow do not include those who declined to respond to various questions.

¹⁶ During this period, the only racial characteristic of the household was determined by the head of household and his or her parentage. The variable reported here is a creation by the US Bureau of the Census to combine race and Hispanic origin. The category of "other race" includes those who indicated other than white, African American, or Puerto Rican parentage (Housing and Vacancy Survey Source and Reliability Statement, 1978, 4). The Bureau of the Census did add a category for Asian and Native American in 1987, but in an effort to keep with the formulation of the previous years these categories were added to "Other."

¹⁷ All income classes were created in 1997 dollars using the 1997 HUD fair housing guidelines.

During the 1978-1987 boom, average real weekly earnings rose by 18% from 1979 to 1990 (Angelo 1995, 106).¹⁸ This is surprising in light of some scholars' contentions that the shift to the service economy lowered wages (Angelo 1995). In the above table, it seems as though the decreases in the percentage of families who were considered poor or working class may be accounted for by the rise in weekly earnings that Angelo documents in her article (1995).

From 1978 to 1987, the Housing and Vacancy Survey did not separate the different sources of income from the total household income, so it is impossible to duplicate Angelo's findings exactly. Table 2.3 illustrates, for those who reported income, the median income and percentile cutoffs for household income. While the median income increased over time, those in the bottom two percentiles, or the lower 20%, saw their income decrease. Likewise, the percentile with the highest income saw their income increase by 12% over time. This may indicate a growing split between the higher income residents and the lower income residents. Mollenkopf indicates that this split is due in part to measures of labor force participation, as well as shifts in industry, occupations and family demographics (Mollenkopf 1996). This was accompanied by an overall decrease in the number of households, indicating that there were fewer people sharing overall greater amounts of dollars.

¹⁸ Unfortunately, the Housing and Vacancy Survey for this period did not ask about occupation or industry. They also did not perform detailed analysis on wages; most of the information for this section is taken from secondary sources.

Table 2.3 Selected Household Income Figures for New York City in 1997 Dollars

Year	Mean	Median	25	75	90
1978	\$ 32,409.21	\$ 25,200.00	\$ 12,600.00	\$ 44,100.00	\$ 65,520.00
1981	\$ 31,621.57	\$ 23,848.84	\$ 11,818.00	\$ 43,225.00	\$ 66,500.00
1984	\$ 32,959.02	\$ 24,586.92	\$ 12,228.26	\$ 46,292.00	\$ 69,275.00
1987	\$ 36,271.78	\$ 29,000.00	\$ 13,292.15	\$ 50,750.00	\$ 76,850.00

Table 2.3 illustrates the general growth of the New York City economy over the 1980s. While household income dropped in 1981 due to the recession, the recovery instituted rapid growth in all sections of the economy. The substantial growth in the 90th percentile exemplifies the changes taking place in New York City at this time. It would appear that the City was becoming wealthier; however, the only growth “class” during this period was the middle class. This is further illustrated when broken down by class as in Table 2.4.

Table 2.4 Mean Household Income in 1997 Dollars by Class

Year	Lower	Working	Middle	Upper
1978	\$11,869.69	\$27,144.88	\$51,192.28	\$112,363.48
1981	\$11,602.00	\$27,040.00	\$51,415.94	\$108,440.65
1984	\$11,534.71	\$26,918.86	\$51,005.95	\$103,418.83
1987	\$11,256.86	\$26,718.38	\$52,165.49	\$102,495.66
% change	-5.44	-1.60	1.87	-9.63

As Table 2.4 illustrates, the overall mean income for middle class residents increased, as the overall number of middle class residents increased as well (Table 2.2). Therefore, while there were more members of the middle class, there was also more

money to be divided among them. Additionally, those members of the middle class who hovered around the median income saw their income increase by over two thousand dollars during this period. This was accompanied by a decrease in income for both the lower and upper income brackets, indicating a narrowing of the middle class bracket over time. The narrowing of the bracket may also indicate a trend towards the increasing bifurcation of society in New York City, with the outer sectors of society increasing while the middle shrinks.

Within the middle class, there were even larger changes. The percentage of the middle class who were white decreased by 9%, while the percentage of the middle class who were African American increased by 5% (Table 2.5). This change was accompanied by a negligible increase in household income by race over time. In other words, the nature of the middle class was changing in New York City. The middle class was becoming less white, a trend that would continue during the 1990s.

Table 2.5 Percent of Income Class Households by Race of Householder Over Time

Year	Group	Poor	Working Class	Middle Class	Upper Class	Total
1978	NPRwhite	52.17	61.03	74.81	89.61	63.09
	NPRBlack	26.40	23.37	16.17	4.81	21.47
	PRican	17.29	11.05	4.52	0.88	11.06
	Other	4.14	4.56	4.51	4.71	4.37
1981	NPRwhite	48.77	60.61	75.35	91.44	61.47
	NPRBlack	27.70	23.45	15.09	6.01	21.89
	PRican	17.52	9.45	4.32	0.22	10.92
	Other	6.01	6.49	5.24	2.33	5.71
1984	NPRwhite	45.18	53.52	69.37	87.72	57.28
	NPRBlack	28.14	27.61	19.30	6.44	23.81
	PRican	17.34	9.54	5.07	1.24	10.87
	Other	9.34	9.33	6.26	4.59	8.03
1987	NPRwhite	42.59	50.65	65.06	86.77	55.82
	NPRBlack	29.09	28.29	21.04	6.23	24.16
	PRican	18.42	10.93	6.35	1.68	11.31
	Other	9.90	10.12	7.56	5.32	8.72

The decrease in the percentage of middle class who were white as well as the overall percentage of whites in New York City contributed greatly to the “circling of the wagons” that occurred in many white middle class neighborhoods (Sleeper 1990, Reider 1985). The decrease in the percent of middle class whites was accompanied by an increase in middle class African Americans and middle class “others.” Due to the nature of the “other” category, it is impossible to discern who moved into the middle class during this period; however, this will be made clear in the following section.

New York City During the 1990s

The Housing and Vacancy Survey changed dramatically from 1987 to 1991. To begin with, the format of the survey itself changed with the addition of new files in order to accommodate the changes in data collection. The survey now had three parts: occupied housing or household, person and vacant unit. Table 2.6 details the basic demographics of New York City over the 1990s. There was an increase in married couples with children during this period, as well as in male householders living alone. The gender distribution of New York City householders remained comparatively stable, as did home ownership rates. During this period, there was a significant increase in the percentage of the middle or upper classes. This, however, may be misleading. The data presented in Table 2.6 contains households who did not report their income. In the 1991 and 1993 Housing and Vacancy Survey, the Census used an income estimation method that allotted household income when one or more of the members of the household did not report income (Housing and Vacancy Survey Codebook 1996, 2-3). In 1996, the Census, when conducting the Housing and Vacancy Survey, changed its reporting procedure to impute values for non-responses based on other cases with similar characteristics. This method was used with race, gender, income, education level, rent and occupation (Housing and Vacancy Survey Codebook 1996, 2-3). This change in allotting method to improve non-response rates taints the reporting of household income and racial breakdowns. Therefore, all figures reported here are approximations.

Table 2.6 presents the race of the householder that was tabulated differently in each year of the survey. In 1991, people of Hispanic origin who did not classify

themselves as one of the racial categories were classified as “Other.” In 1993, these people were allotted to one of the major race categories, while in 1996, the “Other Race” and “Race Not Reported” categories were eliminated and respondents were allotted to the major races due to changes in Census methodology (Housing and Vacancy Survey Codebook 1996, 2-3). In an effort to standardize racial categorizations, the race category is divided into non-Hispanic white, non-Hispanic African American, non-Hispanic Native American, non-Hispanic Asian and Hispanic. In this way, 1996 categories are replicated for 1991 and 1993 data. Despite the allotment of those who did not report their race to other racial categories, the percentage of householders who were white dropped by nearly 2%. This indicates an even greater drop in the percentage of white householders than estimated.

Table 2.6 Basic Demographics for New York City during the 1990s

Gender of Householder	1991	1993	1996	% Change
Male	48.35	48.903	47.42	-0.94
Female	51.23	51.097	52.58	1.36
Type of Household	1991	1993	1996	% Change
Married, no kids	15.78	14.64	15.00	-0.78
Married, kids LT 18	11.95	13.20	13.27	1.32
Married, other adults	6.28	5.98	6.05	-0.23
Married, adults and kids LT 18	4.86	4.83	4.96	0.10
Married, with others (no age given)	0.29	0.00	0.00	0.00
Female HH, alone	20.78	20.44	19.90	-0.87
Female HH, kids LT 18	7.32	7.73	7.79	0.47
Female HH, other adults	8.02	8.27	7.48	-0.54
Female HH, adults and kids LT 18	5.34	4.70	5.02	-0.32
Female HH, with others (no age given)	0.10	0.00	0.00	0.00
Male HH, alone	12.26	12.98	13.28	1.02
Male HH, kids LT 18	0.33	0.56	0.69	0.36
Male HH, other adults	5.08	5.54	5.36	0.28
Male HH, other adults and kids LT 18	0.99	1.13	1.20	0.22
Male HH, with others (no age given)	0.21	0.00	0.00	0.00
Gender for HH not given	0.42	0.00	0.00	0.00
Income Class of Householder	1991	1993	1996	% Change
Working Class	38.61	36.48	34.90	-3.72
Lower Middle Class	17.48	17.28	17.60	0.12
Middle Class	34.17	35.74	35.88	1.71
Upper Class	9.74	10.50	11.63	1.89
Tenure of Household	1991	1993	1996	% Change
Own	28.35	29.00	30.00	1.66
Rent	70.00	69.50	68.80	-1.20
No Cash Rent	1.65	1.50	1.20	-0.46

Table 2.6 continued

Race of Householder¹⁹	1991	1993	1996	% Change
Non-Hispanic White	48.84	49.32	47.08	-1.76
Non-Hispanic African American	22.56	24.14	24.06	1.51
Non-Hispanic Native American	.28	0.20	0.47	0.19
Non-Hispanic Asian	5.02	6.02	7.05	2.02
Hispanic	19.78	20.32	21.34	1.56

Table 2.7 shows the selected household income figures during the 1991 to 1996 period. The large jump in the mean figures is an artifact that may be due more to the methodological changes within the Housing and Vacancy Survey than to any substantial jump in household income during this period.

Table 2.7 Selected Household Income Figures in 1997 Dollars Over Time

Year	Mean	Median	25	75	90
1991	\$ 39,054.72	\$ 28,320.00	\$ 12,135.12	\$ 53,100.00	\$ 85,078.00
1993	\$ 43,240.04	\$ 29,637.00	\$ 13,320.00	\$ 55,056.00	\$ 87,801.00
1996	\$ 44,962.41	\$ 30,600.00	\$ 13,668.00	\$ 56,304.00	\$ 91,800.00

In this dissertation, income class is broken down as a range of household incomes weighted by family size. Table 2.8 presents the mean income for each income class over

¹⁹ The 1991 Housing and Vacancy Survey included "Other Race" and "Race Not Reported" as categories. In this presentation, these categories are excluded due to their omission in later years. The percent of respondents who answered non-Hispanic other was 1.2%, and the percent who did not report their race was 2.32% in 1991.

time in 1997 dollars. Those in the “lowest” category did better than the lower middle or middle classes with a loss of only \$42.46. The size of the working class also shrank the most, 3.72%, over time. Therefore, there were on average *fewer* people sharing slightly less money. The lower middle class fared worst, with a loss of \$298.09. The size of the lower middle class also changed the least over time, so there were approximately the *same number* of people sharing less income. Based on their loss of income share during the 1980s, one could presume that the middle class would have fared the worst of all, having lost both the largest number of people and greatest income share. Yet the middle class did not shrink in size during the 1990s in New York City; in fact, the middle class grew by 1.71%. The only middle class loss was in share of household income, with a decrease of \$133.46 on average. This is surprising, given their overall perception of the early 1990s in New York City as being economically rough for most households, especially their own. The recession was still going on, yet as Angelo indicates, wages rose in comparison to the national average (Angelo 1995). This may account for the relatively small losses in income over time. The upper class did extraordinarily well during this period. They gained less than 2% in population share, but increased their mean income over time by over \$22,000, representing a far greater income share for approximately the same population share. In addition, studies have shown that the majority of people who do not report their income are in the extreme upper or lower income brackets. Therefore, this figure may be weighted upward between 1991 and 1993 due to the Census Bureau’s recalculation of household income during this period.

Table 2.8 Mean Income by Class Over Time in 1997 Dollars.

	1991	1993	1996	\$ Change
Working Class	\$10,659.62	\$10,669.64	\$10,617.16	-\$42.46
Lower Middle Class	\$27,237.17	\$26,724.34	\$26,939.08	-\$298.09
Middle Class	\$53,245.16	\$52,915.09	\$53,111.70	-\$133.46
Upper Class	\$123,346.37	\$151,026.42	\$150,528.14	\$27,181.76
Total	\$39,080.85	\$43,281.59	\$45,005.55	\$5,924.70

Table 2.9 presents the percent of income class broken down by race. Due to the recalculations of the race category between 1991 and 1993, the numbers for whites and African Americans are skewed upward. This may account for a slight undercount in white respondents and a slight overcount in African American respondents (Housing and Vacancy Survey Codebook 1993, 2-2). Therefore, within the middle class over the 1990s, there was a substantial increase in population share for both African Americans and whites, with relatively small income share increases. In both cases, it appears that there were many more people within the middle class sharing an only slightly larger pool of funds. Middle class Hispanics were the only group to lose income share as their population share increased. Therefore, for this group, there were more people sharing much less money on average.

Table 2.9 Percent of Income Class by Race of Householder Over Time

		Poor	Working Class	Middle Class	Upper Class	Total
1991	NHWhite	37.69	38.46	56.19	77.93	48.05
	NHBlack	27.29	27.48	20.17	9.28	23.14
	NHAsian	4.25	6.02	6.63	5.85	5.52
	Hispanic	30.62	27.71	16.53	6.94	23.00
1993	NHWhite	39.16	40.80	56.15	78.42	49.64
	NHBlack	27.12	28.40	22.51	10.99	24.00
	NHAsian	4.65	7.22	7.15	4.77	6.00
	Hispanic	29.07	23.59	14.19	5.83	20.36
1996	NHWhite	36.48	40.47	51.85	76.83	47.41
	NHBlack	27.93	27.99	22.42	10.57	23.94
	NHAsian	5.12	7.55	8.96	6.40	7.08
	Hispanic	30.47	23.99	16.77	6.20	21.58

With the advent of the person-level file, the 1991 Housing and Vacancy Survey allows for a more detailed analysis of what was happening to individuals in New York City during this period. This section will focus on personal income and occupation categories as a modified class category. This modified class categorization was created using the same percentage distribution as the household-level class variable without reference to family size. For all individuals over the age of 18, working poor is classified as 80% of the median and below; lower middle class is from 80% of the median to the median income, middle class is from median income to the 90th percentile of personal income, and upper income is from the 90th percentile and up. This translates into breaking points at \$10,200 for working poor, \$18,870 as the median, and \$53,280 at the 90th percentile for those who reported income. From the 1993 Housing and Vacancy Survey onward, the U.S. Census Bureau eliminated the “Income Not Reported” category and

allocated those individuals to other income brackets based on an allocation algorithm (Housing and Vacancy Survey Codebook 1993). All of the dollar figures are reported in 1997 dollars.

In their discussions on the middle class, both Brint and Wright focus on occupation, specifically on “professional/managerial” occupations as primary middle class jobs (Brint 1995, Wright 1985, 1997). These sorts of occupations are found in 1990 Census codes 3-235. This section will first treat occupation during the 1990s across all classes, and then will focus on the middle class, with a demographic profile of members of the middle class who work in the “professional/managerial” sphere. There were more individuals in the labor force and working in 1996 than in 1991. During the recession from 1991 to 1993, the New York City labor market actually expanded, with unemployment dropping by 4.6%.

Table 2.11 Percentage of All Adults Aged 18 and Over by Selected Occupation

	1991 (N)	1991%	1993 (N)	1993%	%Change 91-93	(N) Change
Exec/Manager	374187	6.84	401380	7.48	0.64	27193
Professional	504786	9.23	560907	10.45	1.22	56121
Technician	78890	1.44	82016	1.53	0.09	3126
Sales	336999	6.16	381106	7.10	0.94	44107
Admin. Support	618246	11.30	633443	11.80	0.50	15197
Service	591724	10.82	670466	12.49	1.67	78743
Repair	77259	1.41	88618	1.65	0.24	11359
Construction	127059	2.32	110396	2.06	-0.27	-16663
Precision Production	69706	1.27	69645	1.30	0.02	-61
Operators	295734	5.41	321946	6.00	0.59	26212
Laborers	115854	2.12	127416	2.37	0.26	11563
Unemployed	703908	12.87	443541	8.26	-4.60	-260367
NILF	1561982	28.55	1463732	27.27	-1.28	-98250

On an individual basis, members of the middle class fared better during 1991 to 1993, with a surprising rise in personal income during this period. From 1991 to 1993, the average personal income of the middle class rose \$642, while from 1993 to 1996 it rose only \$440. New Yorkers had a higher average wage than most of the nation during this period (Angelo 1995), and more residents were employed. Therefore, it seems that the economic malaise that plagued the rest of the nation did not affect New York City.²⁰ Table 2.12 shows middle class personal income by race. Non-Hispanic whites and Non-Hispanic African Americans did not fare as well as members of other groups from 1991 to 1993. Non-Hispanic Whites in the middle class lost money in terms of mean personal income from 1991 to 1993. Non-Hispanic African Americans also lost mean personal income overall, a decline of about \$400. Consequently, it is not surprising that some scholars view voters' failure to vote as a punishment for Dinkins in part for a decline in African American standards of living.

Table 2.12 – Mean Middle Class Personal Income by Race In 1997 Dollars

	1991	1993	\$ Change 93-91	1996	\$ Change 96-93
Non Hispanic White	\$27,848	\$27,750	-98	\$28,152	402
Non Hispanic Black	\$25,960	\$25,530	-430	\$25,531	0.6
Non Hispanic Asian	\$23,600	\$24,420	820	\$26,520	2100
Hispanic	\$23,713	\$25,530	1817	\$25,500	-30

²⁰ This stands in contrast to what others have found about New York City during this same period. While Angelo did find that wages, on the whole, rose for most New Yorkers, The New York City Council found that for most middle class residents their standard of living and hence personal income decreased (Angelo 1995; City Council 1997). This discrepancy may be due to the methodological changes discussed in the Chapter and Appendix A.

Overall Mean	\$24,944	\$25,597	652	\$26,037	440

Conclusion

This chapter began with the observation that the middle class perceived itself to be losing its hold on the American Dream. They were angry and frustrated because to them, prosperity seemed to be slipping away. In New York City, however, life during the 1990s had actually improved for most people. Fewer people lost income and unemployment figures fell below double digits for the first time in a decade. There were also increases in the numbers of families of color who joined the middle class. While middle class white families did not manage to break into the upper class in similar numbers, they certainly did not lose a great deal either in terms of income or population. On the other hand, New Yorkers were unhappy with high crime rates, racial tension, and growing general malaise about city life. Since the Housing and Vacancy Survey provides only demographic data and does not measure attitudes, we shall have to look elsewhere to find the source of the anger, frustration and pessimism that surrounded the 1993 mayoral election.

Chapter 3 How New Yorkers Feel

New York City's economic and demographic changes were not the only changes occurring during the late 1980s. This chapter will explore the changing attitudes of New Yorkers as evidenced by the *New York Times*/CBS News polls from 1985 to 1994. Rudolph Giuliani's victory seemed to begin a more conservative bent to New York City politics. However, as this chapter will show, the attitudes of New Yorkers were not necessarily more conservative, rather, their attitudes were more pessimistic overall, with middle class whites being the most pessimistic. This section will explore the attitudes of New Yorkers in three areas: crime, race relations and quality of life issues. These three issues play a critical role in candidate support and long-term outlook; these issues will be treated in Chapters 4 through 6.

As discussed in Chapter 2, middle class whites had lost a measure of their economic security during the recession of 1989 to 1992. As the city became majority nonwhite during the 1980s, they were fearful of losing social standing and of being trapped in a city they no longer recognized and could no longer afford. Some members of New York City's middle class had begun to be influenced by many of the same factors as the middle class of the U.S. as a whole. The sense of despair facing the middle class had propelled a president to power (Greenberg 1995). To many New Yorkers, Dinkins represented the failure of the political establishment. Dinkins' election in 1989 had been viewed as a return to a kinder, gentler liberal mayor who would not be as combative as Koch nor as inept as Beame. Voters felt he could restore the city to its former glory through negotiation and compromise. Dinkins was also a fixture in the Manhattan

Democratic Party, having risen through its ranks, and was seen as a linkage to its past. Eventually this very connection got Dinkins into trouble.

Figure 3.1 illustrates this dissertation's basic theoretical construct about the 1993 election and how it turned the tide towards Giuliani. The comparison with 1989 is necessary since the same elements were in place, but at the time, they were not enough to help Giuliani defeat Dinkins.

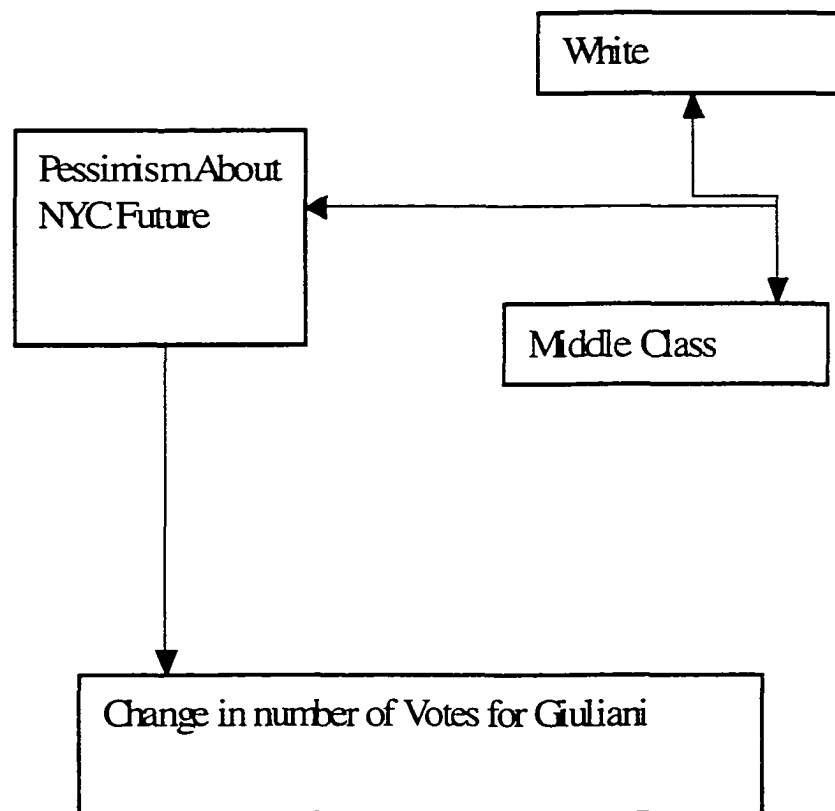


Figure 3.1 Graphical Display of Basic Theory

This chapter will first analyze the general attitudes in New York City from 1985 to 1994, using data from the *New York Times*/CBS News voter polls from 1985 to 1994. These polls are different from exit surveys because they are asked prior to elections, and are meant to be a more in-depth look at the attitudes of New York City residents on a variety of subjects. The number of respondents for each survey ranges from 1200 to 1700. They are not conducted on a regular basis by CBS News, *The New York Times* or Voter News Service, but are conducted on an as-needed basis. The questions are often unique, providing a snapshot of opinions in the city at any given moment.

The attitudes measured by the *New York Times*/CBS News pre-election surveys fall into three areas. The first area covers overall quality of life, including attitudes on crime, housing, schools and racial tensions. The second area deals with attitudes regarding the capability, trustworthiness, or other qualities of candidates. These types of questions are useful when comparing the 1993 contest between Giuliani and Dinkins with their first round in 1989. The third area delves into attitudes on specific cases such as Howard Beach or the Bernie Goetz trial. Since these are events specific to a given time period, they do not contribute to a comparison between 1989 and 1993. Therefore, in this chapter areas one and two will be emphasized.

The State of Mind in New York City

“Quality of life” is an elusive concept. No one scholar has arrived at an overarching definition for quality of life (Stockwell and Neal 1991, 393).²¹ It has been used to describe a variety of things ranging from neighborhood status to how well a person copes following a tragedy. In relation to urban politics, and to New York City in particular, this dissertation defines quality of life as the effect of major urban issues such as crime, race relations and ease of living on a person’s attitude towards the city. Do negative perceptions of crime, race relations and other urban issues make a person more pessimistic towards the long-term outlook of the city? The answer is not easily obtained, nor can one state definitively that there is a one-to-one relationship between attitudes on a particular subject and perceptions of where the city is headed. Nevertheless, this section will trace the development of certain attitudes during the years 1985 to 1994 on crime, race and overall ease of life in New York City in order to provide a context for the 1989 and 1993 elections.

Living in New York City is not an easy task. There are over 7 million people crowded into a small area. Life is always moving, always bustling. In 1985, when asked, “In the next four years, can you see yourself moving out of New York City?” the majority of respondents answered no (53.7%). When the identical question was asked in 1994, however, only 26.7% said that they would want to stay in New York City over the next

²¹ Stockwell and Neal (1991) detail previous efforts to arrive at a measurement of quality of life in urban areas. One example, the ZPG Urban Stress test, is meant to measure possible environmentally based stress for those who live in urban areas (Stockwell and Neal 1991, 401).

four years. Approximately 73% of those surveyed would choose to leave over the next four years if given the chance (*New York Times*/CBS News 1994). This indicates a marked change in the attitudes of most New Yorkers; from acceptance of the effort it takes to live in New York City, to a desire to flee. The 1993 Commonwealth Fund study on why people chose to move from and to New York City provides additional evidence to support this conclusion; fifty-nine percent of those asked responded that they left New York City to have “a better lifestyle” (Commonwealth Fund 1993: Q.C5).²² Another indicator of perception of quality of life in New York City is a question involving long-term outlook for the city.²³ “What is your long range view for the city?” is a potent resource for tapping into how people feel about the city. A person’s long-range view is influenced by a variety of factors, including perceptions of crime and race relations, which will be explored in the next two sections.

Attitudes on Crime

Attitudes on crime—who perpetrates it, how the police are handling it—are influenced by both whether or not one has been a victim of crime and how close one feels crime is to one’s neighborhood. Candidates in any election, particularly on the local level, are keenly aware of the influence of crime on their electoral future. As such, they will

²² Louis Harris and Associates conducted the Commonwealth Fund’s 1993 Survey in order to find out why people move to and from the city. Three thousand people were surveyed, 1500 in-migrants and 1500 out-migrants. Similar questions were posed to each group.

²³ This question was only asked of in-migrants, people who had moved into NYC. It was not asked of out-migrants, people who had moved away from the city.

often run on a “law and order” ticket, promising to lower crime rates and create a safer city.

In 1989, city residents rated crime as the second biggest problem in New York City (26%), and drugs as the number one problem (36.9%). By 1993, however, the number of respondents who answered that crime (35.1%) was the number one problem far outweighed the number who answered drugs (6%) (*New York Times/CBS News* 1989, May 1993). In the Commonwealth Fund survey, safety was the most important concern for all respondents (Commonwealth Fund Q.H1, Q.O1). This change was due in part to an increased crime rate during much of Dinkins’ tenure. This may have caused rising perceptions of crime. By 1993, however, crime rates were actually decreasing (Conason 1995). The decrease in actual crime rates is not reflected in the survey data, as the perceptions of crime rates in the city remained high. Aside from a small blip in 1989, 20% of respondents reported either that they or a family member had been a victim of crime in the *New York Times/CBS News* Surveys from 1985 to 1994. This corresponds with the data from the Commonwealth Fund study that showed that 22% of people moving into New York City were victims of crime (Commonwealth Fund: Q.H6).²⁴

Trying to judge crime rates or even perception of crime rates from survey data is tricky. Personal definitions of fear of crime can range from general perceptions of neighborhood safety to personal reactions to specific incidents (Roundtree and Land 1996, 1354). People’s perceptions of crime in their communities tend to be influenced by socio-demographic factors such as age and gender, physical or social vulnerability,

²⁴ This question was only asked of “in-migrants,” people who had moved into New York City. It was not asked of out-migrants, people who had moved away from the city.

indirect victimization and contextual effects (Roundtree and Land 1996). Contextual effects, such as poor social integration both for the individual and in the neighborhood, physical and social incivility and population size, increase the likelihood that a resident, in areas where these features are prevalent, will believe that there may be more crime than there actually is (Taylor and Hale 1986). This is especially true in New York City where the media tends to latch onto a particular crime, usually a gruesome one (Conason 1995).

In 1985, 38% of respondents said that the crime problem was worse in New York City than in other cities around the country (*New York Times/CBS* 1985). Perception of crime in New York City only seemed to deteriorate with time. In 1989, over 50% of registered respondents felt that a mayor should be able to control the crime rate in New York City (*New York Times/CBS* 1989). By 1993, 41% of respondents reported that their neighborhood was either as safe or less safe than it was in 1989, when Dinkins was first elected (*New York Times/CBS* May 1993), while 45.4% stated that the city as a whole was either as safe or less safe than it was four years previously (*New York Times/CBS* May 1993). While these figures are not majority percentages, it does indicate a perception that Dinkins failed to handle crime in New York City among a substantial portion of the respondents because the city did not appear to become appreciably safer during his tenure.

Dinkins' perceived failure to act on the crime issue was a major factor in the 1993 campaign. In the September 1993 poll, close to 40% of respondents who were registered voters felt that Dinkins was tough enough to handle the crime problem in New York City. In contrast, almost 70% felt that Giuliani would be tough enough (*New York Times/CBS* September 1993). When broken down by race, 75% of white registered respondents felt

that Giuliani was tough enough to handle the crime problem in New York City, while only 25.3% felt that Dinkins was tough enough (*New York Times/CBS* September 1993). For nonwhite registered voters, support for Dinkins moderated the responses somewhat, but Giuliani was still perceived as tougher on crime than Dinkins (57.5% to 53.5%). Close to 50% of all registered respondents felt that Giuliani was tough on crime regardless of income class, but only 30% of registered respondents regardless of class felt that Dinkins was tough enough (*New York Times/CBS* September 1993).

Within the middle class respondents' answers, perceptions of the candidates were further demarcated along racial lines. For middle class whites, 75% felt that Giuliani would be tough enough on crime, while only 21% of middle class whites felt that Dinkins was tough enough on crime. This striking contrast points to the dissatisfaction within the white middle class towards how the city was being run. This also may indicate the success of Giuliani's "law and order" campaign as a veiled racial message. Hagen (1995) states that candidates often raise whites' fear of racial minorities, especially when the opposing candidate is a member of a minority group by using code words such as "law and order" (66). Not surprisingly, for the nonwhite middle class, the differences were not as striking. While 60% felt that Giuliani would be tough on crime, 66% felt that Dinkins had been tough enough to handle the crime problem. Perhaps this was due to the increased number of police patrolling minority communities, or perhaps it was due to the increased accountability in the police force. Unfortunately, the survey questions do not cover these topics. The different perceptions of the candidates between white and nonwhite respondents regardless of income point to how difficult it is to specify crime as a single cause in an election. People define crime differently. For some, crime means

graffiti, while for others crime may mean the murder of a family member. In either case, crime rates and perceptions of these crime rates are critical factors in local elections.

Attitudes on Race Relations

Overall, attitudes on race relations have been shown to have an impact on how people vote. The density of the city makes even the smallest amount of racial tension appear unmanageable. The election of David Dinkins in 1989 was the victory of a deracialized campaign (Perry 1991). Through emphasizing different aspects of his campaign to different groups of voters, Dinkins was able to run not only as a member of the African-American community in New York City, but also as part of a more general liberal Democrat campaign that hoped to transcend some of the racial tension that emerged during the Koch administration (see Chapter 1).

One of the most widely publicized incidents during the Koch administration was the Howard Beach incident, in which a group of white youths beat an African American youth to death. When asked in 1988, "Could an incident like Howard Beach could occur in your neighborhood?" the majority of respondents replied that it was either somewhat or highly unlikely (60.1%) (*New York Times/CBS* 1988). However, when the same respondents were asked if Howard Beach would result in a worsening of race relations, 42.6% replied yes (*New York Times/CBS* 1988). The worsening of race relations began under the Koch administration (Mollenkopf 1994). His neglect of African American,

Hispanic and to a lesser extent Asian issues, in favor of the concerns of big business, did not win him many fans in communities of color (Mollenkopf 1994).

One can see the shift in the perception of race relations by the end of the Koch administration by looking at the results of the same survey question asked in two different years. In 1988, the majority of respondents stated that race relations in the city were the same as they were a year before (54.2%), while 34.4% said that they had worsened over the preceding year. By 1989, the percentage who thought that race relations had remained stable had dropped to 36.7, while the percentage who thought that race relations were worse had risen to 45 (*New York Times/CBS* 1988, 1989). Furthermore, in 1989, 45.2% of the respondents stated that they disapproved of how Koch was handling race relations (*New York Times/CBS* 1989). The respondents also felt that race relations was something over which the mayor had control (56.9%) (*New York Times/CBS* 1989). By 1993, the percentage of respondents who felt that the mayor had control over race relations had dropped by almost 10 points to 47.2% (*New York Times/CBS* May 1993). This indicates that while the respondents may have thought that race relations in the city were worsening, the mayor could not and did not have responsibility for calming them.

Many in the African American community felt that having an African American mayor would increase the attention paid to their grievances (Sleeper 1990). Dinkins was perceived to be somewhat receptive to African American issues and grievances during his tenure. Table 3.1 indicates an overall decrease in the percentage of people who felt that communities of color were ignored under Dinkins. While this is an interesting development, the fact that 43.76 % of African Americans felt that under Dinkins tenure,

New York City government paid too little attention to the needs of communities of color is an important feature of this table.

Table 3.1 illustrates the differences between Dinkins' two main groups of supporters in the 1989 election, African Americans and Jews. At the beginning of Dinkins' term as mayor, rioting broke out in Crown Heights, Brooklyn, home to large communities of Hasidic Jews and recent Caribbean immigrants. Dinkins seemed torn between the two camps, who were both clamoring for him to calm the fighting, and thus reacted slowly. This incident turned the tide of public opinion against Dinkins as a racial conciliator and instead both groups felt that he had turned against them.

Table 3.1 African American and Jewish Relations

Do You Think New York City Government is Devoting Too Much Attention, Too Little Attention or About the Right Amount of Attention to the Need of Blacks and Other Minorities?

Too Little Attention Paid to Black and Other Minorities

	1985	1993	% Change
Non-Jewish Whites	30.47	24.38	-6.09
Jewish Whites	13.12	8.83	-4.29
African Americans	30.32	43.76	13.44
Other	26.09	45.28	19.19
Total	51.62	42.60	-9.02

Too Much Attention Paid to Blacks and Other Minorities

	1985	1993	% Change
Non-Jewish Whites	71.03	56.45	-14.58
Jewish Whites	17.93	22.58	4.65
African Americans	3.45	3.23	-0.22
Other	7.59	17.74	10.16
Total	10.91	15.21	4.30

Source 1: *New York Times*/CBS Polls, Jan. 1985, Sept. 1993. The total N for each year was 1329 for 1985 and 1223 for 1993.

In 1985 and 1993, the *New York Times*/CBS News survey asked the following question: “Do you think New York City government is devoting too much attention, too little attention, or about the right amount of attention to the needs of blacks and other minorities?” Separating the Jewish New Yorkers from whites and African Americans, one can see that the percentage of Jewish New Yorkers who thought that New York City government under Dinkins paid too much attention to the needs of communities of color rose by over 4% (see Table 3.1), while non-Jewish white respondents, the percentage that thought that communities of color received too much attention, dropped by close to 15%. While it is not possible to directly correlate this with the Crown Heights incident, given the traditionally left-leaning views of many Jewish people, as well as their long history of support for African American causes, a shift of over 4% in eight years is remarkable.

Perceptions of how the candidates would handle racial issues were not lost on most New Yorkers. In 1993, approximately 25% of those surveyed stated that if Dinkins were reelected, racial tensions would increase, while only approximately 18% said that they would decrease. Interestingly, while approximately 26% of those surveyed thought that if Giuliani were elected racial tensions would increase, only about 16% thought that they would decrease. The mirroring of the two profiles on race relations is especially interesting, since each tried to portray the other as the “devil” in terms of race relations. Dinkins’ campaign attempted to paint Giuliani as unsympathetic to communities of color, while Giuliani reminded white New Yorkers of how Dinkins apparently played “racial favorites” in his policy and his hiring (McNickle 1993). When the data is broken down by race, the split between whites and nonwhites becomes even greater depending on the candidate. While approximately 35% of registered nonwhites in the surveys thought that

if Giuliani were elected race relations would worsen, only 20% of whites thought that having Giuliani as mayor would make relations worse. For Dinkins, the opposite is true. Twenty-three percent of whites thought that having Dinkins as mayor would make race relations worse, while only 13% of nonwhites thought that he would negatively impact race relations.

Race relations are a critical feature of New York City politics. In a city of over 7.3 million people and over 100 languages spoken, how well people get along is a reflection on the mayor even if he or she is not the cause of the tension. By 1993, it became apparent that for both candidates, race relations were not a particular strength. The impact that these perceptions would have on the voting booth will be explored in Chapter 5.

Attitudes on Quality of Life

The quality of life in a particular area is difficult to research, in part because the conception of quality of life is difficult to distinguish and quantify. Features of a particular area that make life difficult for one person may not bother another in the same way or even at all. A great difficulty in reporting attitudes on quality of life based on the *New York Times*/CBS surveys is in the data itself. Rarely were the same questions asked more than once, so tracing the perceptions longitudinally on a topic such as homelessness or drug sales in the respondents' neighborhoods is extremely difficult. One of the best ways to judge the quality of life in a city over the long term is to look at the number one reported problem over time. Table 3.2 shows the number one reported problem for registered respondents during the June 1989 survey and the May 1993 survey. In 1989,

aside from crime and drugs, the top long-term problems were homelessness (9.6%), housing (5.6%) and education (5.2%). All of these can be considered under the quality of life rubric (*New York Times/CBS News* 1989).

In 1989, homelessness was the number three problem in New York City (*New York Times/CBS News* 1989). Almost 84% of the respondents blamed New York City's government for the homeless problem (*New York Times/CBS News* 1989). Dinkins enacted his homeless policy, hoping to change people's views of how the government treated the homeless. By May of 1993, homelessness had risen by 5 percentage points to be the number two problem in New York City, after crime, with the economy running a close third (*New York Times/CBS News*, May 1993). During this same period, 48% felt that homelessness was something that they mayor could control, and 59.1% stated that they were bothered by panhandlers (*New York Times/CBS News*, September 1993).

Given this information, one would have suspected a higher percentage of people considering panhandlers and the homeless being a greater problem than they were. This points to Dinkins' failure in his homeless policy. Dinkins' primary policy towards the homeless was to spend large amounts of money to house them. Thompson (1996) points to two main reasons why Dinkins' homeless policy failed; first, the advocates themselves, who adopted an elite strategy that distanced them from the population they were supposed to serve. Second, the policy itself, which adversely affected communities who felt that shelters were placed in areas overburdened with other projects, such as drug rehab clinics. In addition, stories detailing waste and fraud within the program flooded the media (Thompson 1996, 658). The combination of these reasons was enough to show how

Dinkins failed the homeless in his policies, and why more people were reluctant to vote for him.

Table 3.2 Top Eight Number One Problems for New York City

	<i>Jan-89</i>	<i>May-93</i>	<i>% Change</i>
Crime	25.86	34.20	8.34
Drugs	37.53	6.06	-31.47
Homelessness	8.72	13.78	5.05
Housing	5.48	2.14	-3.34
Education	5.27	4.75	-0.52
Race Relations	3.75	10.69	6.94
Economy	0.91	12.59	11.68
DK/NA	2.94	2.73	-0.21

Source: *New York Times/CBS News Polls* 1989 and May 1993.

The total N for each survey was 1462 for 1989 and 1223 for May of 1993.

Drugs were also a big problem in New York City during the late 1980s and early 1990s. In 1989, 26.6% of respondents said that they saw people selling drugs in their neighborhood. By 1993, this had risen to 49.6% (*New York Times/CBS News* 1989, September 1993). This would indicate an increased perception that drugs were a problem in individual neighborhoods and for the city overall. However, from looking at Table 3.3 this would be a difficult jump in logic to make. In 1993, drugs were a major problem in New York City; however, crime had eclipsed drugs as a potential number one problem. This may have been because the link between rising crime rates and increased drug sales was apparent by 1993, and that the crime that was caused by drugs was considered far more dangerous than the drugs themselves.

The other major issue in 1993 was the economy. 65% of respondents rated the New York City economy either fairly bad or very bad (*New York Times/CBS News* September 1993), while 75% of respondents said that their family was in the same or worse financial situation as four years before. Interestingly, 50% of those asked stated that the economy was beyond the mayor's control (*New York Times/CBS News*

September 1993). The effect of the economy on voting has been measured only at the national level. In presidential elections, the incumbent suffers when the economy is bad (Rosenstone 1982). In the 1992 presidential election, the failing economy and Bush's apparent lack of interest in it was the main focal point of Clinton's campaign. The salience of national-level economic issues may account for some of the 50% who stated that the economy was not under the mayor's control. It is unclear from the survey data whether people perceived the economy as a local or national problem, or both. Yet, aside from the economy in general, economic issues such as unemployment did not appear on the top five lists of problems in New York City over time.

Liberalism and Conservatism in New York City

It would be easy to link overall dissatisfaction with the city to being more conservative, and then to state that there was an increase in conservatism that precipitated the election of Giuliani. That does not seem to be the case. The proportions of liberal, moderate and conservative New Yorkers remained stable from 1985 to 1993. Each ideological division hovered around 29% to 34% of all respondents, with those who did not respond to the question making up the difference. This does not mean that a certain ideological group was not more likely to be a pessimist than any other group.

Conclusion

Chapter 3 gives a contextual background to the conception of pessimism that will be presented over the next three chapters. During the period between 1985 and 1993, more and more New Yorkers became dissatisfied or disillusioned with one or more aspects of the city's quality of life. While this did not result in a definitive turn towards conservatism, it did result in a refining of the respondents candidate support.

People's perception of the candidates in 1993 were divided between which candidate was more compassionate and which was more effective. Occasionally, these two qualities can occur in the same person. However, as Sigelman et al pointed out, candidates of community of color are more often seen as compassionate but not as effective, while white candidates are seen as effective. The same held true in this election. Dinkins was seen as the more compassionate candidate, while Giuliani was the candidate who could "fix" the city. Broken down by race and income class, Table 3.3 presents how registered voters viewed the two candidates in two different questions. The first question was "Does (the candidate) care about the needs of everyday New Yorkers?" The second question was "Does (the candidate) have what it takes to get things done in this city?"

Table 3.3 Perceptions of the Candidates

	<i>Does (The Candidate) Care About Average New Yorkers?</i>		<i>Does (The Candidate) Have What It Takes to Get Things Done?</i>	
<i>Race and Income Group</i>	<i>Dinkins</i>	<i>Giuliani</i>	<i>Dinkins</i>	<i>Giuliani</i>
White Working Class	65.30%	70.80%	30.60%	57.60%
Nonwhite Working Class	89.10%	39.50%	74.80%	33.30%
White Middle Class	68.50%	74.80%	25.20%	62.20%
Nonwhite Middle Class	86.10%	33.30%	75.00%	38.90%
White Upper Class	66.70%	77.30%	15.20%	60.60%
Nonwhite Upper Class	92.00%	60.00%	68.00%	52.00%
Total	75.90%	58.80%	46.10%	50.70%

The findings were divided along the “traditional” racial lines with nonwhites supporting Dinkins across the board, and whites supporting Giuliani. Yet, these findings did not bode well for Dinkins, whose effectiveness was being questioned after a term as mayor, where he had already had a chance to prove his merit and was found wanting. While both groups found Dinkins at least reasonably compassionate, few whites found Dinkins competent to handle the city’s problems. For white respondents, it seemed that his inability to calm racial tensions as well as his seeming to cut the budget without a plan all pointed towards his lack of a master plan. A plan was the one thing that Giuliani appeared to have. It may not have been a compassionate plan, but as the respondents stated in answer to this question, it was a plan. The next chapter will examine what happened with Dinkins and Giuliani in “Round One.” Chapter 5 will explore the 1993 contest, and Chapter 6 will compare the elections.

Introduction to Chapters 4 to 6

In 1993, New York City was suffering from increased racial tension, more worries about crime and homelessness, and financial difficulties. This atmosphere created a more pessimistic context for the rematch election between Giuliani and Dinkins. This dissertation's main hypothesis states that the pessimistic attitude of New York City residents, filtered by race and class, gave Giuliani an edge over Dinkins. This section serves as an introduction to Chapters 4 to 6. Each of the following chapters will explore the causes of pessimism in the given year, and the factors behind candidate support using the *New York Times*/CBS News pre-election poll from that same year. This introductory section will lay out the theoretical basis for the inclusion of each of the different hypothetical variables included in the exploration of both the roots of pessimism and the factors behind candidate support for the 1989 election, the 1993 election and in the final chapter in this section, it will compare the two election years.

Essentially, the contest between the two candidates would change the direction of New York City politics from more liberal to more conservative. Dinkins represented what some considered to be the last gasp of the liberal/Democratic establishment. He rose through the ranks of the Democratic Party machine and became Manhattan Borough president as a jumping-off point to the mayor's office. His policies were liberal leaning, and tended more towards a government solution to tough problems than a privately based one. Giuliani, in contrast, had never held elected office. He was a former U.S Attorney whose tough prosecutorial style translated into hard on crime and smaller government

conservatism. In keeping with his conservative outlook, Giuliani ran against the then-current liberal policy system, charging that if elected he would cut spending and taxes in addition to eliminating “wasteful” social programs. These policy stances put Giuliani clearly in the conservative end of the political spectrum. Therefore, the two mayoral elections in 1993 and 1989 can be viewed as not simply between two candidates but between two different policy systems as well.

The dependent variable being explored is a change in support for Giuliani that allowed him to win the mayoral election in 1993 when he lost in 1989. The question in both years reads:

“If Dinkins and Giuliani were the only two candidates in the upcoming election for mayor who would you prefer: Dinkins, Giuliani, Neither or Not Voting, or Don’t Know?”

This dissertation theorizes that the increase in support that propelled Giuliani to victory was due primarily to middle class white dissatisfaction or pessimism with the direction that New York City was taking on many levels. However, there are other factors to consider behind candidate preference in both elections such as religion, borough of residence, gender, crime victimization and attitudes on race relations and on the general future of New York City. The resultant model will then be tested first in the 1989 mayoral election in Chapter 4. Chapter 5 will present the 1993 model and its tests, while Chapter 6 will present a comparison between the two years and further analysis of the changes. Each section will have two parts; first an introductory examination of the causes of pessimism

in New York City, and then a detailed examination of the varying degrees of support for the candidates across time.

Long-term outlook, specifically pessimism, was the filtering variable across which the influence of the other variables was felt. The causes of a pessimistic long-term outlook vary across time. New Yorkers are sometimes stereotyped as extraordinarily cynical. However, translating this stereotyped cynicism into answer a question asking about a person's view of New York City in the future is difficult at best. The question in both years reads:

“What is your long range view for the city—do you think that 10 or 15 years from now, New York City will be a better place to live than it is now, a worse place or about the same?”

Focusing on those who answered “a worse place”—the pessimists—allows for testing of national-level theories about middle class dissatisfaction on a local level. On the national level, middle class dissatisfaction has been seen as a contributing factor to both Clinton's 1992 presidential win, and the 1994 election of a Republican majority in Congress (Teixeira 1996). If this national-level pessimism or malaise about the future could translate down into local elections, then the premise that it was the depressed middle class who prompted the political changes on the national level would garner further support. The middle class, particularly middle class whites, was the most pessimistic of any racial or class group in New York City (see Chapter 6 for more explanation). Middle class whites were also the only group for whom pessimism

increased from 1993 to 1989. Therefore, this dissertation hypothesizes that race and class will be the largest contributing factors to pessimism regarding life in New York City.

According to retrospective voter theory, if a person has a negative long-term outlook, he or she would be less likely to support the incumbent party and its candidates, as the incumbent party is forming the policies that will shape the future. Retrospective voting theory states that an individual voter analyzes rationally whether his or her situation (financially or otherwise) has improved over the incumbent's term in office. If the individual voter's situation has improved, then the incumbent stands a greater chance of staying in office. If the individual voter's situation has not improved, then the incumbent stands a greater chance of losing the election (Downs 1965; Popkin 1991). While pessimism's effect on incumbency is not a factor in the 1989 election, as the incumbent Mayor Koch was defeated in the primary, it is still critical, as Dinkins represented Koch's liberal policy legacy.²⁵ Additionally, long-term outlook's effect on a person's candidate preference is particularly important in 1993 when Dinkins' tenure as mayor and his more progressive policies were tested. This dissertation hypothesizes that those who answered that they were pessimistic about New York City's future were more likely to support Giuliani, while those who answered optimistically were more likely to support David Dinkins in both contests, particularly in 1993.

²⁵ I acknowledge the Koch was not the prototypical liberal in terms of policy, especially in his relations with the business community. However, he was and still is far more liberal on social policy than Giuliani, and therefore I consider him a liberal for the purposes of this dissertation.

Hypothesis 1: A respondent's long-term view of New York City's future had a significant effect on his or her candidate preference. Those who answered that New York City would be worse off over the next 10 to 15 years will support Giuliani. Those who answered that the city would improve will support Dinkins. Those who answered the city would remain the same could prefer either candidate.

Additionally, as middle class whites were the largest pessimistic group in 1993 and nonwhites of all classes had decreased levels of pessimism, it stands to reason that race and class would also have an influence on levels of pessimism. Therefore, this dissertation hypothesizes that race and class will be the two main contributory factors behind long-term outlook in both election years.

Hypothesis 1a: A respondent's race and income class will be the two largest predictors of pessimism across time.

Race is always a critical factor in urban elections, especially when one or both of the candidates are from communities of color. In New York City, whites tend to vote for whites and nonwhites for nonwhites. Yet, Carsey found that in some New York City communities, the closer they live to a predominately African American neighborhood, the more likely whites are to vote for an African American candidate (Carsey 1995).²⁶ The white liberal community helped to elect Dinkins both as borough president of Manhattan and as mayor of New York City. Dinkins ran a "deracialized campaign" in both elections

²⁶ This view has been disputed by Huckfeldt and Kohfeld (1989), Giles and Hertz (1994) and Weakliem (1997), who state that whites who live in heavily nonwhite neighborhoods, i.e. higher threat neighborhoods, are less likely to vote for African American candidates. As all of these studies are on the national level, rather than the local level, it is difficult to directly compare the results.

by concentrating on issues that would appeal to members of all races through a progressive agenda. At the same time, he was careful not to neglect the African American community that was his major support base by promising to appoint more members of that community to high-level positions than any previous mayor (Sleeper 1990; Thompson 1996).

Giuliani also was careful not to alienate his natural support base—the conservative white ethnic community—through carefully worded anti-crime rhetoric, promises to cut taxes and reduce spending on welfare programs.²⁷ He also sought support from some of the more conservative members of the Latino community but was relatively unsuccessful, even though his social politics were close to the Catholic Church's views on these issues (Sleeper 1990; Mollenkopf 1994). Ironically, Giuliani did not receive the support of the Conservative Party in either election. Instead, he ran on both the Liberal Party and the Republican Party ticket.²⁸ Both parties are relatively small and predominately white. However, his conservative social policy proposals did win him the support of many Catholics. As the primary support bases for each candidate are divided by race and political viewpoint, this dissertation hypothesizes that support for the candidates will be divided by race as well as political viewpoint to some degree.

Hypothesis 2: Overall, whites will support Giuliani, while nonwhites will support Dinkins regardless of political affiliation.

²⁷ The phrase “tax and spend” is also used by conservatives to paint more liberal politicians as being softhearted and overly generous to the poor and homeless (Hagen 1995).

²⁸ The Liberal Party in New York City is not made up of liberals in the progressive sense. Rather, it consists of liberals in the more traditional free-market meaning of the word.

Hypothesis 3: Liberals will support Dinkins overwhelmingly while Conservatives will support Giuliani. Moderates or those who don't know their ideology will not have a strong preference for either candidate.

Income class is also a factor in voting decisions. Individuals with lower income tend to be nonwhite and not to vote as often (Scammon and Wattenberg 1990). However, when presented with a progressive agenda and a credible candidate, lower income voters do come to the polls (Hill and Leighley 1992), and this dissertation hypothesizes that they supported Dinkins in both elections. Middle-income individuals were the subjects of a great deal of scrutiny during the early 1990s. They were the subjects of numerous studies that delineated their depression. Their pervasive dissatisfaction with government and the status quo has led the middle class to support whomever can best appeal to their diminishing sense of importance (Tolchin 1994). Therefore, this dissertation hypothesizes that middle income individuals will support whomever does not represent the administration in power. In 1989, that could have been either candidate but by 1993, Giuliani was the clear favorite. Upper-income individuals tend to vote quite often (Converse 1964). Furthermore, they tend to be conservative (Siegelman 1994). This dissertation hypothesizes that they supported Giuliani in both elections.

Hypothesis 4: Lower-income individuals will support Dinkins in both elections. Middle-income individuals are affected by other factors and could have supported either candidate in 1989, but in 1993, they will be solidly behind Dinkins. Upper-income individuals will support Giuliani in both elections.

Since the mid 1800s, Jews have held positions of political importance in New York City. However, it was not until 1973 that New York City had a Jewish mayor. Jews in New York City have always been strongly Democratic and strongly liberal (Arian et. al. 1990; Siegelman 1994). As such, they have continuously supported the Democratic candidate for mayor, especially when he has had liberal tendencies. The defeat of Ed Koch in the mayoral primary in 1989 was a victory for the liberal Jewish community who resented his stance towards communities of color and felt abandoned by his pro-business stance on many projects (Mollenkopf 1992). However, it was also a defeat for more conservative outer-borough Jews who had supported him throughout his tenure as one of their own. Liberal Jews were strongly behind the candidacy and victory of David Dinkins in New York City (McNickle 1993). Yet, after the Crown Heights incident, they began to doubt their convictions (Thompson 1996). Therefore, this dissertation hypothesizes that in 1989, Jews were more likely to support Dinkins than non-Jews. By 1993, however, Jews would be almost as likely to support Giuliani.

Hypothesis 5: Jews are more likely to support Dinkins overall. However, in the 1993 contest, their support for him will drop to match that of non-Jews, and as such, being Jewish would cease to be a causative factor in deciding between candidates.

Residents of the outer boroughs of New York City carry a moderately undeserved reputation for conservatism.²⁹ This conception of the outer borough

²⁹ In reality, they are probably no more conservative than the average moderate living outside of New York City, yet there are a few main stereotypes that stand out, namely Archie Bunker, the main character in the Footnote continued on next page

resident has been somewhat corroborated by scholars, namely Rieder (1985). His work on the residents of Canarsie depicts a neighborhood that was scared and dismayed by the influx of African Americans into their formerly white environment (1985). This dissertation theorizes that Giuliani's veiled racial messages would appeal to those outer borough residents who felt disillusioned about New York City as it changed from majority white to majority nonwhite. Manhattan residents, on the other hand, are depicted as much more liberal than those of the outer boroughs (Arian et. al. 1990). They elected David Dinkins as the first African American Borough president; therefore it stands to reason that their liberalism, combined with the previous support of Dinkins would result in residents of Manhattan supporting Dinkins' candidacy, while outer-borough residents would support Giuliani.

Hypothesis 6: Manhattan residents will support Dinkins. Residents of the outer boroughs will support Giuliani.

Hispanic origin is not combined with race in this model to test for the overall influence on Hispanics on the model, regardless of race. Hispanics were a critical swing constituency in both election years. As a minority group in New York City comprising only about 25 percent of the population, many assumed that the Hispanic community would automatically support Dinkins (NPR 1993). By 1993, however, more Hispanics questioned Dinkins' ability to address their concerns (NPR 1993), and

1970s television show, *All in the Family*. He assailed all people who were different from him, and railed against all liberal viewpoints.

they began to look for someone else to represent them. This dissertation hypothesizes that in both elections Hispanics will favor Dinkins over Giuliani, but that in the 1993 election the margin between the two candidates will be much closer. Non-Hispanics will split their preferences according to other preferences or characteristics.

Hypothesis 7: Hispanics in 1989 will strongly support Dinkins. By 1993, Hispanics will be more evenly split between Dinkins and Giuliani. For non-Hispanics, preferences will be more evenly split between the two candidates in both elections.

Gender is often a critical factor in elections. The gender gap, as it is often referred to, finds women far more likely to support a Democratic or liberal candidate than a Republican or conservative. This is because Democrats are traditionally seen as being stronger on women's issues and education and are mostly pro-choice. Republicans, on the other hand, are more likely to be pro-gun, pro-death penalty, and in general against the myriad social programs that help women. For this reason, this dissertation hypothesizes that women will be consistently more for Dinkins than for Giuliani, while men will react in the opposite manner.

Hypothesis 8: Women will support Dinkins, while men will support Giuliani.

Education is always a factor in voting and candidate support. Generally speaking, the more educated one is, the more likely it is that one will participate politically. The reverse is also true; the less educated one is, the less likely it is that one will participate. This may be due to the strong relationship between income levels and education. As years

of education increase so does earning potential, and as earnings increase so does likelihood of political participation. In other words, typically, if one is more educated, one earns more and is more likely to vote. However, this does not relate to candidate preference or political viewpoint. Being more educated does not make a person more likely to vote in any particular political direction (i.e. liberal or conservative). Therefore, this dissertation hypothesizes that an individual's level of education will not be related to candidate preference.

Hypothesis 9: An individual's level of education will not be a predictor of candidate preference.

Before his nomination by the Republican Party to run for mayor, Rudolph Giuliani was the U.S. State's Attorney in charge of eliminating organized crime from the city. He was a tough attorney who was pro-death penalty and for victims rights. The crime rate in New York had been rising since the mid-1980s, leading to an atmosphere of tension and fear. The rise in crime rates did not begin to subside until the late days of Dinkins' term, and then only slightly (Ward 1997). Giuliani painted Dinkins as soft on crime and presented himself as a crime-fighting expert due to his experience as an attorney. In 1993, Dinkins' apparent failure to lower crime rates made it easier for Giuliani to characterize Dinkins as soft on crime and against victims' rights. Since a critical feature of both elections was the emphasis on crime and crime rates, this dissertation hypothesizes that victims of crime will be more likely to support Giuliani, while people who were not victims of crime would be likely to support either candidate or to have no opinion.

Hypothesis 10: Crime victims will be strongly for Giuliani. People who were not victims of crime will have no clear preference between the two candidates.

A decline in race relations was another feature of the period up to 1989 and between the two elections. As New York City's first African American mayor, Dinkins was elected with the expectation that he could calm racial tension. Yet, both the Korean store boycott and the Crown Heights riots worked against him (Thompson 1996). His inability to act decisively in these situations left many wondering if he could calm rising racial fears in New York City. Those who thought race relations were bad, this dissertation hypothesizes, are not only more likely to be pessimists about New York City's future, but are also more likely to be split in 1989 between the two candidates and to be for Giuliani in 1993. This dissertation theorizes that they will be split between the two candidates in 1989, because although Dinkins ran on a platform of racial conciliation, Giuliani was an unproven entity in 1989. People may have thought that Giuliani could not make race relations any worse than they already were, and so were able to support him as a mayoral candidate. By 1993, race relations in the city were perceived to be worse than in 1989 (*New York Times/CBS News* 1993); Dinkins had apparently failed in his quest to unify the city under a "rainbow" banner (Thompson 1996). Therefore, those who thought race relations were generally bad were more apt not to support Dinkins and to either support Giuliani or be placed in the "Neither/No Vote" category. Those who thought that race relations were generally good, this dissertation hypothesizes, will be more likely to

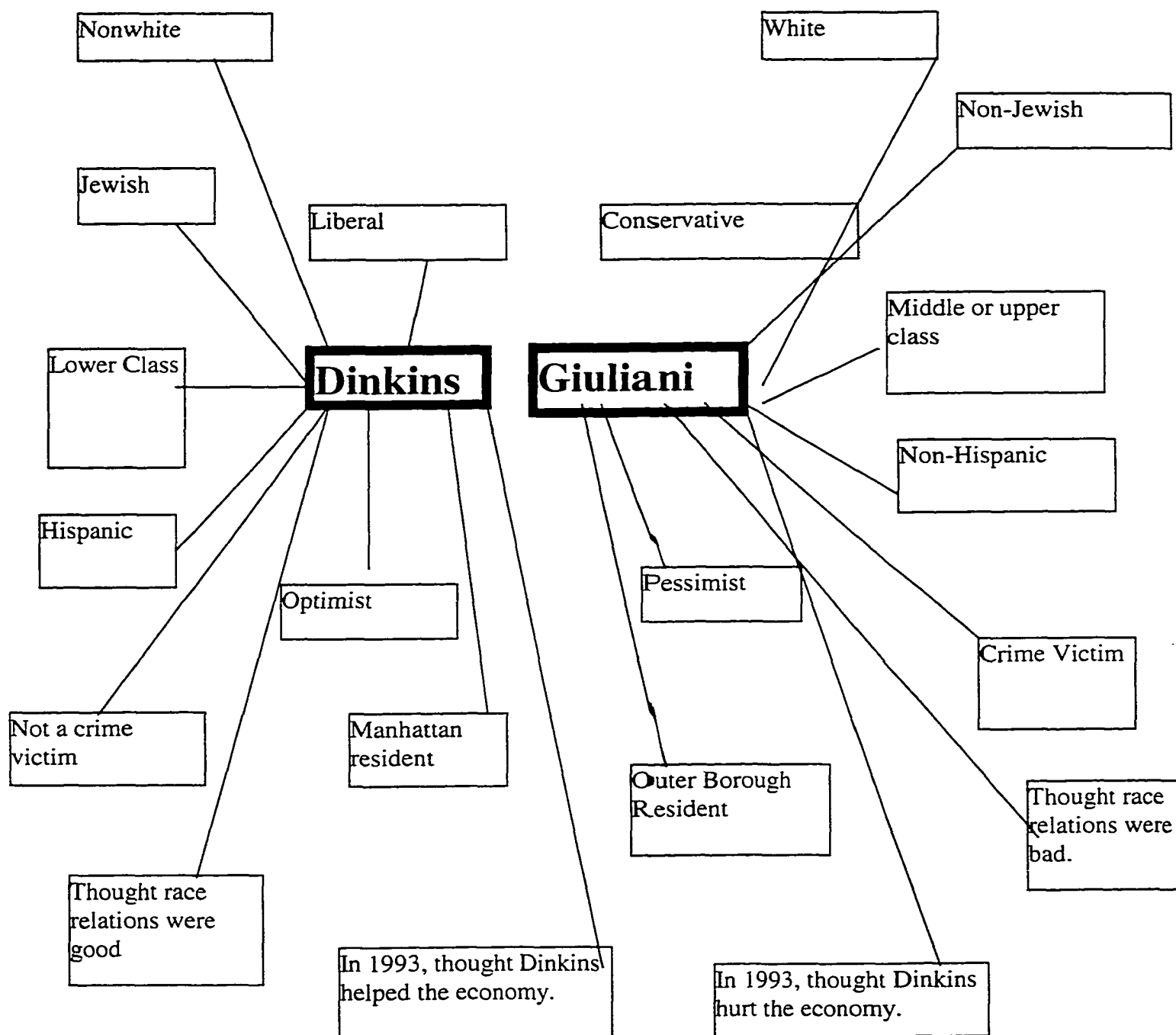
support Dinkins, as they either approved of his racial conciliation strategy or they approved of the job he was doing up until that point.

Hypothesis 11: Those who thought that race relations were generally bad in 1989 will be more likely to be split between the candidates, while by 1993, they will be more likely not to vote for Dinkins. Those who thought that race relations were generally good in both elections will be more likely to support Dinkins.

The final variable in my model appears only in 1993. The stock market crash in 1987 ushered in a recession for New York City that had caused not only a 7.5 billion dollar deficit (Thompson 1996) by the time Giuliani was elected, but had caused over 10 percent unemployment in the city for the first time in close to a decade (Bureau of Labor Statistics 1994). In addition, the economy in the early 1990s was a hot campaign topic as it was linked not only to middle class dissatisfaction but also to Clinton's victory in 1992 (Teixeira 1996). Therefore, in 1993, a variable was added, measuring the respondent's opinion of how Dinkins had handled New York City's economy over the previous four years. The question asked was: "Do you think that in the last four years David Dinkins has helped the city's economy, hurt the city's economy, or not made much difference to the city's economy?" (*New York Times/CBS News Poll*, May 1993). This dissertation hypothesizes that those who thought that Dinkins had hurt the economy were Giuliani supporters in 1993 and strongly pessimistic. Those who thought that Dinkins had made no difference were split between the two as other factors came into their election decisions, and those who thought that Dinkins had helped the economy were Dinkins supporters.

Hypothesis 12: Those who thought that Dinkins hurt the economy will be for Giuliani, those who thought that Dinkins made no difference will be split and those who thought that Dinkins had helped the economy will be for Dinkins.

Summarizing the model into two categorizations: white, conservative, middle or upper class, outer borough, non-Jewish, non-Hispanic, pessimistic, crime victims who thought that race relations were bad would support Giuliani. Nonwhite, liberal, Jewish, lower class, Manhattan resident, optimists, who were not crime victims, who thought that race relations were satisfactory, would support Dinkins (see Figure 1).

Figure 1

The contests between these two candidates not only would determine policy direction for the next four years, but also the overall scope and shape of policy for the next decade and into the next century. Would New Yorkers reject the more traditional progressive policy framework in favor of a more conservative, more “non-New York” way of handling social and economic problems, or would they continue to embrace the liberal/progressive New York way of treating these issues? The ability of this dissertation’s model to explain these occurrences will be examined in Chapters 4, 5 and 6. “Round One,” the 1989 election, will be discussed in Chapter 4; “Round Two,” the 1993 election, will be discussed in Chapter 5, and Chapter 6 will compare the two elections.

Chapter 4 Round One

The 1989 election came at a critical juncture in New York City history. The incumbent mayor, Edward Koch, was defeated in the Democratic primary by David Dinkins, the Manhattan Borough president. This presented the first opportunity in more than two decades for voters to choose between two new candidates rather than between a challenger and an incumbent. Koch's defeat in the primary did not come as a surprise; he had become more and more hostile to African American and Hispanic interests throughout his tenure, and when the opportunity presented itself to these communities to vote for a person of color, they did. Koch's previous strategies to appeal to Jewish and white Catholic middle class New Yorkers did not work in his favor in 1989 (McNickle 1993). The corruption surrounding his party and supporters, particularly in Queens, left a bad taste in many voters' mouths (Mollenkopf 1992).³⁰ Koch's administration also suffered through its image as the last bastion in a long line of white ethnic political machines, representing the old regime in New York City government.

David Dinkins was the first person of color to run for the office of mayor of New York City. Since his election as Manhattan Borough president in 1987, he had been seen as a possible mayoral contender in the 1989 election. Jesse Jackson's strong 1988 presidential candidacy signaled to many New Yorkers that the time was ripe for an African American mayor (Mollenkopf 1992). Dinkins' victory in the Democratic primary

³⁰ Beginning in 1986, there was a corruption scandal that spread from the Bronx and Queens Democratic Party offices to Koch's administration. It resulted in a large number of convictions, as well as the suicide of Queens' party leader, Donald Manes (Mollenkopf 1992).

in September of 1989 was due to the support of Hispanics, white liberals and African Americans, all of whom had been alienated by Koch in previous contests, and who had supported Jesse Jackson for president in 1988 (Mollenkopf 1992; McNickle 1993). Dinkins was also boosted by his calls for harmony following the Bensonhurst riots and the Central Park “wilding” incidents (McNickle 1993).³¹ His victory in the primary represented a new face for New York City; Dinkins represented a more urbane, less combative style seemed to suit the influx of wealth that occurred in the early 1980s.

The changing demographics in New York City, as discussed in Chapter 2, seemed to cement the desire to have a person of color lead a city that was no longer majority white. Dinkins had strong appeal among African Americans who were eager to elect one of their own, but also among Hispanics, who represented the other large “minority” group in New York City.³² Simply winning the support of African Americans and Hispanics would not be enough for Dinkins to win the general election. To do so, he would have to court various groups of white ethnic voters throughout the city; in particular, Jewish liberals who still held positions of power within the Democratic party and as union

³¹ The Central Park “wilding” incident occurred in April of 1989, when a group of African American teens beat and raped a white female jogger in the park. After their arrest, the teens joked about the incident, prompting many in the city to become horrified at the prospect of this type of incident happening again. It also gave credence in the minds of some voters to Giuliani’s themes about the recurrent lawlessness that was overtaking the city. The Bensonhurst incident was the killing of a young African American male by a gang of white youths. This incident prompted large-scale protests by African Americans in Bensonhurst. Dinkins’ appeals for calm increased his strength as his opponents realized that hostile comments would make him stronger. (McNickle 1993, 304-305).

³² The word *minority* is in quotations here because even though Hispanics were only about 25 percent of the total population at this point, when this percentage is combined with the percentages of other groups of color, they total over 50 percent of the population.

leaders. His ability to appeal to these distinct voting blocs would determine his victory or defeat.

Giuliani was somewhat of an unknown at this juncture. He had begun to make a name for himself as a U.S. attorney in high-profile cases, but he was far from a household name. Giuliani's main strength was as the "anti-Dinkins" candidate. Running as a Republican, Giuliani clearly did not represent the New York City political establishment. He saw opening for a candidate who did not wish to continue with "politics as usual." His emphasis on law and order, smaller government and lower taxes was meant to appeal to the so-called "Reagan Democrats" who had abandoned the Democratic Party during the 1980s. Giuliani's style was also quite different from Dinkins'. Where Dinkins was conciliatory, Giuliani was gruff and forceful. The contest between the two candidates was one of the most bitterly hostile in recent memory.

In order to establish a comparison between the two elections, the same hypotheses were used whenever possible. Therefore, this chapter's hypotheses are similar to those for the 1993 election with one main exception: economic issues were not as salient in 1989 as they were in 1993. The 1992 presidential election, coming on the heels of a recession, pushed the economy into the foreground of voters' minds. While the 1987 crash occurred only a few years prior to the election in 1989, the *New York Times*/CBS News poll did not ask any questions regarding New York City's economic performance or personal economic standing, so no attitudinal questions relating to the economy were included in the exploration of the causes of pessimism and the analysis of the factors behind candidate selection. The hypotheses are as follows:

Hypothesis 1: A respondent's long-term view of New York City's future would have a significant effect on his or her candidate preference. Those who answered that New York City would be worse off over the next 10 to 15 years would support Giuliani. Those who answered that the city would improve would support Dinkins. Those who answered that the city would remain the same could prefer either candidate.

Hypothesis 1a: A respondent's race and income class will be the two largest predictors of pessimism across time.

Hypothesis 2: Overall, whites will support Giuliani, while nonwhites will support Dinkins regardless of political affiliation.

Hypothesis 3: Liberals will support Dinkins overwhelmingly. While Conservatives will support Giuliani, moderates or those who don't know their ideology will not have a strong preference for either candidate.

Hypothesis 4: Lower-income individuals will support Dinkins in both elections. Middle-income individuals will tend slightly towards Giuliani, and upper-income individuals also will support Giuliani.

Hypothesis 5: Jews would be more likely to support Dinkins overall. Non-Jews would be split between the two candidates, as other factors may come into play.

Hypothesis 6: Manhattan residents would support Dinkins. Residents of the outer boroughs would support Giuliani.

Hypothesis 7: Hispanics would strongly support Dinkins. For non-Hispanics, preferences would be more evenly split between the two candidates in both elections.

Hypothesis 8: Women would support Dinkins, while men would support Giuliani.

Hypothesis 9: An individual's level of education would not be a predictor of candidate preference.

Hypothesis 10: Crime victims would be strongly for Giuliani. People who were not victims of crime would have no clear preference between the two candidates.

Hypothesis 11: Those who thought that race relations were generally bad would be more likely to be split between the candidates, as their effect on race relations was not yet proven. Those who thought that race relations were generally good in both elections would be more likely to support Dinkins.

The data used for the analysis in this chapter is taken from the 1989 *New York Times*/CBS News telephone poll conducted in June of that year.³³ There were 1461 total respondents from across the five boroughs. The sample was created using a stratified random digit dialing protocol, and asked questions regarding both general social issues and the upcoming election (*New York Times*/CBS News 1989, 3). Where necessary, the modifications made to the data are indicated, and the influence these modifications may have on the final results is discussed.

Pessimism in 1989

Life in New York City during the 1980s was one of contrast; on the whole, the rich got richer and the poor became poorer (see Chapter 2). There was also a fair amount of racially based migration during this period. Many whites left the city. Those white residents who remained in New York City saw their overall political status decline, as the majority of New York City's population became increasingly nonwhite. Nonwhites also faced various hurdles as immigration soared during the 1980s. All of this created a city in transition, with large amounts of indecisiveness on what direction the city should take.

The emergence of David Dinkins as a contender for the mayor's office was a signal to many that the possibility of racial harmony was imminent. However, to those who felt threatened by the changes taking place in New York City in 1989, Giuliani represented security. He promised a return to the "good old days" of law and order where people knew who they were and what their "place" was. This chapter's first hypothesis is that being a member of the middle class and being white are the two strongest indicators of long-term pessimism in 1989.

Long-term outlook is a product of an individual's situation. A person's financial and social conditions color his or her long-term outlook. Pessimism about New York City's future, or a negative long-term outlook for living in New York City, is the main mediating variable between the intersection of race and class and candidate preference. The question in the 1989 *New York Times*/CBS News survey reads:

"What is your long range view for the city—do you think that 10 or 15 years from now, New York City will be a better place to live than it is now, a worse place or about the same?" (Q1, p.3).

In 1989, approximately 49% of those surveyed responded that they thought that New York City would be a worse place to live in 10 or 15 years. The question that this section hopes to answer is: what contributes to a person being pessimistic about New York City's future? Was it a question of demographics or was it a question of political

³³ It would have been ideal had the *New York Times*/CBS News conducted a survey in November immediately prior to the election. However, the survey used for this analysis was the only survey conducted by the *New York Times*/CBS News service until the exit polls on election day.

ideology? This question will first be addressed through a series of crosstabulation results and then through a multivariate logistic regression.

The dependent variable for this section is “longbad.” It is a dummy variable where 1 equals a pessimistic response and 0 equals anything but a pessimistic response (i.e. optimism and neutral about New York City’s future). It was created in this manner to isolate the causes for a pessimistic outlook for New York City. Feeling pessimistic about New York City’s future was most common response in 1989. The crosstabulations of “longbad” by the independent variables of race, income class, gender, age, level of education, borough of residence, Hispanic origin, religion (Jewish or Non-Jewish), crime victimization and opinion on race relations will be examined in the following paragraphs.

Life in New York City got somewhat harder for a large percentage of the population by 1989. The increased gap between wealthy and poor New Yorkers was complicated by the fact that with lower income groups there was increased competition for jobs as more immigrants arrived. Another factor was crack cocaine, which decimated poorer neighborhoods (usually neighborhoods of color) by increasing the crime rate and further marginalizing the population. Therefore, one would expect that more nonwhite and more low-income respondents would be pessimistic about the city’s future. Surprisingly, this was not the case.

While a larger percentage of nonwhites were pessimistic, the chi-square was highly insignificant, indicating a lack of association between pessimism and race when considered independently from other variables (chi-square=3.0497, prob.=0.218). Additionally, lower-income respondents were more likely *not* to be pessimistic (52.98%), but again, the association between pessimism and income class is not statistically

significant (chi-square=7.3493, prob.=0.062) (See Appendix 4.1 for the crosstabulation). Therefore, in light of the logistic regression results of the independent variables on “longbad,” these two variables should also be insignificant.

The variables that were significantly associated with pessimism were not those that were originally expected during the initial examination of the crosstabulations, i.e., income class and race. People who responded that they were pessimistic tended to be conservative, middle aged, having some college education but not a degree, Hispanic, living in the outer boroughs, and of the opinion that race relations were generally bad. Being a victim of crime was not significantly associated with pessimism for these respondents, and neither was religion. (For a fuller elaboration on the crosstabulations please see Appendix 4.1).

Often within statistical analysis one wants to examine the causes behind a phenomenon rather than a simple association between variables. In these situations it is more appropriate to use a higher-level multivariate analysis, rather than relying on the results of chi-squares. Table 4.1 presents two sets of odds ratios taken from two logistic regression equations in an attempt to explain and predict the likelihood of being pessimistic about New York City’s future. The first equation (Model A) is the fully saturated model incorporating all the hypothesized variables. Model B represented the second equation and is the more parsimonious version with containing only the statistically significant predictors from Model A providing a reduced set of predictors.

Logistic regression is a form of regression analysis whose goal is to determine the best-fitting logistic curve to a group of data points. This method is used with nominal data where the event in question is coded 0 or 1, thereby violating one of the assumptions

of ordinary least square (OLS) regression methods. OLS regression methods demand that the dependent variable should be interval in nature, and a dependent variable measured in terms of 0 and 1 does not meet this qualification. Logistic regression parameters are estimated using the maximum likelihood estimation method that makes a series of successive approximations of the true population parameters (iterations). The goal is to use the sample data to make estimates of the population parameters that maximize the likelihood of having obtained these observed sample values. The maximum likelihood procedure is repeated until one can no longer estimate the true population parameters from the observed sample values. The independent variables in a logistic regression can be of any variable type. In this dissertation, wherever they were not interval-level variables, dummy variables were created and used as a set. For example, if there were three values for race in the original data set (white, nonwhite and DK), there would be two dummy variables, one where white equals one with nonwhite as the reference group, and the other where don't know equals one with nonwhite as the reference group. In this manner, all the possible value combinations will be included.

Odds ratios and standard coefficients are the two main ways to present the results of a logistic regression; standard coefficients are the alternate way.³⁴ An odds ratio illustrates the amounts by which the odds favoring a 1-unit increase in your dependent variable increase for every 1-unit increase in your independent variable. In other words, in the case of a dichotomous dependent variable, the odds ratio is the ratio of the odds that

³⁴ The coefficients for both models (the saturated and the parsimonious) are presented in Appendix 4.2, along with the log-likelihood tests determining the strength of the contribution of each variable to the final model.

$Y=1$ when $X=1$ to the odds that $Y=1$ when $X=0$. For example, the odds ratio for the probability of pessimism for borough of residence is 1.5 in model A (Outer borough residence =1, Manhattan residence=0). This means that the odds of being a pessimist are 1.5 times greater when one is an outer borough resident than when one lives in Manhattan.

Obtaining an odds ratio equal to 1 means that there is no relationship between the dependent and the independent variable. Obtaining an odds ratio greater than 1 indicates a positive relationship between the dependent variable, in this case becoming a pessimist in the long-term, and the independent variable. In other words, the odds of becoming a pessimist are increased by the amount of the odds ratio with each 1-unit increase in the X variable controlling for all other variables (Hamilton 1999, 233). Obtaining an odds ratio of less than 1 indicates a negative relationship between the dependent and independent variable. This means that the odds are greater not to be a pessimist with each 1-unit increase in the independent variable. The first set of odds ratios is the saturated model with all variables included. The second set of odds ratios (Model B) presents the more parsimonious model.³⁵

³⁵ It should be noted that all variables included in the parsimonious model were tested for their necessity using the log-likelihood test. A log-likelihood test helps to determine the contribution each variable makes to the given equation in terms of whether or not the chi-square is reduced. To run a log-likelihood test one starts with a set of predictors, compute the log-likelihood for the full equation, then remove one predictor of interest, and rerun the log likelihood test. If log-likelihood test is reduced or stays the same, then the variable is included in the final calculations. If the chi-square for the log-likelihood with that predictor removed is not reduced or becomes insignificant at $p=.05$, then it is safe to "dispose" of the variable in question from the model.

Table 4.1 — Odds Ratios for Two Models of Pessimism in 1989

<i>Variable</i>	<i>Model A</i>		<i>Model B</i>
Age 18-29 (30-44) ³⁶	0.72* (.104)		.72* (.104)
Age 45-64 (30-44)	0.99 (.15)		.981 (.145)
Age 65 and over (30-44)	0.59* (.099)		.57* (.091)
LT HS Grad (BA)	1.18 (.224)		-
HS Grad (BA)	0.95 (.14)		-
Some College (BA)	1.24 (.186)		-
Jewish (Non-Jewish)	1.1 (.192)		-
Outer Borough (Manhattan)	1.5* (.217)		1.48* (.21)
Race Relations Generally Good (Generally Bad)	0.55* (.07)		.55* (.069)
Race Relations Don't Know (Generally Bad)	0.64* (.109)		.64* (.108)
Crime Victim (Not a Victim)	0.88 (.122)		-
Low Income (Middle Income)	.793 (.108)		.85 (.109)
High Income (Middle Income)	.72* (.119)		.72* (.114)
Don't Know Income (Middle Income)	.961 (.209)		1.00 (.212)
Don't Know Race (Nonwhite)	.802 (.401)		-
White (Nonwhite)	.917 (.112)		-
Don't Know Ideology (Moderate)	.882 (.194)		.94 (.201)
Conservative (Moderate)	1.35* (.187)		1.39* (.191)
Liberal (Moderate)	.773* (.105)		0.787 (.106)
Final Log Likelihood Model A	-969.09236		
X ² (20) Model A	86.89		
Final Log Likelihood Model B	-973.02023		
X ² (12) Model B	79.03		
Number of Iterations	4		
% Correctly Predicted	61.19%		
Number of Cases	1461 ³⁷		

³⁶ The reference category for the dummy variable is shown in parentheses. Significant values are marked at $p < .05$ with an asterisk *.

³⁷ The total number of unweighted cases in the June 1989 survey was 1461. I performed the analysis only on the unweighted cases because the weights increased the significance due to the effect of the increased N on the chi-square. Additionally, the weights seemed to multiply the cases by the proportions within the survey, rather than the proportions of the various demographics in the New York City population.

The full results for model A and B are reported in Table 4.1. As can be seen in the table, age was a significant predictor of not being pessimistic in regards to New York City's future.³⁸ In the 1989 survey, respondents who were relatively young (18 to 29) or comparatively old (65 or older) were likely not to be pessimistic with an odds ratio of .72 for young people, and .57 of old people. Therefore, the reference group (those aged 30 to 44) was more likely to be pessimistic than both the youngest respondents and the oldest respondents. Those in older middle age (45 to 64) did not have a significant relationship with the dependent variable.

The state of race relations in an urban area can contribute to long-term outlook. By 1989, race relations were generally perceived to be deteriorating within New York City. The Howard Beach incident in 1985, the "wilding" incident in 1987 and the Bensonhurst incident all affected race relations overall (McNickle 1993). Unfortunately, their impact on this equation cannot be measured, since the *New York Times*/CBS News survey in June of 1989 did not ask questions concerning these incidents. If the respondent thought that race relations in New York City were generally good, the respondent was less likely to be pessimistic with an odds ratio of .55 than those who thought race relations were generally bad. Those who had no opinion about race relations had an odds ratio of .64. Therefore, respondents who thought that race relations were good or had no opinion on the matter were more likely to think that New York City would remain the same or improve over the next 10 to 15 years based on the odds ratios.

³⁸ Only significant results will be reported here.

Living in the outer boroughs was a contributing factor to pessimism with an odds ratio of 1.48. An odds ratio of 1.48 means that if one lived in the outer boroughs of New York City (the Bronx, Brooklyn, Queens or Staten Island) one was 1.48 times more likely to be pessimistic about New York City's long-term future than if one lived in Manhattan. Additionally, being conservative ideologically rather than moderate influenced respondents to be more pessimistic about New York City's future with an odds ratio of 1.39. The dummy variable comparing being liberal to being moderate was significant in model A, but removing race from the equation might have tampered with the significance of the variable so in model B, only conservatives were significant and that made respondents much more likely to be pessimistic.

Having high income also made respondents less pessimistic, while the other income categories, low income, middle income and "don't know" income, were not significant statistically. Therefore, only for high-income people was the relationship between the dependent variable and the independent variable significant. It makes sense that over the course of the 1980s, being in a high-income bracket (over \$60,000 a year in household income) meant that respondents were more likely to be optimistic. Whether this translates into pocketbook voting remains to be seen. Interestingly, race did not play a role in the final model, as both the white and nonwhite dummy and the "don't know race" versus nonwhite dummy were not significant. This is surprising, given that Koch in the primary, and Giuliani in the general election, both made race-based appeals.

Based on the model represented in Table 4.1, the null hypothesis of Hypothesis 1a could not be rejected. A respondent's race was not a statistically significant predictor of pessimism controlling for other variables in the model even though income class was

statistically significant. Whether or not race and income will affect candidate preference will be examined in the next section.

According to the analysis presented in this section, a person was more likely to be pessimistic if he or she lived in the outer boroughs and was politically conservative. However, these results only hold true for the sample at hand. It is not advisable to generalize to heavily the adaptability of these figures to the overall population. One way to increase the usefulness of the model is using recycled predictors as shown in Table 4.2. Recycled predictors measure the average effect of a given independent variable on the predicted probability of pessimism controlling for other variables across the distribution of the actual covariate patterns observed in the sample data. The research presented in this dissertation is not a rigorous causal analysis as there are too many other variables that cannot be accounted for by the data. But rather, the analysis represents an interpretative effort to determine the possible reasons behind the reported rise in pessimistic outlooks in New York City and its possible effect on candidate selection. Using recycled predictors is helpful in these situations, because one cannot read the “effect” of a given predictor on the dependent variable in a logistic regression model the way one can in OLS regression. In logistic regression, the dependent variable is measured as the probability $Y=1$ where the estimated effects of X on Y are conditional. In other words, the dependent variable in a logistic regression equation is the likelihood of Y happening when X happens under certain conditions. These conditional effects are based on the probability of the dependent variable as influenced by other predictors in the model. Therefore, under one set of conditions (defined by a particular covariate pattern for a respondent), variable X might

have a negligible effect on Y , but under another set of conditions X may have a large effect on Y sample and population being studied.

Recycled predictors allow the researcher to control these effects of the other variables on the model by effectively isolating the effect of the specific independent variable in question on the dependent variable. Using the model fit from the underlying logistic regression and using the estimates of the β vector obtained from the model fit, you can predict $\text{Prob}(Y=1)$ for any value combination of the X vector (i.e., female, nonwhite, poor, liberal). Since there are so many possible covariate patterns, it is unwieldy to report the probability for all of them. Another reporting method involves substituting the means for the X values except for the one of interest, and then reporting the predicted $\text{Prob}(Y=1)$ for all covariate patterns. However, the means might have no correspondence to any particular covariate pattern, i.e., the mean of sex (e.g., .54).

Following the gender example, recycled predictors use the actual model fit and sample data, changes all the respondents in the data to men ($\text{sex}=1$), computes the predicted probability for all observations and then averages the result across the sample. Once this is completed, the same process is repeated, except all the respondents are now changed to women ($\text{sex}=0$). The two “recycled predictors” are then compared. The difference between these values is the “adjusted” average effect of gender on $Y=1$ (the dependent variable) controlling for all other variables and for the covariate pattern in the data. Crosstabulations simply state the percentage of males versus the percentage of females who are pessimistic without controlling for the effects of other variables.

Table 4.2 reports the comparison of the unadjusted predictors taken from the bivariate crosstabulations with the adjusted predictors created using the recycled predictor method.

Table 4.2— Unadjusted and Adjusted Predictors for Pessimism in 1989

<i>Variable³⁹</i>	<i>Unadjusted</i>	<i>Adjusted</i>
	<i>(Cross tabs)</i>	<i>(Recycled)</i>
Manhattan	40.07%	41.70%
Outer Borough	51.44%	51.04%
Low Income	47.02%	41.14%
Middle Income	53.83%	52.10%
High Income	45.12%	44.20%
Income DK	48.03%	52.18%
Liberal	42.11%	43.23%
Moderate	48.88%	48.93%
Conservative	58.46%	56.79%
Ideology DK	46.15%	47.40%
Race Relations Good	39.69%	40.10%
Race Relations. Bad	54.93%	54.48%
Race Relations DK	42.70%	43.92%
Age 18-29	47.09%	46.22%
Age 30-44	53.64%	54.04%
Age 45-64	53.85%	53.58%
Age 65 and Over	39.80%	40.50%

Looking at the results for the predictor borough of residence in Table 4.2, the simple crosstabulation results indicate that Outer Borough residents are 11 percentage points more likely to be pessimistic than Manhattan residents are. According to the adjusted probabilities, a majority of the other borough residents, controlling for all other variables, still tended towards pessimism with about a nine percentage point difference from those respondents who live in Manhattan. In simple terms, this means that if

³⁹ The results reported are the results for the probability of pessimism only and were created using the model fit from Model B (the parsimonious model).

everyone lived outside of Manhattan (holding everything else constant), there would be a greater likelihood of being a pessimist about New York City's future.

Manhattan has a higher per capita income than the outer boroughs. According to Table 4.2, individuals with high income will be less pessimistic. High-income respondents had an adjusted probability of long-term pessimism of 44.20%. Middle-income respondents had a 52.10% adjusted probability of being pessimistic about New York City's future. This is substantially higher than the two other groups who declared income. Therefore, even statistically controlling for a lot of other possible reasons, income class differences seem highly and nonlinearly correlated with pessimism. In other words, income class matters independent of the effects of race, borough of residence etc.

Political ideology had a great deal to do with long-term outlook in New York City. Conservatives would be the least happy in New York City due to its strongly liberal history, and correspondingly would have the highest levels of pessimism holding everything else constant (56.79%). Liberal respondents, in turn, had the lowest adjusted probability at 43.23% with moderate respondents falling in the middle at 48.93%.

Race relations are critical to the well being of any city, especially one as diverse as New York City. Poor perceptions of race relations generally translate into a pessimistic outlook for the city's future. Those who felt that race relations were generally bad had an adjusted probability of 54.58% of also being pessimistic, while those who thought that race relations were good had an adjusted probability of 40.10% of being pessimistic. Therefore, on average, if respondents thought that race relations were bad, they were likely to be pessimistic as well, whereas if they thought that race relations were good, they were more likely not to be pessimistic.

The final significant predictor, age, is interesting in that it belies conventional wisdom. The oldest respondents in 1989 were the least pessimistic of all the age groups with a 40.5% adjusted probability. This may be because more elderly people own their own homes or live in rent-stabilized units and they are therefore buffeted from dramatic shifts in the real estate market. They may also be retired and therefore immune to the effects of layoffs and plant closures. Those age groups that were majority pessimistic holding everything else constant were the middle-aged groups (30 to 44 and 45 to 64).

Being pessimistic about the future of New York City can be considered a resident's right at least according to the stereotypes. The analysis of the logistic regression equation shows that those who lived in the outer boroughs, earned in the middle income range, politically conservative, thought race relations were bad, and were middle aged tended to be pessimistic. 1989 was the first mayoral election year with two new candidates in over two decades. Voters were finally going to get a chance to choose a new direction for their city. The following section will examine the results of this choice incorporating the pessimism variable as a predictor in the model for candidate selection.

The 1989 Election

The 1989 election came on the heels of the strongest showing ever by an African American candidate for president, Jesse Jackson. It also came at a time when New York City was in flux. During the 1980s, New York City enjoyed tremendous economic growth. The decade also saw the middle class having a smaller share of the wealth than in the previous decade (see Chapter 2). The combination of these factors led to many middle

class New Yorkers feeling “squeezed” by the poor and the rich. New York City over the course of the 1980s also went from approximately 20% African American, to close to 30% (see Chapter 2). It was the first time in history that whites were no longer the majority of the population. The number of middle class white households shrank the most during the 1980s by close to eight percent. However, they still accounted for the largest percentage of the electorate. This section will examine the effect of these changes on candidate support.

Dinkins represented the “coming of age” of African Americans in New York City. The political power of African Americans had increased since the 1920s, when they first began to make substantial inroads into the Democratic Party (Sleeper 1990). The large-scale movement of African Americans to the outer boroughs during the 1950s and 1960s exacerbated racial tension on the neighborhood and local party level.⁴⁰ African Americans faced stronger resistance in the Brooklyn and Queens party machinery and as such, were more radical than their Manhattan counterparts (Sleeper 1990). Yet, by 1989, both sides of the African American community recognized the opportunity that they had in David Dinkins and joined to support him. In 1989, Dinkins ran a deracialized campaign focusing on improving the lives of New Yorkers through traditional liberal ideals such as increased services for those in need (Thompson 1996). Deracialization is a strategy employed by many African American candidates in non-majority African American cities, and it is intended to take the focus off the race of the candidate and his or her perceived biases (Perry 1996). Dinkins succeeded somewhat in his endeavor but it was

⁴⁰ See the discussion of the Oceanville/Brownsville School District fight in Chapter 2 for an example.

marred by Giuliani's focus on law and order, which served as thinly veiled racial arguments (Hagen 1995).

Concurrently, Giuliani was amassing support within Koch's traditional base, outer-borough whites. Outer-borough whites are overwhelmingly working class or middle class and tend to be more politically conservative than Manhattan residents. As more and more middle class whites left the outer boroughs and more nonwhites moved in, the middle class whites who remained were the most likely to be feeling "squeezed." If Giuliani could have tapped into this growing dissatisfaction, he could have won the election. He was also beginning to make inroads into the Hispanic community in New York City by espousing support for more conservative social values popular within the largely Catholic community. With his focus on law and order, reduced spending on social services, and quality of life, Giuliani was able to maintain large portions of Koch's base as well as obtain new ones like the ever-growing contingent of Hasidic Jews in Brooklyn. Giuliani actively courted the Jewish community by attempting to paint Dinkins as being soft on crime and overly concerned with African American issues (McNickle 1993).

Still, Giuliani could not count on support from all whites or Hispanics. Dinkins, as Manhattan borough president, had enjoyed a large amount of support from the white liberal community in Manhattan. These middle or upper class, college educated whites embraced progressive ideals both socially and economically. In David Dinkins, white liberals saw a chance for racial conciliation in New York City. Dinkins was not a "radical" Black Power supporter; rather, he resembled white liberals in his political attitudes (Sleeper 1990). Moreover, many Hispanics supported Dinkins because they saw him as closer to their community and its issues than Giuliani (McNickle 1993).

As in the previous section exploring long-term pessimism in New York City, the analysis of the candidate selection model will begin with a brief examination of the crosstabulations between the primary explanatory variables and the dependent variable. The discussion will continue with the multivariate analysis, a multinomial logistic regression. Based on the overall model, race, income class and long-term outlook should have significant associations in the crosstabulations with the dependent variable, candidate support. However, the only crosstabulation of the variables from the original model that was statistically significant was race broken down as white, nonwhite, don't know (chi-square=97.2385, prob.=0.000). Within the cross-tabulation, whites supported Giuliani by a large margin (60.77%), and nonwhites supported Dinkins (68.61%). Those who answered, "don't know" to the race question also favored Giuliani by 55.56% (See Appendix 4.2 for a full elaboration). Both pessimists and middle-income class respondents supported Giuliani; however, the resultant chi-square from the crosstabulation analysis was not significant.

The other significant associations were political ideology, level of education and borough of residence. While political ideology and borough of residence both make sense in this model, the appearance of level of education as having a significant association with candidate preference is surprising. When broken down by reported level of education, candidate preference is evenly split between the two candidates. In the group with the lowest level of education (those with less than a high school degree), however, the percentage of respondents who preferred neither candidate or did not intend to vote was remarkably high (12.55%) corresponding with the literature on low levels of educational attainment and voting. The same variables that were significant in the

crosstabulations should be significant in the more rigorous multinomial logistic regression.

A multinomial logistic regression essentially creates a series of comparative logistic regressions that compare two or more nominal values in the dependent variable with each other. Multinomial logistic regression is used particularly in cases such as this when each value of the dependent variable is critical to the research. In this analysis, the first pairing is between those who preferred Dinkins to those who preferred Giuliani; the second compares those who did not like either of the candidates compared with Giuliani (Giuliani being the reference group). Odds ratios for a multinomial logistic regression are defined as the amount by which the predicted odds favoring $y=j$ as opposed to $y=base\ category$ are multiplied for each unit increase in X_k holding all other things equal (Hamilton 1997, 246). For this analysis, the regression was run twice. One regression used all the variables formed into dummies: gender, long-term outlook, political ideology, race, income class, borough of residence, crime victim or not, perception of race relations, level of education, Hispanic origin and age creating model A or the saturated model. If one of the dummies was statistically significant, then all of the dummies in the set were included as variables. The variables that were insignificant were eliminated from the equation, and the regression was rerun creating model B or the parsimonious model. Tables 4.3 and 4.4 present the odds ratios for the multinomial logistic regression on the dependent variable, candidate preference.⁴¹ The question used for the dependent variable reads:

⁴¹ Please see Appendix 4.2 for the coefficients and log-likelihoods for the models that follow.

“If Dinkins and Giuliani were the only two choices for mayor, which would you prefer, Dinkins, Giuliani, Neither Candidate or Not Vote, or Don’t Know?”⁴²

The sample size for this part of the chapter was 838. This represents the unweighted cases of all registered respondents who had an opinion on the dependent variable question. Those who answered “don’t know” were excluded from the analysis with no obvious effect to the strength of the question. The first part of the discussion will focus on the results of the ““Neither/No Vote”” versus Giuliani comparison, followed by the results of the Dinkins versus Giuliani comparison.

⁴² The question unfortunately does not distinguish between those respondents who preferred neither candidate and those who did not plan to vote at all. While it may be assumed that those who preferred neither candidate may have voted in the November election, whom they ultimately would support cannot be determined.

Table 4.3 Odds Ratios for the Results Comparing "Neither/No Vote" to Giuliani in 1989

<i>Variable</i>	<i>Model A</i>	<i>Model B</i>
<i>"Neither/No Vote" v. Giuliani Comparison</i>		
Male (Female)	.600 (.220)	
Pessimistic Long Term (Stay Same)	.675 (.305)	
Optimistic Long Term (Stay Same)	1.15 (.586)	
Don't Know Long Term (Stay Same)	1.88 (1.33)	
Liberal (Moderate)	.847 (.390)	.935 (.417)
Conservative (Moderate)	1.26 (.505)	1.16 (.448)
Don't Know Ideology (Moderate)	.695 (.624)	1.26 (1.04)
White (Non White)	.391* (.158)	.390* (1.52)
Don't Know Race (Nonwhite)	1.58 (1.51)	1.90 (1.51)
Low Income (Middle Income)	1.34 (.589)	
High Income (Middle Income)	.791 (.424)	
Don't Know Income (Middle Income)	2.55 (1.61)	
Outer Borough (Manhattan)	1.11 (.513)	.935 (.415)
Crime Victim (Not a victim)	1.28 (.540)	
Race Relations Good (Bad)	1.62 (.602)	
Don't Know Race Relations (Bad)	1.06 (.637)	
Jewish (Non Jewish)	2.55 (1.24)	1.90 (.875)
Less Than High School (BA)	2.30 (1.22)	
High School Grad (BA)	.689 (.328)	
Some College (BA)	.385 (.232)	
Hispanic (Non-Hispanic)	1.18 (.538)	1.48 (.348)
Age 18 to 29 (30-45)	.513 (.217)	.566 (.292)
Age 45 to 64 (30-45)	1.15 (.514)	1.60 (.681)
Age 64 and over (30-45)	.542 (.291)	1.22 (.552)

Table 4.3 discusses the "Neither/No Vote" versus Giuliani equation. There is only one significant predictor in the "Neither/No Vote" versus Giuliani comparison: race. The

white versus nonwhite dummy had an odds ratio of .390. This means that the predicted odds for whites favoring “Neither/No Vote” are .390 times the predicted odds for them favoring Giuliani. Therefore, white respondents are more likely to support Giuliani than to prefer either candidate or not vote at all.

Table 4.4— Odds Ratios for the Dinkins versus Giuliani Comparison in 1989

<i>Variable</i>	<i>Model A</i>	<i>Model B</i>
<i>Dinkins V. Giuliani Comparison</i>		
Male (Female)	.813 (.134)	—
Pessimistic Long Term (Stay Same)	.969 (.199)	—
Optimistic Long Term (Stay Same)	1.23 (.298)	—
Don't Know Long Term (Stay Same)	1.51 (.603)	—
Liberal (Moderate)	1.69* (.330)	1.74* (.335)
Conservative (Moderate)	.881 (.177)	.883 (.174)
Don't Know Ideology (Moderate)	1.31 (.601)	1.32 (.587)
White (Non White)	.143* (.028)	.140* (.026)
Don't Know Race (Nonwhite)	.269 (.207)	.287 (.208)
Low Income (Middle Income)	1.15 (.235)	—
High Income (Middle Income)	1.03 (.231)	—
Don't Know Income (Middle Income)	1.31 (.501)	—
Outer Borough (Manhattan)	.575* (.118)	.559* (.111)
Crime Victim (Not a victim)	1.23 (.252)	—
Race Relations Good (Bad)	.718 (.135)	—
Don't Know Race Relations (Bad)	.868 (.244)	—
Jewish (Non Jewish)	1.74* (.399)	1.77* (.395)
Less Than High School (BA)	.925 (.278)	—
High School Grad (BA)	.864 (.187)	—
Some College (BA)	1.06 (.231)	—
Hispanic (Non-Hispanic)	.485* (.116)	.483* (.112)
Age 18 to 29 (30-45)	.597* (.134)	.608* (.135)
Age 45 to 64 (30-45)	1.35 (.298)	1.40 (.298)
Age 64 and over (30-45)	.886 (.218)	.997 (.218)

In the Dinkins versus Giuliani comparison as shown in Table 4.4, being white was also a strong predictor of preferring Giuliani with an odds ratio of .140. Whites were likely to prefer Dinkins at .140 times the amount that they were likely to prefer Giuliani. This indicates a very strong amount of support among whites, holding all other factors constant. This indicates that the second hypothesis, that whites would support Giuliani and nonwhites would support Dinkins, is consistent with the results of the analysis at this point.

Being Hispanic also meant support for Giuliani with an odds ratio of .483. This is surprising, in view of the literature on the 1989 election, which reported that Hispanics turned out heavily for Dinkins (Mollenkopf 1992; McNickle 1993; Thompson 1996). Accordingly, one might have thought that because Hispanics are considered a community of color they are more likely to support an African American candidate. It is possible that Dinkins could be perceived as having more in common with Hispanics for this reason. However, in this sample, Hispanics were strongly against Dinkins as a candidate. This possible discrepancy will be discussed in Chapter 6. In Giuliani's main support base, the outer boroughs, residents also supported Giuliani with a relative risk ratio of .559 or almost half the amount of support for Dinkins.

One of the two strongest predictors that indicated support for Dinkins was being liberal ideologically, with an odds ratio of 1.74. This means that liberals were 1.74 times more likely to support Dinkins over Giuliani than moderates. The dummies for conservative versus moderate or not knowing ideology were not statistically significant. Therefore, it is difficult to determine whether or not being conservative ideologically

indicated a preference for Giuliani, even though in the crosstabulations, conservative respondents indicated a preference of 57% for Giuliani.

Being Jewish was the strongest predictor for Dinkins with an odds ratio of 1.77. This translates into Jews being 1.77 times more likely to support Dinkins over Giuliani than non-Jews controlling for race. This supports Hypothesis 4, that Jews would prefer Dinkins in 1989. The presence of both liberalism and being Jewish as the predictors of support for Dinkins are indicators that Dinkins was able to reach his primary support base of liberals and an extension of that group, Jewish liberals. Jewish liberals have long an important part of the New York City political scene. They were behind Koch's election to his first term to Congress, and have primary roles in the Manhattan Democratic Party. They were, aside from African Americans, Dinkins' strongest supporters at this point in time. Since there were no other surveys conducted by the *New York Times*/CBS News polling organization until the exit polls in November, one should remember that this is merely evidence of a high level of support rather than a prediction of victory.

The absence of both income class and long-term outlook in the final model does not support Hypotheses 1 and 3, which stated that long-term outlook and income class were significant variables in the model. This limits the usability of the general model in specific case of the 1989 mayoral campaign. Additionally, the absence of perceptions of race relations or whether or not a person was a crime victim completes the absence of any sort of perception-based questions from the equation. The critical factors in the 1989 election were all demographically based; in other words, whom a voter supported or whether or not a voter supported anyone was a factor of who the voter was and where the voter lived, rather than what he or she believed.

Figures 4.1 and 4.2 present the odds ratios and the coefficients for a multinomial logistic regression on the dependent variable, candidate preference.⁴³ The figures represent the results of model B, the parsimonious model, from Tables 4.3 and 4.4. Normally, odds ratio figures only show two comparisons between the three values, as in Tables 4.3 and 4.4. In these tables, we cannot see the third relationship between the variables, Dinkins versus “Neither/No Vote.” Figures 4.1 and 4.2 are advantageous in that they allow us to explore all three relationships inherent in the multinomial logistic regression with candidate choice as the dependent variable (Dinkins versus Giuliani, Dinkins versus “Neither/No Vote” and Giuliani versus “Neither/No Vote”). The plots illustrate the direction, magnitude and significance of the odds ratios between the three values shown as three letters, G for Giuliani, D for Dinkins and N for “Neither/No Vote.” D and N are placed in reference to G, which has been designated as the reference category. When the letter appears to the right of the reference letter, it connotes a positive relationship; when the letter appears to the left, a negative relationship. The letters are situated between two scales. The bottom scale is the coefficients from the logit equation, while the upper scale is the exponential value of the coefficient (or the odds ratio). The magnitude of the change from the reference value (in this case Giuliani) to the other values (D and N) is the size of the letter. For example, the sizes of the letters (D & G) in the white versus nonwhite dummy row in Figure 4.1 are larger than the sizes of the letters representing the “Neither/No Vote” (N). This indicates that the magnitude of the odds ratio comparing the odds of selecting Giuliani to the odds of selecting Dinkins for whites

⁴³ Please see Appendix 4.2 for the coefficients and log-likelihoods for the models that follow.

is quite large. The lines connecting the letters represent insignificance. If there is a line connecting the two letters, then the relationship between the independent variable and the dependent variable is insignificant.

The white versus nonwhite dummy had a relative risk ratio of .390, as shown in Figure 4.1. This means that the predicted odds for whites favoring “Neither/No Vote” are .390 times the predicted odds for Giuliani. Therefore, white respondents are more likely to support Giuliani than to prefer either candidate or not vote at all. Being white was also a strong predictor of preferring Giuliani to Dinkins with a relative risk ratio of .140. Whites were likely to prefer Dinkins at .140 times the amount that they were likely to prefer Giuliani. This indicates a very strong amount of support among whites holding everything else constant. In Giuliani’s main support base, the outer boroughs, residents also supported Giuliani with an odds ratio of .559 or almost half the amount of support for Dinkins.

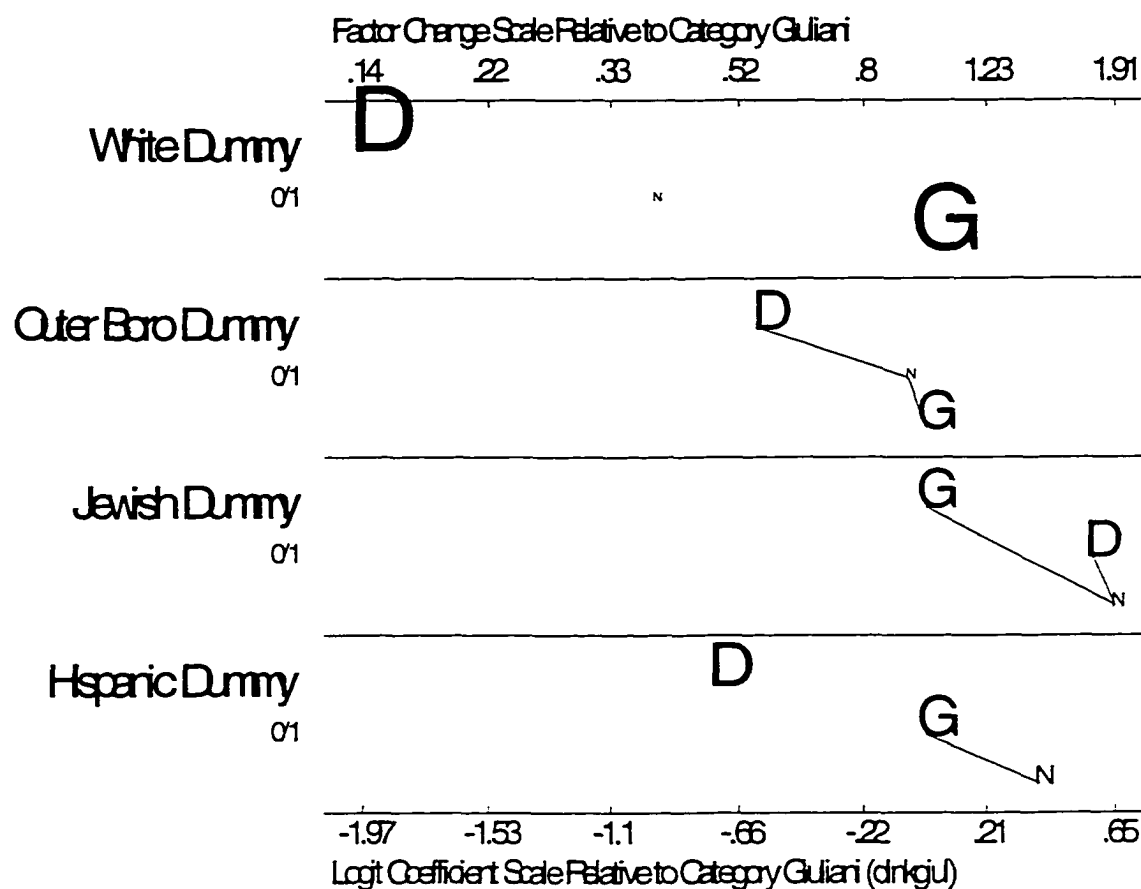


Figure 4.1 Graphical Representation of Selected Relative Risk Ratios from the Multinomial Logistic Regression on Candidate Choice

One comparison that was not illuminated by the relative risk ratio tables is the relationship between supporting Dinkins and supporting “Neither/No Vote.” In Figure 4.1, if respondents answered that they were Hispanic, they were .78 times as likely to support Dinkins than to not vote. In other words, there is a decrease in the odds of voting for Dinkins when a respondent is Hispanic, controlling for race, even if the other choice

involves not voting at all. The opposite is true if one is Jewish. When the discrete change is smaller, (judging from the size of the letters) the direction is opposite. Jews, controlling for race, (who are primarily white) were far more likely to support Dinkins than Giuliani in this election. Being Jewish was the strongest predictor for Dinkins with a relative risk ratio of 1.77. This translates into Jews being 1.77 times more likely to support Dinkins over Giuliani than non-Jews.

Three of the variables in Figure 4.2 have no significant relationships between the values forming a triangle. Only two variables in Figure 4.2 have significant relationships between Dinkins and Giuliani. As shown in Tables 4.3 and 4.4, younger individuals (aged 18 to 29) are more likely to support Giuliani than those aged 30 to 44, while liberals are more likely to support Dinkins than moderates.⁴⁴

⁴⁴ These figures were created using a Stata do-file written by Scott Long. It was created to go along with his book, *Regression Models for Categorical and Limited Dependent Variables*, and is downloadable from his website.

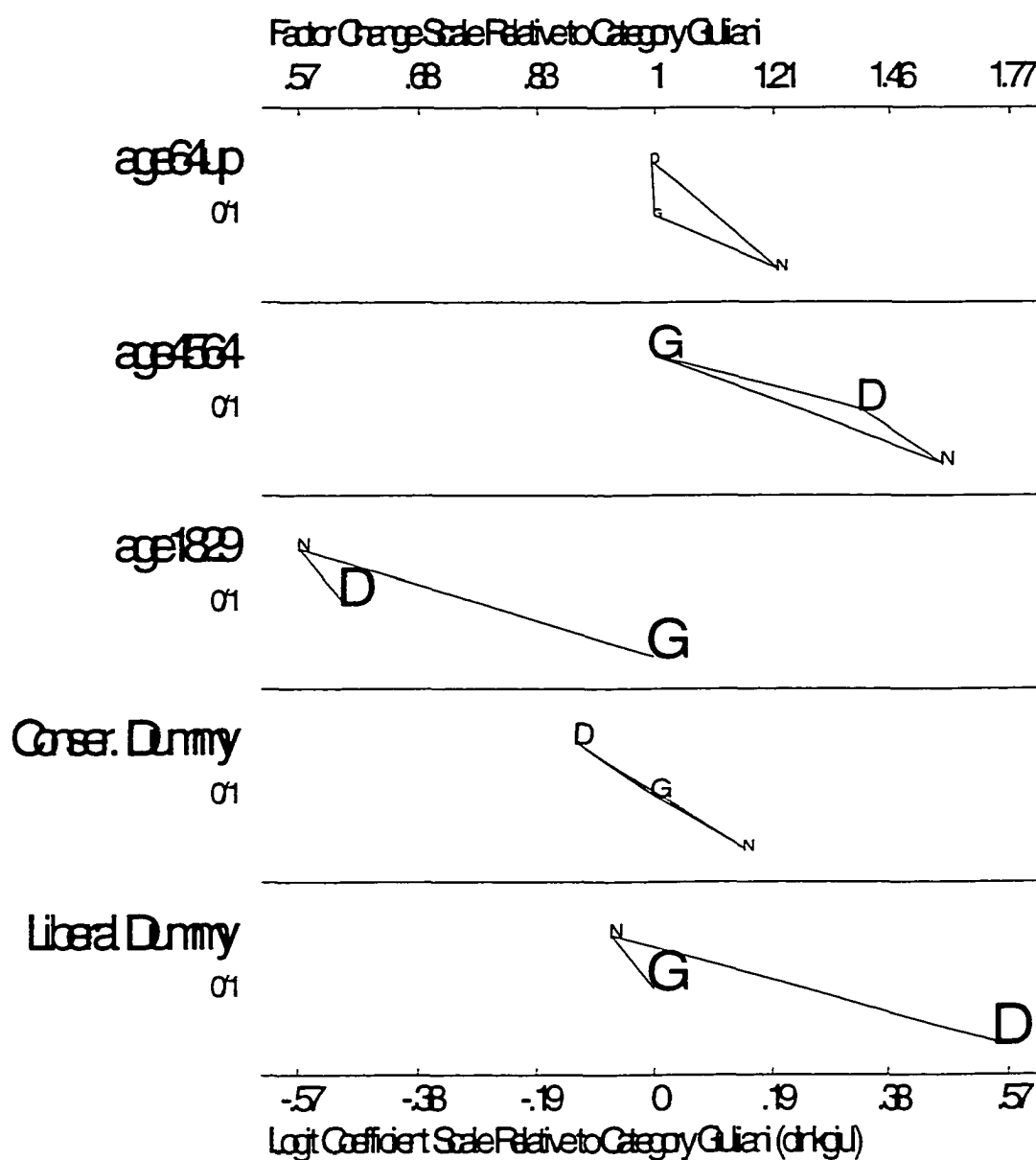


Figure 4.2 Graphical Representation of Selected Odds Ratios from Multinomial Logistic Regression on Candidate Choice

The absence of both income class and long-term outlook in the final model, model B, limits the usability of the general model in 1989. Two of the determinants of

pessimism (see Table 4.1) were race and income class. The absence of income class as a standalone predictor of the model indicates that a respondent's level of income, while a determining factor in their tendency towards pessimism, was not a consideration when choosing a candidate to support. This does not provide support for either hypothesis 3 or for the concept of retrospective voting. If a person's economic status decreased during Koch's last term, one might suspect that he or she would support the candidate who did not represent the establishment, i.e. Giuliani. However, since income class is not a significant predictor, this theory cannot be verified.

Recycled predictors provide a final analytic technique to illustrates the results of the parsimonious model, model B. Table 4.5 and Table 4.6 present the recycled predictions for the final model: model B. Recycled predictors compute the "average" probability for a given characteristic across the sample controlling for other variables across the distribution of the covariate patterns in the sample itself. The usual methods of presenting results of a logistic regression are partial derivatives or computing the probability for X holding other predictors at their means. However, the effect of X on Y varies with the covariate pattern, and the pattern itself appears with varying frequency in the sample and population being studied.⁴⁵ Holding the other predictors at their means can result in either meaningless means in regards to dummy variables, or in probabilities that are less than zero or greater than 100%. In an effort to illustrate the differences between the actual covariate pattern and the recycled pattern, Table 4.5 and Table 4.6

⁴⁵ The danger of using the means to produce probabilities from the model is that the research could wind up with a mean that essentially means nothing. For example, a mean of .74 in a dummy for white versus nonwhite means nothing in reality.

have two columns of predictors: the unadjusted probabilities based on crosstabulations, and the adjusted probabilities based on the method of “recycled predictors.” Each value of the independent variable has three “recycled predictors,” one created using the model fit from the Dinkins versus Giuliani equation, one created using the model fit from the “Neither/No Vote” versus Giuliani equation, and one using the model fit from the Dinkins versus “Neither/No Vote” equation. These were created using the equation from Model B, the parsimonious model from Table 4.3 and Table 4.4. In this model, income class and long-term outlook, two of the main hypothesized predictors do not appear as significant predictors. Therefore, they will not appear in the tables.

Table 4.5 Recycled Predictors of Candidate Support in 1989

<i>Variable</i>	<i>Unadjusted</i>	<i>Adjusted</i>
	<i>(Cross Tabs)</i>	<i>(Recycled)</i>
Liberal Dinkins	58.70%	55.80%
Liberal Giuliani	37.65%	40.50%
Liberal "Neither/No Vote"	3.64%	3.68%
Moderate Dinkins	42.47%	43.98%
Moderate Giuliani	52.71%	50.89%
Moderate "Neither/No Vote"	4.82%	5.13%
Conservative Dinkins	40.17%	41.07%
Conservative Giuliani	53.22%	52.72%
Conservative "Neither/No Vote"	6.55%	6.19%
Ideology DK Dinkins	50.00%	49.20%
Ideology DK Giuliani	43.33%	45.14%
Ideology DK "Neither/No Vote"	6.67%	5.63%
Outer Borough Dinkins	44.26%	44.47%
Outer Borough Giuliani	50.52%	50.30%
Outer Borough "Neither/No Vote"	5.22%	5.22%
Manhattan Dinkins	57.49%	56.44%
Manhattan Giuliani	38.32%	39.35%
Manhattan "Neither/No Vote"	4.19%	4.20%

Looking at political ideology in Table 4.5, one can see that respondents who replied that they were liberal ideologically had an adjusted probability of 55.80% to support Dinkins while they had an adjusted probability of 40.50% to support Giuliani. The liberal support of Giuliani is higher than expected, even though the liberal party endorsed Giuliani for mayor in 1989. Liberalism in New York City is relative. Even those who consider themselves conservative are usually more liberal than conservatives in other parts of the nation (Arian et. al. 1990). However, the difference in liberal support for the two candidates is smaller than was suspected, given the relative risk ratio for the equation. Moderate respondents in 1989 were more likely to support Giuliani by 50.89%

to 43.98% for Dinkins controlling for all other variables. The adjusted probability of supporting "Neither candidate or not voting" for moderates is rather high at 5.13%. It is higher still for conservatives, 6.19%. Perhaps the conservative respondents felt that Giuliani was not conservative enough, so neither candidate was meeting their needs.⁴⁶ The adjusted probability for preferring Giuliani for conservative respondents is surprisingly low (52.72%), while the adjusted probability for preferring Dinkins was much higher than initially suspected (41.70%). This is especially unexpected, given Dinkins' liberal and progressive stand on many issues.

Borough of residence had a similar split in candidate support within the recycled predictors in the opposite direction from political ideology for Dinkins versus Giuliani. Respondents in the outer boroughs had an adjusted probability of 50.3% of supporting Giuliani, and an adjusted probability of supporting Dinkins at 44.47%. Residents of Manhattan had an adjusted probability of supporting Giuliani at 39.35% and supporting Dinkins at 56.44%. This does indicate much stronger support for Dinkins among Manhattanites, and it corresponds with the unadjusted predictors. It also corresponds with the conventional wisdom surrounding this election. Dinkins largest base of support was Manhattan where he had served as borough president. Manhattan has a large liberal community, and the African American community in Manhattan was more inclined to support Dinkins than the community in the other boroughs (Mollenkopf 1992; Sleeper 1990; McNickle 1993).

⁴⁶ The survey did not address the existence of a more conservative candidate such as a member of the Conservative Party (Ronald Lauder).

The age of the respondent, as shown in Table 4.6, also had an influence on voting behavior. Of those respondents aged 18 to 29, the adjusted probability of preferring Giuliani was 60.08% to 36.77% preferring Dinkins. Perhaps this was due to an influx of people living in New York City within that age bracket. Respondents aged 30 to 44 were more evenly split but their probability changed directions. The unadjusted probability was 49.44% for Dinkins and 45.82% for Giuliani. However, the adjusted was 45.71% for Dinkins and 49.88% for Giuliani. This may have to do with the nature of recycled predictions with the recycled predictions being done with everyone being aged 30 to 44 for example with everything else held constant. Upper middle age respondents aged 45 to 64 were more likely to support Dinkins rather than Giuliani 51.4% to 42.63%, holding other factors constant. Respondents aged 65 and over preferred Giuliani with an adjusted probability of 49.45% to 45.23%. In the literature, age does not seem to be a significant factor when examining the causes of Dinkins election. He simply may have been more popular among the older respondents in the survey because of his more compassionate stance towards the elderly and their issues.

Table 4.6 Recycled Predictor Table continued from Table 4.5

<i>Variable</i>	<i>Unadjusted</i>	<i>Adjusted</i>
	<i>(Cross Tabs)</i>	<i>(Recycled)</i>
White Dinkins	34.04%	31.62%
White Giuliani	60.77%	63.30%
White Neither/No Vote	5.19%	5.06%
Non-White Dinkins	68.61%	72.01%
Non-White Giuliani	26.54%	23.37%
Non-White Neither/No Vote	4.85%	4.61%
Race DK Dinkins	44.44%	49.07%
Race DK Giuliani	55.56%	50.92%
Race DK Neither/No Vote	0%	0%
Non-Jewish Dinkins	46.90%	45.11%
Non-Jewish Giuliani	48.13%	50.18%
Non-Jewish Neither/No Vote	4.79%	4.71%
Jewish Dinkins	46.88%	55.16%
Jewish Giuliani	46.88%	38.26%
Jewish Neither/No Vote	6.25%	6.56%
Hispanic Dinkins	41.61%	32.75%
Hispanic Giuliani	50.36%	59.51%
Hispanic Neither/No Vote	8.03%	7.74%
Non-Hispanic Dinkins	47.93%	47.68%
Non-Hispanic Giuliani	47.65%	48.27%
Non-Hispanic Neither/No Vote	4.42%	4.03%
Age 18-29 Dinkins	40.68%	36.79%
Age 18-29 Giuliani	55.93%	60.08%
Age 18-29 Neither/No Vote	3.39%	4.41%
Age 30-44 Dinkins	49.45%	45.71%
Age 30-44 Giuliani	45.82%	49.88%
Age 30-44 Neither/No Vote	4.73%	5.88%
Age 45-64 Dinkins	50.25%	51.49%
Age 45-64 Giuliani	43.22%	42.63%
Age 45-64 Neither/No Vote	6.53%	5.88%
Age 65 and Over Dinkins	45.45%	45.23%
Age 65 and Over Giuliani	49.20%	49.45%
Age 65 and Over Neither/No Vote	5.53%	5.33%

The variables shown in Table 4.6 all concern racial and demographic characteristics. Race had the largest difference between the unadjusted probability and adjusted probability for each candidate. White respondents preferred Giuliani to Dinkins with an adjusted probability of 63.30% to 31.62%. What kept the adjusted probability of preference for Dinkins high was the preference of Jews for Dinkins that mediated the probability for whites and Dinkins. Nonwhites had no religious mediating factor so the differences in probability between the two candidates were greater. Of nonwhite respondents, 72.01% had an adjusted probability supporting Dinkins, while only 23.27% of the nonwhite respondents preferred Giuliani. A possible factor that should have made the probability of support for Giuliani higher was the Hispanic preference for Giuliani over Dinkins. On the contrary, it appeared to have little effect, as the percentage of nonwhites who preferred Giuliani was still less than one-quarter of the respondents.

As stated above, Jewish respondents had a higher adjusted probability for Dinkins than Giuliani 56.44% to 39.35%. This was lower than expected, given the Jewish-Liberal link. However, Giuliani's courting of conservative Hasidic groups raised the adjusted probability for his support within that community (McNickle 1993).⁴⁷ Non-Jewish respondents were more evenly split with adjusted probabilities of 50.18% for Dinkins and 45.11% for Giuliani with only 4.71% as "Neither/No Vote." Hispanic respondents, controlling for race, were split in the other direction from the Jewish respondents with an adjusted probability of 59.51% for Giuliani and 32.75% for Dinkins. These results are the opposite of the adjusted probability for nonwhites where the support was for Dinkins.

⁴⁷ Level of observance was not asked in this survey.

Non-Hispanic respondents also controlling for race were evenly split, with 47.68% adjusted probability for Dinkins and 48.72% adjusted probability for Giuliani supporting Hypothesis 6.

Conclusions

The 1989 mayoral election was extraordinarily close. The two candidates were separated by only 47,000 votes (Mollenkopf 1992). The respondents to the June 1989 *New York Times*/CBS News poll were split almost evenly between Dinkins and Giuliani. Those who stated a preference (i.e. who did not answer “don’t know”) were divided with 46.9% for Dinkins, 48.1% for Giuliani and 5% for neither candidate. The close race continued until the November election with Dinkins’ victory.

Dinkins was able to win the election based on the support of nonwhites, Jews and liberals (Mollenkopf 1992; Thompson 1996). This was borne out in the general model as nonwhites, Jews and liberals all had a strong propensity to support Dinkins (see Tables 4.4 and 4.5). Yet, the model did not entirely account for what was occurring within the 1989 sample survey. The general theory stated that an individual’s race and income class both alone and tempered by their long-term outlook had the strongest influences on candidate preference. However, in 1989, neither income class nor long-term outlook was a significant predictor in the multinomial logistic regression controlling for all other influences. They were not even significantly associated with candidate support when looking at the chi-squares generated with the crosstabulations. Therefore, in 1989 out of

the three primary variables in the general model, only race was an important and statistically significant predictor of candidate preference. A respondent's race also reacted in according to Hypothesis 2; whites supported Giuliani and nonwhites supported Dinkins.

There were also other strong predictors of candidate preference in 1989, such as religion, Hispanic origin and age that did not appear in the general model. A respondent's level of education did not matter in the final equation, lending support to Hypothesis 8. Being a victim of crime, gender, and a respondent's opinion of race relations were all statistically insignificant, disallowing the rejection of the null hypothesis for Hypotheses 9, 10 and 11. Whether or not the model holds for the 1993 election will be the subject of the following chapter, where the changes that allowed for this victory will be examined.

Chapter 5 Round Two

The 1993 mayoral election differed from the 1989 contest in many significant ways. Each election had the same candidates supported by their respective voting blocs; yet, by 1993, the blocs had shifted. No longer could Dinkins be assured of the Jewish liberal vote, or, for that matter, of the African American vote. His handling of the Crown Heights incident angered both sides of his core coalition. Jewish supporters thought that he had not done enough, while African Americans thought that his apology for his handling of the crisis was misplaced (Thompson 1996). Additionally, the stock market crash of 1987 and subsequent economic downturn damaged the New York City economy and fueled a blossoming budget deficit. Prior administrations had sought to mediate conflict among the different political factions by “throwing money at them” (McNickle 1993). However, by the time Dinkins was inaugurated in 1990, the city was faced with a large budgetary shortfall (Thompson 1996). Dinkins’ handling of the deficit through cuts in government employment appeared to be a policy without a plan. The cuts angered many African Americans, as they saw Dinkins as acting against their community. Since the 1960s, civil service jobs had been a primary means for African Americans and other groups of color to move into the middle class. Dinkins’ limiting of these opportunities through his budgetary policy seemed like a slap in the face (Thompson 1996). The combination of budget cuts, the Crown Heights incident and the planned hiring of five thousand new police officers was too much for some in the African American community, so they opted to stay away from the polls rather than support Dinkins (Thompson 1996).

Dinkins created an atmosphere in which it would have been difficult for him to be reelected, especially when faced with a strong opponent. He could not solve the city's economic woes, as they were national in origin. He also failed to control crime and racial tension due to his conciliatory rather than confrontational governing style (Thompson, 1996). As mayor, Dinkins operated in an placatory manner, seeking compromise over conflict. His personal style had seemed a strong point in his favor in 1989, but by 1993, this same style was his downfall. He could not mediate away rising conflict over the budget, the homeless, the sharp rise in crime rates or the increase in racial tension. Giuliani's personal style, while offensive to some, was seen as more effective in dealing with the city's problems. Giuliani began his campaign in 1993 seeking to project a "take charge" image of a mayor who would put union leaders, the homeless and criminals in their places, and restore the city to its former glory.

His strategy worked. By May of 1993, it was obvious that the November election would be a Dinkins versus Giuliani rematch. This chapter will use data from the May 1993 *New York Times*/CBS News poll.⁴⁸ The May survey, with 1273 total respondents, was taken using a modified random digit dialing method developed by Leslie Kish and modified by Charles Backstrom and Gerald Hursh. The sampling frame was New Yorkers aged 18 and over (*New York Times*/CBS News 1993, 3). The survey analyzed in this chapter showed pessimism about the city's future at 50.3% of those surveyed, a rise of the 1989 figure. When broken down by race, with 58% of whites being pessimistic about the

⁴⁸ There were two other polls conducted in 1993 by the *New York Times*/CBS News organization prior to the November election. They occurred during the last week of September and the first week of October. The surveys addressed only some of the concerns I hoped to address in this chapter. Only the May 1993 Footnote continued on next page

city's future versus 42.5% of nonwhites, it becomes apparent that the candidates' traditional voting blocs were divided on how the city was would fare in the future. Dinkins' traditional bloc—African Americans—felt that the city was improving, while Giuliani's traditional voting block—moderate and conservative whites—felt that the city was deteriorating.

Even with Dinkins' small victories in the areas of community policing and other programs, he always seemed to land in the center of race-based battles. As discussed in Chapter 3, the riots in Crown Heights are one example. Dinkins' role in the riots illustrates his difficulties. There were three main groups of expectations placed on Dinkins in his efforts to control the rioting. The first set of expectations originated from his office; as Mayor, he was expected to keep order. As an African American Mayor, additional expectations were placed on him; during his tenure race-based problems were not supposed to happen. The second set of expectations came from the African American community itself. From the time of his candidacy, some in the African American community felt that Dinkins was not "black" enough. He was not from the "ghetto," he did not belong to any radical movement during the 1960s and 1970s and he socialized heavily with whites (Sleeper 1990; Thompson 1996). The potential that he could side with the Hasidic Jewish community against African Americans in this incident, as evidenced by his apologies for his handling of the incident, angered many leaders in the Brooklyn African American community, spurring them to exert pressure on him to "stick with his own kind." The third set of expectations was from the white liberal Jewish

survey had the question on long-term outlook for the city and other long-range questions similar to the 1989 survey to be usable.

community, who expected him to side with them and stem anti-Semitic statements arising out of the more radical factions of the African American community. When he did not, or did not do enough, the white liberal Jewish community felt abandoned and betrayed by the man they had elected as racial conciliator.

The hypotheses for this chapter remain similar to the hypotheses first posed in Chapter 4 for 1989 with some differences:

Hypothesis 1: A respondent's long-term view of New York City's future had a significant effect on his or her candidate preference. Those who answered that New York City would be worse off over the next 10 to 15 years will support Giuliani. Those who answered that the city would improve will support Dinkins. Those who answered that the city would remain the same could prefer either candidate.

Hypothesis 1a: A respondent's race and income class will be the two largest predictors of pessimism across time.

Hypothesis 2: Overall, whites will support Giuliani, while nonwhites will support Dinkins regardless of political affiliation.

Hypothesis 3: Liberals will support Dinkins overwhelmingly and Conservatives will support Giuliani, while moderates or those who do not know their ideology will not have a strong preference for either candidate.

Hypothesis 4: Lower-income individuals will support Dinkins in both elections. Middle-income individuals will be solidly behind Giuliani. Upper-income individuals will also support Giuliani.

Hypothesis 5: Jews will be more likely to support Dinkins overall. Non-Jews will be split between the two candidates

Hypothesis 6: Manhattan residents will support Dinkins. Residents of the outer boroughs will support Giuliani.

Hypothesis 7: Hispanics will strongly support Dinkins. For non-Hispanics, preferences will be more evenly split between the two candidates in both elections.

Hypothesis 8: Women will support Dinkins, while men will support Giuliani.

Hypothesis 9: An individual's level of education will not be a predictor of candidate preference.

Hypothesis 10: Crime victims will be strongly for Giuliani. People who were not victims of crime will have no clear preference between the two candidates.

Hypothesis 11: In 1993, those who thought that race relations were generally bad will be more likely not to vote for Dinkins. Those who thought that race relations were generally good in both elections will be more likely to support Dinkins.

Hypothesis 12: Those who thought that Dinkins hurt the economy will be pessimistic about New York City's future. Those who thought that Dinkins made no difference will be split between being optimistic or pessimistic about New York City's future, and those who thought that Dinkins had helped the economy will be optimistic about New York City's future.

The final hypothesis, number 12, was added based on the economic problems New York City was experiencing during the 1993 election campaign, and due to the salience of the economy during the 1992 presidential campaign. The 1992 presidential election was decided in part on economic issues and how these issues affected the middle class (Greenberg 1995; Tolchin 1994; Teixeira 1996). This particular variable is useful because it specifically relates the economy to people's perceptions of how the city was doing. It is instrumental in testing the viability of pocketbook voting in New York City politics. If the respondents felt that Dinkins (and hence the establishment as he was an incumbent) was responsible for the state of the economy, then they might be more likely to support his removal from office. The New York City economy was at its worst since the 1970s during Dinkins' term, therefore this variable can be used as a proxy for how people

perceived their own economic situation, and how it may have influenced their long-term outlook.

Pessimism in 1993

The 1993 rematch election between incumbent David Dinkins and Rudolph Giuliani was decided by a very narrow margin (Mollenkopf 1994). While one might view the two elections as mirror images of one another, the contexts in which they both occurred were very different. As discussed in Chapter 4, the 1989 election turned on racial and borough-based divisions, with the respondent's long-term outlook for New York City did not result in it a significant factor.

This chapter presents the hypothesis that a person's long-term view of the city is a strong mediating factor in candidate preference. Traditionally, in New York City politics, race, and to some degree class, are major causative factors in elections. However, this dissertation maintains that in the 1993 rematch election between Giuliani and Dinkins, long-term outlook filtered the effects of race and class. The continuing deterioration of long-term outlook is further evidenced by the increased perception that both race relations and the economy in New York City were corroding—the influence of race relations on an individual's long-term outlook, and the state of the New York City economy during the period preceding the campaign. Under the mayoral tenure of David Dinkins, perceptions of race relations worsened rather than improved, as was hoped for prior to his election in 1989. Only 25.5% of those surveyed in May of 1993 stated that they thought race

relations were generally good.⁴⁹ An additional question further emphasizes the blame for race relations on Dinkins; 43.4% of respondents stated that the mayor could do a lot about race relations. However, when this is broken down by race, 52.3% of whites say that the mayor can do a lot about race relations, while 63.9% of nonwhites say that the mayor *cannot* do a lot about race relations. Therefore, it would not be unreasonable to conclude that whites blamed Dinkins for the decline in race relations, while nonwhites were hesitant to do so.

The second factor is that the economy in New York City had been greatly affected by the recession of 1989 to 1990. The fall of the stock market in October of 1987 precipitated a drop in property prices as well as layoffs in white-collar industries (see Chapter 2). By September of 1993, 64.7% of those surveyed stated that they thought New York City's economy was either fairly bad or very bad. This perception of the New York City economy was not split along racial or class lines. Therefore, people who previously could afford to be liberal or optimistic about New York City's future could no longer afford to do so.

Long-term outlook, as a whole, is measured by the question:

"What is your long term outlook for New York City? A) Things will get better, B) Things will stay the same, C) Things will get worse or D) Don't know/didn't answer."

⁴⁹ The question in May of 1993 was as follows: "Do you think race relations in New York City today are generally good or generally bad?" There were three possible answers: "generally good, generally bad and don't know/not answered."

The exploration of the relationship of long-term outlook with other variables will be first examined in a look at the crosstabulations. The analysis will then continue with a logistic regression in an attempt to determine the causes of a pessimistic long-term outlook in 1993.

Hypothesis 1a states that race and income class are the two strongest hypothetical predictors of long-term outlook. This dissertation theorizes that this is the case based on the national phenomenon of middle class (particularly middle class whites') dissatisfaction with the way their lives had turned out, and specifically with the failure of the American Dream to materialize for them as it had for their parents (Ehrenreich 1990; Newman 1989; Greenberg 1995; Hochschild 1994). The variable "longbad" was created as a dummy variable where 1 equals a pessimistic outlook and 0 equals anything but a pessimistic outlook. Within the crosstabulations of both race and income class with "longbad," race is the only statistically significant variable (chi-square=6.8638, prob.= 0.032).⁵⁰ Income class was not significantly associated with "longbad"; it is not expected to appear as significant in the logistic regression to follow (a full elaboration of the cross-tabulations can be found in Appendix 5.1).

Political ideology, age of respondent, borough of residence, the respondent's opinion of race relations and the respondent's opinion of how Dinkins handled the economy all had significant associations with "longbad" in the crosstabulations. Of those who thought that Dinkins hurt the economy, 59.13% were pessimistic. Of those who thought that Dinkins had helped the economy, however, 51.83% were pessimistic as well.

⁵⁰ For the crosstabulations themselves, please see Appendix 5.1.

It is unclear from the results of the crosstabulations whether or not those who thought Dinkins helped the economy thought that maybe the economy was a national-level concern and Dinkins had done all he could; or whether they thought that there were other reasons to be pessimistic about New York City's future. From this, it is inferred that Hypothesis 12 will not be positively ascertained due to the apparent inverse relationship between thinking that Dinkins had helped the economy and being optimistic about New York City's future.

Due to the complex nature of a pessimistic long-term outlook, a multivariate approach is more elaborative than a simple bivariate approach. The multivariate approach that will be used is a logistic regression with "Longbad" as the dependent variable. There are a number of other potential causes of long-term pessimism with New York City, for example, the number of homeless people a person sees on the street, feelings about specific incidents such as the Crown Heights riots, perceptions of New York's personality compared to other cities and perceptions of crime within a respondent's neighborhood (see page 87 for further discussion). The May 1993 poll did not ask these types of questions. To judge the effects on long term outlook in 1993, the perception questions on the quality of race relations were included, such as if the respondent or a member of his or her immediate family was a victim of a crime, and the respondent's view of Dinkins' relationship to the economy in a logistic regression with demographic characteristics such as race, income class, political ideology, age and borough of residence.

A logistic regression determines the best-fitting logistic curve to a group of data points. It is used with a dependent variable that is coded 0 or 1, such as "longbad." These types of dependent variables violate a primary assumption of OLS regression—that the dependent variable must be interval level. The parameters for logistic regression are

estimated using the maximum likelihood estimation method where a series of iterations of successive approximations of the true population characteristics are taken from the sample data. The results of a logistic regression can be presented in two main formats, standard coefficients and odds ratios. The problem with using standard coefficients is that a coefficient is interpreting how much of a change in Y would we suspect from a 1-unit change in X . The change can be represented as β change in Y for each change in X . However, the difficulty arises that often it is hard to interpret what a change with a magnitude of β means with a dependent variable (Y) that is coded zero or one. Therefore, it is more common to report the results using odds ratios. Odds ratios are the amount by which the odds favoring a one-unit increase in your dependent variable increase for a one-unit increase in your independent variable. Stated differently, the odds ratio is the odds that when $Y=1$ that $X=1$ to the odds that when $Y=1$ that $X=0$. For example, the odds ratio of being pessimistic when one is a resident of the outer boroughs is 2.03 from Model A in Table 5.1. This means that the odds of being a pessimist are 2.03 times greater for outer borough residents than they are for people who live in Manhattan.

Table 5.1 presents the odds ratios for the fully saturated and parsimonious logistic regression for pessimism in 1993.⁵¹ The predictors used in the logistic regression are dummies created from the variables of race, borough of residence, views of race relations, educational attainment, being a victim of crime, Hispanic origin and views about Dinkins and the economy. Since they were nominal-level variables, dummy variables were created. If one of the dummy predictors is significant, it follows that all of the predictors

⁵¹ The coefficients and model for the logistics regression of pessimism in 1993 are presented in Appendix 5.1.

that represent a certain variable must be included as a set to serve as an accurate proxy for the variable within the equation.

Table 5.1 Odds Ratios for the Causes of Long Term Pessimistic Outlook, Saturated and Parsimonious Model⁵²

<i>Variable</i>	<i>Model A</i>	<i>Model B</i>
Liberal (Moderate)	.800 (.119)	-
Conservative (Moderate)	1.24 (.188)	-
Don't Know Ideology (Moderate)	1.08 (.290)	-
White (Nonwhite)	1.35* (.184)	1.31* (.156)
Don't Know Race (Nonwhite)	.553 (.270)	.562 (.275)
Low Income (Middle Income)	1.03 (.145)	-
High Income (Middle Income)	.911 (.194)	-
Don't Know Income (Middle Inc.)	.899 (.224)	-
Race Relations Good (Bad)	.506* (.071)	.495* (.068)
Don't Know Race Relations (Bad)	.472* (.087)	.478* (.086)
Crime Victim (Not a Crime Victim)	.815 (.118)	-
Outer Borough (Manhattan)	2.03* (.325)	2.08* (.321)
Less than HS (BA)	.774 (.167)	-
High School Graduate (BA)	.895 (.146)	-
Some College (BA)	.966 (.163)	-
Dinkins Help Economy (No Difference)	1.13 (.182)	1.11 (.176)
Dinkins Hurt Economy (No Difference)	1.55* (.255)	1.56* (.257)
Don't Know about Dinkins and Economy	.870 (.222)	.866 (.218)
Jewish (Non-Jewish)	1.00 (.193)	-
Hispanic (Non-Hispanic)	1.13 (.184)	-
Final Log Likelihood Model A	-814.33952	
X ² Model A (20 df)	91.53	
% Correctly Classified ⁵³	61.40%	
Final Log Likelihood Model B	-820.01901	
X ² Model B (8 df)	80.17	
% Correctly Classified	61.64%	
Number of Iterations	4	
N ⁵⁴	1241	

⁵² Significant predictors at $p < .05$ are marked with an asterisk *.

⁵³ Percent correctly classified refers to the accuracy of the model in estimating how often the event would occur out of the total number of events.

The parsimonious model, Model B, has as predictors white or nonwhite (whitedum), having a positive view of race relations or not knowing how good or bad race relations are in New York City versus thinking that race relations are generally bad, borough of residence (outer borough versus Manhattan) and believing that Mayor Dinkins hurt the economy over the last four years instead of not making a difference. Within model B, being a resident of an outer borough and feeling that Dinkins hurt the economy were the strongest predictors of pessimism. In other words, being a resident of the outer boroughs increased the odds of being a pessimist by a factor of 2.08. Another way to say this is that living in Manhattan makes voters less likely to be pessimistic about New York City's future. Likewise, thinking that Dinkins hurt the economy made a respondent 1.59 times more likely to be a pessimist than if he or she felt that Dinkins did not make a difference with the economy. The dummy that compared the view that Dinkins helped the economy with Dinkins making no difference in the economy was statistically insignificant. Therefore, Hypothesis 12 cannot be confirmed and the null hypothesis stands.

However, given that those who felt that Dinkins hurt the economy were more likely to be pessimists, it will be interesting to see if pessimism has any effect on candidate preference and provides some evidence of pocketbook voting. Being white was also a strong predictor of being a pessimist in 1993. Whites were 1.31 times more likely

⁵⁴ The total N for the 1993 the *New York Times*/CBS News survey is presented here. I felt that it was important to see the causes of pessimism regardless of whether or not the respondent was a registered voter because they also contribute to the overall mood of the city.

to be pessimistic than nonwhites were. Since income class was not a contributor to pessimism, the null hypothesis for Hypothesis 1a stands.

An additional method of presentation is using the recycled predictor method. As explained in Chapter 4, the results of these equations are presented using “recycled predictions.” Using the model fit from the logistic regression, recycled predictors provide a way to estimate the overall average effect of a particular independent variable on the probability that $y=1,2...j$ conditional on X while controlling for other predictors. The advantage of using recycled predictors over partial derivatives and computing probabilities for X holding the other predictors at their means is that due to the nature of logistic regression, the effect of X varies with the covariate pattern. These covariate patterns have varying frequency in the sample and population being studied.⁵⁵

Recycled predictors effectively isolate the effect of the specific independent variable in question on the dependent variable. Averaging predicted probabilities from a model fit for a particular value of X across all the existing covariate patterns weighted by their frequency allows the resultant adjusted probability to be compared with the unadjusted probability taken from the bivariate crosstabulations. For example, to compute the average prediction for Hispanics versus non-Hispanics using this model, “hispdum” would be set equal to 1 for all cases. In doing so, a researcher can pretend that all respondents are Hispanic holding everything else constant, and is then able judge the adjusted probability at which they would be pessimistic about New York City’s future (see Stata 4.0, 1995). The process can then be repeated the process for non-Hispanics.

⁵⁵ Holding the other predictors at their means can create a covariate pattern with no correlation with reality in the actual data. For example, a mean of .5 in the dummy variable sex scored 0 or 1.

The two recycled predictors for Hispanics and non-Hispanics can then be compared. Table 5.2 shows the “recycled predictors” generated from the model fit of the parsimonious logistic regression compared with the crosstabulation or unadjusted results.

Table 5.2 Pessimistic Long-Term Outlook for New York City 1993: Unadjusted Estimates and Adjusted Estimates

<i>Variable</i>	<i>Unadjusted</i>	<i>Adjusted</i>
	<i>(Cross Tabs)</i>	<i>(Recycled)</i>
White	53.66%	53.80%
Non White	47.70%	47.47%
Don't Know Race	33.33%	34.39%
Manhattan	35.83%	36.69%
Outer Boroughs	54.15%	53.90%
Race Relations Good	38.94%	40.38%
Race Relations Bad	58.05%	57.23%
Don't Know Race Relations	38.89%	39.53%
Dinkins Hurt Economy	59.13%	59.09%
Dinkins Made No Difference	48.31%	48.63%
Dinkins Help Economy	51.83%	51.02%
Don't Know Dinkins Economy	45.95%	45.25%

Given the small distinctions between the recycled predictions and the unadjusted probabilities, the results are representative of the sample. As such, both whites and residents of the outer boroughs had an approximate 54% adjusted probability of being a pessimist. While it is tempting to infer that these are in fact the same individuals, it would be incorrect to do so given the structure of the model. Logistic regressions are multiplicative and interactive, as each variable exists in relationship to its positions with the other variables. It makes sense that those individuals who lived in the outer boroughs

of New York were more likely to be pessimistic. The outer boroughs of New York City tend to be more middle class and white than Manhattan; therefore, their residents are more likely to feel threatened (see Chapters 1 and 2).

Another interesting finding is that income class is not a predictor of pessimism. It was originally anticipated that the question on Dinkins and the economy might be hiding the influence of income class on the likelihood of being pessimistic by serving as a proxy for income class. However, even without that question in the model, income class is not significant (see Appendix 5.1). Therefore, a person's level of income did not influence their long-term outlook for the city, and again the null hypothesis for Hypothesis 1a stands. Only race and not income class was a predictor of pessimism in 1993. This is true although a majority of white and nonwhite middle class respondents were pessimistic. Furthermore, a respondent's political viewpoint was insignificant in the full model, i.e. liberal, conservative or moderate. Therefore, one might assume that it was only those things that affected the respondents' immediate vicinity or quality of life overall that would cause them to become pessimistic.

Two perception questions appeared in the final model for pessimism: the respondent's opinion of race relations and the respondent's opinion of how Dinkins affected the economy. Whether or not a respondent or a member of his or her family was a victim of crime, which had been intended to serve as a proxy for opinions about crime rates, was not a significant predictor. Perhaps this is because crime is seen as part of the "price to pay" for living in New York City (Kaufman 1999), or perhaps it is because having personally been a victim of crime does not translate into how a respondent views the crime rate in the city. The influence of race relations on the model is not surprising

considering the racial tension that was paramount during Dinkins' tenure. The perception that Dinkins failed fulfill his promise—as a uniter of the city and reducer of racial tensions—led a person's opinion on race relations to become the second strongest predictor of pessimism.

A respondent had the strongest adjusted probability of being a pessimist if they felt that Dinkins hurt the economy over the previous four years, with a recycled predictor of 59%. This adjusted probability exists controlling for income class or race. It also corresponds with the national mood at the time because as an individual's economic standing declines the less likely they are to support whomever is in office (i.e. the 1992 election).⁵⁶ Therefore, those who felt that Dinkins had hurt the economy (including but not limited to the respondent's own economic standing) would be more likely to think that New York City was declining, and having Dinkins remain in office would hasten the fall. Unfortunately, the survey questions asked in May of 1993 do not allow for further exploration of this issue.

In September of 1993, the *New York Times*/CBS News surveys asked two illuminating questions in regards to respondents' views of the economy.⁵⁷ The first was "Can the Mayor Control the Economy?" Approximately 45% of the respondents, regardless of race or income class, felt that he could. The second question involved candidate choice and perceptions of the economy. Registered voters were asked for both

⁵⁶ Please see the section in Chapter one on pocketbook voting for more information.

⁵⁷ Unfortunately for my research, the same questions were not asked in the May survey. The inclusion of these types of questions would have allowed for a fuller exploration of pocketbook voting and its effect on the election.

candidates, “If he [Dinkins or Giuliani] was elected what would be the impact on the economy?” Nearly 16% stated that if Dinkins was re-elected the economy would get worse, while only 9.6% of the respondents stated that if Giuliani was elected the economy would be worse off. The results of my analysis of candidate support will be presented in the next section.

1993 Equation

Initially, this dissertation intended to focus on how race and income class had affected New Yorkers’ choice of candidates the 1993 election. It soon became apparent that there was another significant variable that needed consideration, long-term outlook. A person’s race and income class affects his or her long-term outlook. It stands to reason that the poorer a person is the more pessimistic he or she might be (although income class is not a direct cause of pessimism). Additionally, long-term outlook also affects an individual’s candidate preference. If the individual voter feels that the city is headed in the wrong direction in the long term, chances are he or she will not support the administration in power that is charting the city’s direction.

There is a longstanding argument in the literature on voting behavior on whether voters are “bankers” or “peasants” (MacKuen, Erikson and Stimson 1992). A voter who is a “banker” considers the nation’s entire economic future before casting a ballot. A “peasant” only considers his or her own economic standing before voting (MacKuen, Erikson and Stimson 1992). For urban dwellers, the concept of “banker and peasant”

becomes more complicated. While economic concerns are a major factor in urban life, they are not the only concerns. Crime rates and race relations impact the city dweller on a daily basis. The nature of their impact is tempered by where an individual lives, his or her level of education, race and income class, age and personal political ideology. It is not enough to simply categorize urban voters as “bankers” or “peasants,” because those terms do not envelop the full nature of city living. Rather, the terms “optimist” and “pessimist” are better suited to the study of urban voting behaviors.

As seen in the previous section, the main contributions to being a pessimist about New York City’s future were an individual’s race (being white), where he or she lives (outside of Manhattan), his or her view of race relations (generally bad) and his or her view that Dinkins had an effect on the economy. The factors that contributed to not being a pessimist were not being white, living in Manhattan, thinking that race relations were good or having no opinion on the subject, and thinking that Dinkins made no difference in the economy. From the preceding categorizations of pessimists and non-pessimists, it seems that the pessimist profile closely matches that of a typical Giuliani supporter. Giuliani’s supporters were usually outer-borough whites with a low opinion of Dinkins’ handling of race relations or the economy. On the other hand, Dinkins’ supporters closely match the profile of non-pessimists. His supporters tended to be nonwhite and/or Manhattan residents who were generally satisfied with where the city was headed. How well these profiles match the actual respondent preferences is the subject of this section. The section will begin with an examination of the results of the crosstabulations, and will continue with a multivariate analysis using multinomial logistic regression.

The crosstabulations provide preliminary confirmation of these profiles. Being a pessimist was significantly associated with supporting Giuliani (60.65%), while being an optimist was significantly associated with supporting Dinkins (67.76%) ($\chi^2=60.9238$, $\text{prob.}=0.000$) (See Appendix 5.2 for the crosstabulations). The results of this cross-tabulation between long-term outlook and candidate support give some indication that Hypothesis 1 may be supported. Race, as would be expected, was also significantly divided with whites supporting Giuliani and nonwhites supporting Dinkins. This statistically significant cross-tabulation provides a starting point to the profiles given by the probability of being pessimistic in the previous section is correct. A respondent's opinion on race relations also fits with the characteristics of candidate supporters provided by the pessimist equation. Those respondents who thought that race relations were generally bad were also pessimists as shown by the previous section and Giuliani supporters as indicated by the crosstabulations. The respondents who thought that race relations were generally good were optimists and Dinkins supporters, giving further credence to the idea that the profiles established by the regression of the causes of long-term pessimism is correct. The final characterization of pessimist or optimist was borough of residence. Building on the pessimist model, outer-borough residents were not only more likely to be pessimists; they were more likely to support Giuliani. In contrast, Manhattanites were more likely to be optimists, and were more likely to support Dinkins. Therefore, it seems that the profiles as to what constitutes a pessimist and what constitutes a Giuliani supporter are remarkably similar, as are the profiles of an optimist and a Dinkins supporter.

Two other variables were significant from the crosstabulations that were not in the pessimistic profile, income class and religion. Income class was significantly associated with candidate preference in such a way that it provides support for Hypothesis 3. Lower-income respondents preferred Dinkins, while middle- and upper- income respondents preferred Giuliani (chi-square=17.6718, prob.=. 007). The cross-tabulation of religion (Jewish versus non-Jewish) and candidate support did not conform to the hypothesis. Hypothesis 5 stated that Jews were more likely to prefer Dinkins, while non-Jews would be split. In the crosstabulations, Jews were not more likely to prefer Dinkins; instead, they were more likely to prefer Giuliani 58.56% to 32.43%. Whether this reversal of support will hold when other variables are taken into account will be seen in the multivariate analysis.

All of the variables for the model were transformed into dummies and used in a multinomial logistic regression.⁵⁸ Multinomial logistic regression can be explained as a method of artificially creating mini-logistic regression comparisons when a nominal dependent variable has more than two categories. It is used in cases where all the values of the dependent variable are critical to the research. In this case, as in Chapter 4, the dependent variable is paired into those who prefer Dinkins compared with those who prefer Giuliani, and into those who prefer “Neither/No Vote” to Giuliani. The tables present the odds ratios for each equation (See Appendix 5.2 for the coefficients). Odds

⁵⁸ All of the variables were added and then removed from the equation individually after being tested using the likelihood ratio test. This test measures the strength of the model with the variable to the model without the variable. The smaller the likelihood ratio, the stronger the model. A variable was seen not to contribute to the model if the likelihood ratio did not change or became insignificant. The results of these tests are included in Appendix 5.2.

ratios for a multinomial logistic regression are the amount by which the predicted odds favoring $y=j$ as opposed to $y=base$ category are multiplied for each unit increase in X holding everything else constant (Hamilton 1997, 246).

The question used as the dependent variable measures candidate preference, not actual voting behavior (see Chapter 7 for an analysis of actual election district results).

The question read:

“If Dinkins and Giuliani were the only two candidates for Mayor, which would you prefer, Dinkins, Giuliani, Neither Candidate/No Vote, or Don’t Know?” (*New York Times/CBS News* May 1993).

This question was asked only of registered voters, thereby decreasing the N by over 400. Additionally, the N was decreased by those who answered “Don’t Know/Not Answered” to the question, amounting only 15 respondents that did not affect betas or log-likelihood (see Appendix 5.2). The total number of observations for this section was 762. In the odds ratios as presented in Table 5.3 and Table 5.4, a relative risk ratio greater than 1 indicates support for either Dinkins or “Neither/No Vote” (depending on the category). An odds ratio of less than one indicates support for Giuliani.

Table 5.3 Odds Ratios from the Multinomial Logistic Regression for Candidate Support – “Neither/No Vote” Section

<i>Variable</i>	<i>Model A</i>	<i>Model B</i>
<i>“Neither/No Vote” v. Giuliani Comparison</i>		
Male (Female)	.660 (.260)	-
Pessimistic Long Term (Stay Same)	.396* (.174)	.474 (.202)
Optimistic Long Term (Stay Same)	.268 (.219)	.287 (.230)
Don't Know Long Term (Stay Same)	.473 (.555)	.623 (.698)
Liberal (Moderate)	1.37 (.623)	1.50 (.656)
Conservative (Moderate)	.383 (.206)	.413 (.214)
Don't Know Ideology (Moderate)	.942 (1.08)	1.02 (1.15)
White (Non White)	.281* (.144)	.371* (.172)
Don't Know Race (Nonwhite)	3.98 (1.00)	3.26 (1.00)
Low Income (Middle Income)	3.09* (1.51)	2.98* (1.33)
High Income (Middle Income)	2.45 (1.44)	2.44 (1.38)
Don't Know Income (Middle Income)	2.54 (2.16)	2.53 (2.11)
Outer Borough (Manhattan)	.753 (.402)	.683 (.497)
Crime Victim (Not a victim)	.310 (.199)	-
Race Relations Good (Bad)	.464 (.273)	.483 (.273)
Don't Know Race Relations (Bad)	.814 (.643)	.638 (.497)
Jewish (Non Jewish)	2.41 (1.17)	-
Less Than High School (BA)	2.06 (1.57)	-
High School Grad (BA)	1.07 (.608)	-
Some College (BA)	1.75 (.951)	-
Hispanic (Non-Hispanic)	.401 (.257)	.410 (.255)
Age 18 to 29 (30-45)	.439 (.252)	-
Age 45 to 64 (30-45)	.885 (.425)	-
Age 64 and over (30-45)	.531 (.366)	-
Final Log Likelihood Model A ⁵⁹	-454.41696	
X ² Model A (48 df)	368.55	
Final Log Likelihood Model B	-462.48583	
X ² Model B (22 df)	352.42	
Number of Iterations Model A	34	
Number of Iterations Model B	32	

In both models, many demographic variables such as gender, level of education and age were not significant. Religion was also not an influential factor in either comparison. The “Neither/No Vote” versus Giuliani comparison will be discussed first, followed by the Dinkins versus Giuliani comparison.

As shown in Table 5.3, the “Neither/No Vote” comparison, having a low income was the largest indicator of not supporting either candidate in 1993. The odds ratio was 2.98, which translates into the odds of not supporting either candidate or not voting at all over supporting Giuliani being almost three times as high for those with low income. This is an important finding for two main reasons. One is that in the literature on voting, income is a primary indicator of not voting (Burnham 1987; Teixeira 1989; Hill and Leighley 1992). The other is that in New York City, the majority of low-income individuals are nonwhite. The fact that a large preference for neither candidate far outdistances the odds of a nonwhite respondent preferring Giuliani shows the extent of the dislike of Giuliani within the nonwhite population of New York City.

The other significant variable in the final model is race, white versus nonwhite. Whites in this survey were more likely to support Giuliani than the option of “Neither/No Vote.” In essence, since logistic regression is multiplicative and interactive, if voters were nonwhite and low income, they were more likely not to prefer either candidate or not vote than to vote for Giuliani. The combination of nonwhite and low income leading to a respondent’s preference of not supporting Giuliani implies that the characterizations of

⁵⁹ The final log likelihoods, chi-squares and number of iterations for both models are for the entire set of odds ratios (for the Dinkins versus Giuliani comparison and for the “Neither/No Vote” comparison).

Dinkins' supporters as being nonwhite and in part poorer than Giuliani supporters is true. These respondents would rather not vote than vote for Giuliani.

One interesting development in this part of the model is that pessimism for the long-term outlook of New York City became insignificant statistically within the more parsimonious model for "Neither/No Vote" versus Giuliani. After running a likelihood ratio test to see if it contributed to the more parsimonious model, the results showed that it did not. If looked at alone (without the Dinkins versus Giuliani comparison) it could have been safely removed (see Appendix 5.2).

The Dinkins versus Giuliani comparison had more predictors than the "Neither/No Vote" versus Giuliani. The statistically significant indicators of support for the candidates were: being politically liberal, feeling that race relations in the city were generally good, not having an opinion on race relations in New York City, having a pessimistic long-term outlook, being an outer borough resident and being white.

Table 5.4 Odds Ratios from the Multinomial Logistic Regression Models for Candidate Preference in 1993 between Dinkins and Giuliani⁶⁰

<i>Variable</i>	<i>Model A</i>	<i>Model B</i>
<i>Dinkins V. Giuliani Comparison</i>		
Male (Female)	.827 (.165)	-
Pessimistic Long Term (Stay Same)	.398* (.095)	.411* (.096)
Optimistic Long Term (Stay Same)	1.55 (.451)	1.53 (.434)
Don't Know Long Term (Stay Same)	1.27 (.673)	1.28 (.660)
Liberal (Moderate)	2.34* (.539)	2.34* (.531)
Conservative (Moderate)	.485* (.121)	.479* (.119)
Don't Know Ideology (Moderate)	.846 (.466)	.867 (.460)
White (Non White)	.057* (.014)	.060* (.014)
Don't Know Race (Nonwhite)	.228 (.190)	.222 (.183)
Low Income (Middle Income)	1.61* (.384)	1.51 (.330)
High Income (Middle Income)	1.05 (.327)	1.09 (.184)
Don't Know Income (Middle Income)	1.31 (.570)	1.20 (.512)
Outer Borough (Manhattan)	.420* (.106)	.391* (.097)
Crime Victim (Not a victim)	.845 (.196)	-
Race Relations Good (Bad)	2.22* (.505)	2.27* (.502)
Don't Know Race Relations (Bad)	2.73* (.883)	2.54* (.808)
Jewish (Non Jewish)	1.22 (.349)	-
Less Than High School (BA)	1.15 (.454)	-
High School Grad (BA)	.814 (.213)	-
Some College (BA)	1.23 (.336)	-
Hispanic (Non-Hispanic)	.214* (.063)	.221* (.063)
Age 18 to 29 (30-45)	.951 (.245)	-
Age 45 to 64 (30-45)	1.01 (.254)	-
Age 64 and over (30-45)	.758 (.264)	-

According to table 5.4, if voters were liberal rather than moderate they were 2.34 times more likely to support Dinkins over Giuliani. Conservatives had odds of having

⁶⁰ The same variables were used for each part of the regression. A variable was only dropped from the model if it became insignificant in both comparisons. The coefficients and models are presented in Footnote continued on next page

.479 times the support for Dinkins than Giuliani. Dinkins ran as an established liberal who took full advantage of New York City's tendency to be more liberal than the rest of the country (Arian et. al. 1990). He courted the liberal vote throughout his candidacy and first term as mayor, while Giuliani appealed to conservatives through his law and order rhetoric.

A person's perceptions of race relations also played a role in candidate preference. Feeling that race relations were generally good translated into having 2.27 times greater odds of supporting Dinkins over Giuliani, while not having an opinion on race relations translated into having odds 2.54 times greater of supporting Dinkins over Giuliani than if you thought race relations were bad. Given the tenor of the election surrounding race and racial issues—racial incidents such as Crown Heights taking center stage and the veiled race baiting through Giuliani's law and order campaign—it is highly probable that unless a person thought that race relations were an issue, he or she would be inclined to support the incumbent.

Whites had the least favorable odds of supporting Dinkins, .06 times the odds of nonwhites supporting Dinkins. This indicates an incredible amount of support for Giuliani within the white respondents. In addition, being Hispanic also indicated support for Giuliani by odds of .221 times the amount of support for Dinkins. This may have been due to Giuliani's choice for public advocate, a popular Puerto Rican politician. Another possible contributing factor may have been his traditional, conservative stance on issues that appealed to the largely catholic Hispanic community in New York.

Long-term outlook played a role in the Dinkins versus Giuliani comparison although it did not in the final model of the “Neither/No Vote” comparison with Giuliani. Being a pessimist gave a respondent the odds of .411 of supporting Dinkins instead of Giuliani when compared with people who thought that the city would remain the same for the next 10 to 15 years. The dummies for optimist versus stay the same and “don’t know” versus stay the same were statistically insignificant.

In the comparison between Dinkins and Giuliani, income class became insignificant in the parsimonious model with a p-value of .055 after being significant in model A. Its borderline significance combined with its having no change in the likelihood ratio test indicates that income class was not a contributor of the final indication of support for either candidate, thereby providing support for the null hypothesis with Hypothesis 3.

What makes a multinomial logistic regression interesting is that there are two or more comparisons imbedded in the equation, or three possible outcomes. In this case, support for Dinkins or support for Neither candidate/No Vote are set equal to 1, while support for Giuliani is set equal to 0. Figures 5.1 and 5.2 are graphical representations of the coefficients generated by the multinomial logistic regression—Model B, the parsimonious model. The figures were created using a program written by Scott Long taken from his 1997 book on regression for categorical and limited dependent variables (Long 1997). The figures illustrate the direction, magnitude and significance of the pairs of odds ratio or relative risk ratio arrangements created during the regression. A main advantage to using this method is that in a multinomial logistic regression, there are as many comparisons as there are values of the dependent variable. However, odds ratios or

relative risk ratio tables show less than the total number of comparisons. In this equation, there is the odds ratio for Dinkins or Giuliani, Giuliani or “Neither/No Vote”, or Dinkins or “Neither /No Vote.” Their respective first letters represents the three options: D for Dinkins, G for Giuliani and N for “Neither/No Vote.” The actual change from the reference category, in this case Giuliani, for each pair of outcomes is illustrated in two ways. The bottom scale is the coefficient of that variable in the model, while the upper scale is its exponential or odds. A letter to the left of the reference value, in this case G for Giuliani set equal to an odds ratio of 1, indicates an odds ratio less than zero or a negative coefficient. A letter to the right of the reference value indicates an odds ratio greater than zero or a positive coefficient. The direction or the magnitude of the change is the distance between the letters, where the greater the distance the larger the odds ratio. The size of the letters determines the discrete amount of change between one value and another value of the dependent variable: the larger the change, the larger the letter. Finally, a line between any two letters represents an *insignificant* relationship between the independent variable and that pair of values of the dependent variable at $p > .05$.

Figure 5.1 shows that for all the variables plotted the magnitude of selecting Giuliani or Dinkins is similar, as the letters are the same size. The odds ratios for having a positive view of race relations or being liberal and supporting Dinkins are approximately the same as the letters are the same distance apart. In addition, as shown by the absence of a line between Giuliani (G) and Dinkins (D), being Hispanic, liberal, from one of the outer boroughs and thinking that race relations are generally good are all significant. However, the odds ratios do not all have the same direction with being from an outer borough and being Hispanic, indicating a greater preference for Giuliani. In the models,

many of the demographic in both groups' variables such as gender, level of education and age were not significant. Religion also was not an influential factor in either comparison.

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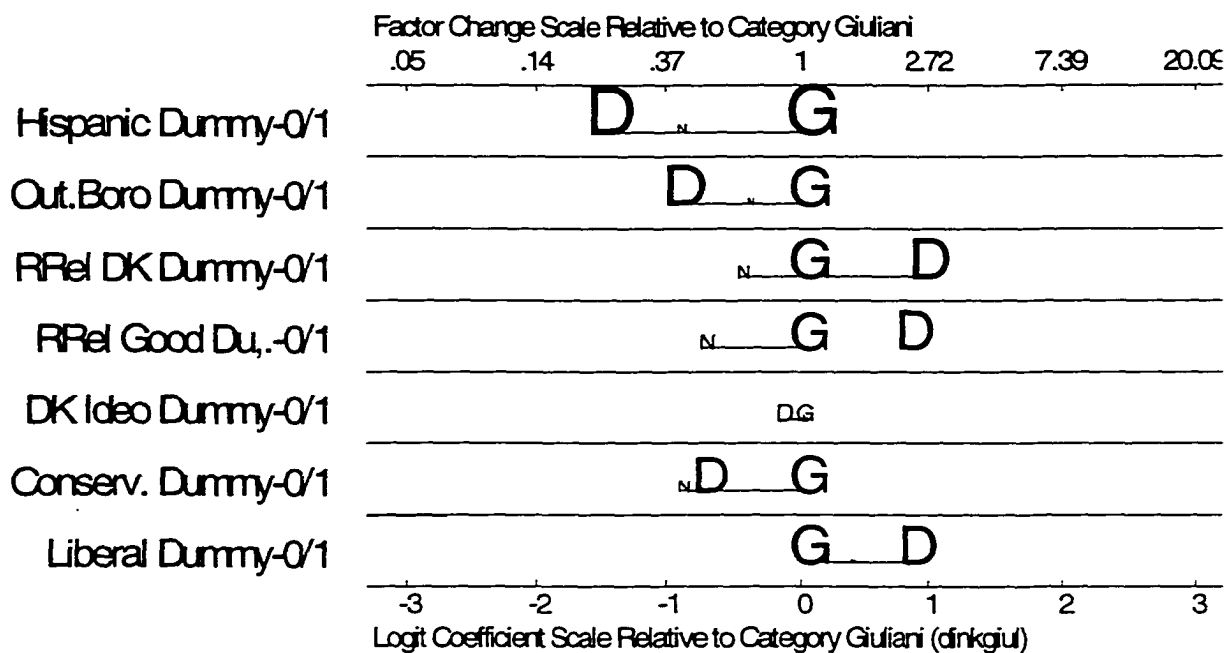


Figure 5.1 Odds Ratio Plot for Multinomial Logistic Regression on Candidate Choice

According to Figure 5.1, if voters were liberal they had odds that were 2.34 times greater to support Dinkins than if you were a moderate. Conservatives had odds of being .479 times less of supporting Dinkins than moderates. As shown in Figure 5.2, having a

low income was the largest indicator of not supporting either candidate in 1993. The odds ratio was 2.98, which translates into the odds of not supporting either candidate or not voting at all over supporting Giuliani being almost three times as high for those with low income. Whites in this survey were more likely to support Giuliani than the option of “Neither/No Vote.”

In Figure 5.2, the only independent variable where all the variables have a significant relationship is being white versus being non-white (white dummy). In this comparison, the odds of supporting either one of the candidates are higher than supporting neither candidate or not voting if one was white. Looking at the pessimist versus stay the same comparison, one can easily see how large the change is between Dinkins and Giuliani, as the odds of being a Dinkins supporter are .37 times more likely if you were a pessimist than if you thought the city would remain the same long term. Contrasting this comparison with the optimist versus stay the same comparison (longgood), one can see that the relationship between not voting or preferring none of the candidates to supporting Dinkins is statistically significant; as an optimist your odds of supporting Dinkins are greater. This relationship was hidden in the original presentation of the relative risk ratios because only two out of the three possible comparisons were shown. How these hidden relationships will play out within the recycled predictors remains to be seen.

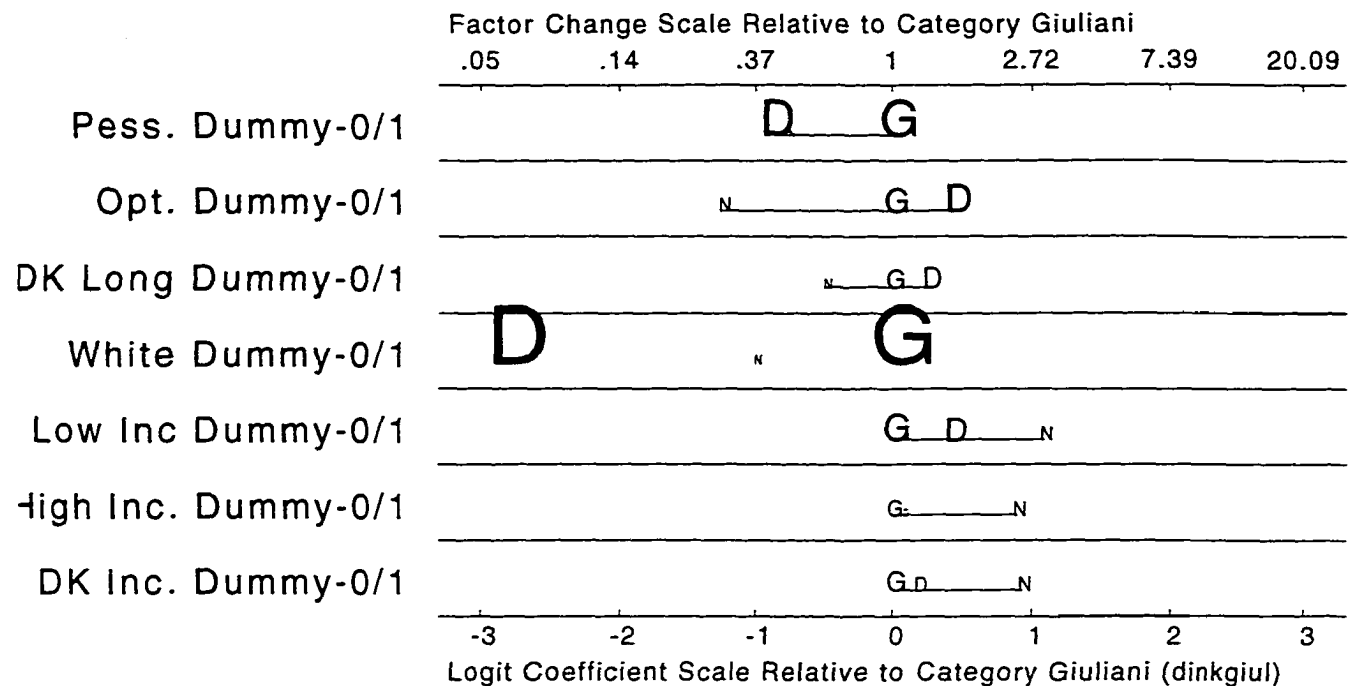


Figure 5.2 Odds Ratio Plot of Multinomial Logistic Regression on Candidate Choice

Tables 5.5 and 5.6 show two columns of predictors, unadjusted probabilities taken from crosstabulations and adjusted probabilities created using the recycled predictor method, as discussed in Chapter 4. In other words, the established effects of a variable on Y vary based on the respondent's particular pattern of answers. Recycled predictors have the advantage of presenting the overall average effect of X on Y . Therefore, by looking at

the tables, the average effect of each of the predictors on each outcome of Y can be analyzed.

The tables show that the variables that were significant predictors have the effect of reducing some of the unadjusted probabilities. Looking at the actual probabilities, one would suspect that being liberal, nonwhite, living in Manhattan, having a low income and having a positive outlook both for the city and for race relations would indicate a strong amount of support for Dinkins when compared with unadjusted probabilities. However, when looking at the adjusted probabilities, with the exception of being nonwhite, the adjusted probabilities all decrease in the amount of support for Dinkins. Correspondingly, those characteristics previously identified for supporters of Giuliani—being conservative, white, living in the outer boroughs, having a middle or high income and being pessimistic about the city's future and race relations—are also moderated by the recycled predictors.

Table 5.5 — Unadjusted and Adjusted Predictors for the Multinomial Logistic Regression 1993

<i>Variable</i>	<i>Unadjusted</i>	<i>Adjusted</i>
	<i>(Cross Tabs)</i>	<i>(Recycled)</i>
Liberal Dinkins	61.57%	58.95%
Liberal Giuliani	33.62%	36.09%
Liberal "Neither/No Vote"	4.80%	4.95%
Moderate Dinkins	46.31%	45.82%
Moderate Giuliani	48.99%	49.33%
Moderate "Neither/No Vote"	4.70%	4.84%
Conservative Dinkins	31.90%	35.54%
Conservative Giuliani	65.24%	61.76%
Conservative "Neither/No Vote"	2.86%	2.70%
Ideology DK Dinkins	56.00%	43.49%
Ideology DK Giuliani	40.00%	51.29%
Ideology DK "Neither/No Vote"	4.00%	5.21%
White Dinkins	28.60%	27.63%
White Giuliani	66.44%	67.56%
White "Neither/No Vote"	4.95%	4.80%
Nonwhite Dinkins	73.87%	75.61%
Nonwhite Giuliani	22.90%	21.17%
Nonwhite "Neither/No Vote"	3.32%	3.22%
Race DK Dinkins	50.00%	52.41%
Race DK Giuliani	50.00%	47.50%
Race DK "Neither/No Vote"	0.00%	0.00%
Outer Borough Dinkins	43.30%	44.19%
Outer Borough Giuliani	52.45%	51.56%
Outer Borough "Neither/No Vote"	4.25	4.24%
Manhattan Dinkins	63.33%	58.54%
Manhattan Giuliani	32.67%	37.38%
Manhattan "Neither/No Vote"	4.00%	4.08%
Hispanic Dinkins	45.79%	29.99%
Hispanic Giuliani	50.47%	66.86%
Hispanic "Neither/No Vote"	3.74%	3.15%
Non-Hispanic Dinkins	47.48%	50.66%
Non-Hispanic Giuliani	48.24%	45.11%
Non-Hispanic "Neither/No Vote"	4.47%	4.22%

Political ideology remains divisive within candidate support. Fifty-eight percent of liberals have an adjusted probability of support for Dinkins compared with an adjusted probability of 36% supporting Giuliani. Conservative respondents overwhelmingly favor Giuliani with an adjusted probability of 61.76%, while conservative respondents have an adjusted probability of 35.54% of favoring Dinkins holding everything else constant. The adjusted probability of favoring Dinkins for conservative respondents is somewhat higher than suspected, in light of Giuliani's candidness about his conservative message compared to previous candidates in the New York City mayoral elections. It was initially suspected that that for conservative respondents, Dinkins represented the prototype liberal and thus would have garnered a lower percentage of probability overall. Those with a moderate viewpoint were split evenly between the two candidates. For all the respondents who stated an ideological preference, the adjusted probability of favoring "Neither/No Vote" hovered around 3%. An interesting occurrence happened when looking at the "Don't Know" category within the political ideology variable: a reversal of the apparent preferences between the unadjusted and adjusted probabilities. The unadjusted probabilities show greater support for Dinkins, while the adjusted probabilities show greater support for Giuliani. While the significance of this is unclear, it may be due to the small number of respondents who answered in this manner rather than any theoretical factor.

Race and Hispanic origin are the only two variables where the adjusted probabilities are considerably higher than the unadjusted. The second hypothesis argues that whites supported Giuliani and nonwhites supported Dinkins. Looking at the recycled predictors, one can see that this indeed holds true. White respondents had an adjusted

probability of 67.56% of supporting Giuliani, whereas nonwhite respondents were more likely to support Dinkins with an adjusted probability of 75.61%. This does not mean that there was an absence of support for either candidate within different racial groups. However, on average, support for each candidate was broken along racial lines in this survey. Hypothesis 2 stated when broken down by race, the white respondents would support Giuliani, and the nonwhite respondents would support Dinkins. Using adjusted probabilities holds all other values constant, so that the effect of a single variable can be isolated, thereby giving strong support for Hypothesis 2.

One might suspect Hispanics, who are often lumped with other ethnic groups into the term “people of color,” to have the same candidate preferences as other nonwhites. Yet, Hispanics, controlling for race, overwhelmingly preferred Giuliani to Dinkins with adjusted probabilities of preference of 66.86% to 29.99% respectively. Non-Hispanic respondents also controlling for race preferred Dinkins to Giuliani with adjusted probabilities with a margin of approximately 5 percentage points. This is the preference one might expect from non-Hispanic African Americans. However, the preference for Hispanics for Giuliani was unexpected. One reason behind this might be that the Hispanic community was and should be distinguished from other ethnic communities in New York City rather than grouped with other minorities. Another reason is that the non-Hispanic group included many African Americans who represented Dinkins’ traditional support base. A third reason may be that Giuliani supported many of the same traditional (Catholic) values as many Hispanics did. These findings contradict the theory concerning Hispanics, which, based on the literature surrounding the elections and urban elections in general, hypothesized that Hispanics would prefer Dinkins instead of Giuliani

(Hypothesis 7). In this situation, the exact opposite happened, with Hispanics strongly preferring Giuliani.

The outer borough of New York City versus Manhattan split is discussed frequently in the literature and history of New York City (Arian et. al. 1990; Sleeper 1990; Rieder 1985.) Hypothesis 6 states that Giuliani would find more support among outer-borough respondents. This hypothesis was illustrated by the recycled predictions; however, the distinction between the respondents was not as sharp as originally suspected. Outer-borough residents had an adjusted probability of supporting Giuliani of 51.56%, while they had an adjusted probability of 44.19% in support of Dinkins. For Manhattanites, the split was greater, although not by as much as the unadjusted probabilities would have us believe. Of Manhattan residents, 58.44% had an adjusted probability for Dinkins and 37.39% had an adjusted probability for Giuliani.

Table 5.6 — Continuation of Table 5.5, Recycled Predictor Tables

<i>Variable</i>	<i>Unadjusted</i> <i>(Cross Tabs)</i>	<i>Adjusted</i> <i>(Recycled)</i>
Pessimistic Long Term Dinkins	34.84%	39.00%
Pessimistic Long Term Giuliani	60.65%	56.63%
Pessimistic Long Term "Neither/No Vote"	4.51%	4.36%
Stay the Same Long Term Dinkins	55.19%	51.93%
Stay the Same Long Term Giuliani	38.80%	41.93%
Stay the Same Long Term "Neither/No Vote"	6.01%	6.12%
Optimistic Long Term Dinkins	67.76%	60.97%
Optimistic Long Term Giuliani	30.92%	37.49%
Optimistic Long Term "Neither/No Vote"	1.32%	1.53%
Don't Know Long Term Dinkins	60.71%	57.09%
Don't Know Long Term Giuliani	35.71%	39.38%
Don't Know Long Term "Neither/No Vote"	3.57%	3.52%
Low Income Dinkins	55.73%	50.27%
Low Income Giuliani	38.93%	43.65%
Low Income "Neither/No Vote"	5.34%	6.08%
Middle Income Dinkins	43.06%	45.58%
Middle Income Giuliani	54.17%	51.94%
Middle Income "Neither/No Vote"	2.78%	2.57%
High Income Dinkins	40.21%	45.55%
High Income Giuliani	53.61%	48.71%
High Income "Neither/No Vote"	6.19%	5.73%
Don't Know Income Dinkins	46.51%	46.99%
Don't Know Income Giuliani	48.84%	47.29%
Don't Know Income "Neither/No Vote"	4.65%	5.72%
Race Relations Good Dinkins	63.16%	55.86%
Race Relations Good Giuliani	34.93%	42.18%
Race Relations Good "Neither/No Vote"	1.91%	1.96%
Race Relations Bad Dinkins	37.58%	41.62%
Race Relations Bad Giuliani	56.90%	52.78%
Race Relations Bad "Neither/No Vote"	5.52%	5.60%
Don't Know Race Relations Dinkins	62.60%	57.41%
Don't Know Race Relations Giuliani	35.37%	40.18%
Don't Know Race Relations "Neither/No Vote"	2.44%	2.42%

The first hypothesis was that a respondent's long-term view of New York City's future had a significant effect on his or her candidate preference. Pessimists about the future would support Giuliani, while optimists would support Dinkins. Long-term outlook was shown to be a significant predictor of candidate preference proving this hypothesis. Pessimists had a greater adjusted probability for Giuliani while optimists had a greater adjusted probability for Dinkins. While these results confirm the first hypothesis, it was expected that holding everything else constant, those respondents who were pessimistic would have been much stronger in their preference for Giuliani than the adjusted probability of support at 56.63%. An adjusted probability of closer to 70 to 80% was originally anticipated to conclusively support this part of the hypothesis. Furthermore, close to 40% of the pessimistic respondents had an adjusted probability for Dinkins.

Those respondents who felt that New York City would remain essentially the same for the next 10 to 15 years had an adjusted probability of supporting Dinkins of 51.93%, compared with an adjusted probability of support for Giuliani of 41.93%. This corresponds with the conventional wisdom concerning incumbents, "If it ain't broke, don't fix it." However, those who preferred "Neither/No Vote" who felt that New York City would remain the same had the highest recycled probability of all the variables at 6.12%.

The optimists had the most polarized adjusted probabilities of all the long-term groups. Optimist respondents had an adjusted probability of 60.97% to support Dinkins, while they had an adjusted probability of 37.49% to support Giuliani. Only 1.53% of the respondents fell into the neither or no vote category. Perhaps, if these could be broken

down into “Neither” or “No Vote” distinctions, the majority of these respondents would turn out to be non-voters. Optimists by definition are happy with the way things are, so it would make sense to keep the same mayor. Additionally, those who answered don’t know to the long-term outlook question strongly supported Dinkins with a recycled predictor of 57% compared to Giuliani’s 39%.

Race relations were also an important factor in candidate support in the model presented in Table 5.4. Here, as in long-term outlook, the results were not as polarized as initially suspected. It had seemed logical that those respondents who thought that race relations were generally good would have very high probable support for Dinkins. However, their adjusted probability was only 55.86%. A sizable percentage of this group, 42.18%, had an adjusted probability in support of Giuliani. Perhaps this is because those who supported Giuliani thought that the mayor could affect race relations and as such the actual person doing the mayor’s job didn’t matter; maybe they thought that supporting Giuliani could not hurt race relations. However, given the racially tinged mayoral race in 1989 between the same two candidates, both of these reasons are highly unlikely. Correspondingly, it was surprising that such a high percentage of people who thought that race relations were bad supported Dinkins (41.62%) versus Giuliani (52.78%). Many people blamed Dinkins for the deterioration of race relations during his tenure, especially since many elected him to fix race relations to begin with. It stands to reason that this is why 5.6% of the respondents had an adjusted probability of supporting neither candidate or saying that they did not plan to vote.

Income class was the final hypothetical predictor of candidate preference. Hypothesis 3 stated that low-income individuals would support Dinkins more than

Giuliani; this was shown by the regression and reinforced by the recycled predictors. Low-income respondents had an adjusted probability of 50.27% for Dinkins and 43.65% for Giuliani, with more than 6% having an adjusted probability that they would not vote or support none of the candidates. A much larger recycled probability of low-income support for Dinkins was suspected, given that the majority of the people who are low income in New York City are nonwhite, and race, controlling for all other variables, was the single biggest predictor of candidate support in the analysis. The recycled probability of support among middle class respondents for Giuliani of only 51.94% seemed low, as a majority of people in the middle class is white. However, a large amount of Dinkins' middle class support came from Manhattan, where the middle class is more racially mixed, so his adjusted probable level of support at 45.55% is not so surprising. It was also suspected that high-income individuals would be stronger for Giuliani given that income group's traditional tendency toward conservatism; however, the support between the two candidates was nearly evenly split with an adjusted probability of 45.55% for Dinkins and an adjusted probability of 48.71% for Giuliani. Therefore, as with most of the hypotheses for 1993, Hypothesis 3 was supported. In contrast, the analysis using the adjusted probability method provided distinctions between groups of supporters that were not as high as originally suspected. Interestingly, gender, level of education and age did not factor in the analysis of candidate support or pessimism.

Conclusion

The 1993 contest between Giuliani and Dinkins resulted in a reversal of fortunes. The analysis of the May 1993 *New York Times*/CBS News poll showed that respondents who were pessimistic, white, living in the outer boroughs and who thought that race relations were bad were more likely to support Giuliani. Giuliani advocated cuts in social programs and stronger measures on crime specifically in order to mobilize voters similar to the respondents who supported him in this analysis. In many cases, the differences between the adjusted probabilities of support for the candidates were much smaller than the unadjusted probabilities of support for the candidates, closing the gap between the two candidates overall. Additionally, the hypothesized model of candidate support seemed to work better for 1993 than for 1989. A direct comparison between the two elections follows in Chapter 6.

Chapter 6 A Post-Fight Analysis: A Comparison of the 1989 and 1993 Elections

As stated previously, the years between the two elections were difficult ones for New York City. The national economic depression, escalating budget deficit, and rise in racial tension took a toll on Dinkins' and his administration. This chapter will compare the analysis of the two election years, 1989 and 1993. It will also end the portion of this dissertation that analyzes the *New York Times*/CBS News Surveys.

The effect of the national economic depression on New York City was moderately severe. While wages did not drop as much as they did in other parts of the nation, members of the middle class in New York City lost ground overall, in particular middle class whites (See Chapter 2; Angelo 1995; City Council 1997). Therefore, it is reasonable to assume that middle class whites in the city were feeling the same level of depression as their counterparts across the nation (see Chapter 1 for more discussion). This dissertation hypothesizes that this depression was also behind the election of Rudolph Giuliani as mayor in 1993. If this class-level anxiety or depression were behind Giuliani's election, one would expect to see a number of changes between 1989 and 1993 in both the causes of pessimism and candidate support. The first change one might expect would be that an individual's income class is a far larger contributor to pessimism than in 1989. Although this assumes that an individual's long-term outlook is influenced by his or her economic standing, it takes into account that an individual's view of their long-term future is skewed by his or her income class. Given that the middle class in New York City saw their overall share of the pie shrink between 1989 and 1993, income class should contribute to long-term pessimism more in 1993 than in 1989.

The second change one might expect is that income class should also play a greater role in candidate support. Both retrospective and pocketbook voting predict that an individual's decrease in economic standing makes him or her more likely to vote against the incumbent. The questions in the surveys do not address individuals' economic standing in and of itself. However, from the Census data analysis in Chapter 2, we know that overall, middle-income class individuals' economic standing declined during this period. The definition of income class in Chapters 3 through 6 approximates the more detailed definition in Chapter 2. Therefore, it is safe to assume that those in the middle-income class in Chapters 3 through 6, although they were not the same individuals, suffered the same fate as middle-income class respondents in Chapter 2. Therefore, income class should be a stronger influence in 1993 than in 1989 on candidate choice.

The final predicted change is in long-term outlook. Given all the negative changes that occurred in New York City, pessimism should play an increasing role in increasing support for Giuliani. Overall, voters tend to take stock in their surroundings before an election. New York City was less safe and worse off financially in 1993 than in 1989. If Giuliani could speak forcefully on these issues, people who were pessimistic about New York City's direction would theoretically support him as representing possibility for change.

Pessimism in 1989 and 1993

Pessimism in 1993 was caused by different factors than in 1989. In order to compare the causes of pessimism in each election year, the independent variables were kept identical for each equation, with a single exception. In 1993, an additional question was added, which asked how the respondent perceived Dinkins' handling of the economy during his tenure. This question was added for two reasons. First, the recession of 1989 to 1992 profoundly affected the economic situation for many Americans. There were widespread layoffs, primarily in white-collar professions, falling home prices and rising inflation. The recession was felt everywhere, but in New York City it had a particular effect due to the dependence of New York City's economy on financial sector jobs (see Chapter 2). The loss of these high-paying jobs and firms combined with a drop in housing prices further eroded a deteriorating tax base. It became Dinkins' job to steward the city successfully through these tough economic times. On the national level, when an economy sours, the party and the president in power are blamed and they tend to lose the next election (Popkin 1990, Rosenstone 1982). The second reason for adding this question was to see if this characteristic of national-level politics is carried over to the local level.

Table 6.1 – Adjusted Probabilities for Pessimism for 1989 and 1993⁶¹

Variable	1989 Adjusted (Recycled)	1993 Adjusted (Recycled)
White	-	53.80%
Non White	-	47.47%
Don't Know Race	-	34.39%
Manhattan	41.70%	36.69%
Outer Boroughs	51.04%	53.90%
Race Relations Good	40.10%	40.38%
Race Relations Bad	54.48%	57.23%
Don't Know Race Relations	43.92%	39.53%
Dinkins Hurt Economy	-	59.09%
Dinkins Made No Difference	-	48.63%
Dinkins Help Economy	-	51.02%
Don't Know Dinkins Economy	-	45.25%
Low Income	41.14%	-
Middle Income	52.10%	-
High Income	44.20%	-
Income DK	52.18%	-
Liberal	43.23%	-
Moderate	48.93%	-
Conservative	56.79%	-
Ideology DK	47.40%	-
Age 18-29	46.22%	-
Age 30-44	54.04%	-
Age 45-64	53.58%	-
Age 65 and Over	40.50%	-

Looking at the adjusted predictors side by side in Table 6.1, the only two variables that are consistent between the two years are borough of residence and the respondent's perception of race relations. Borough of residence divided the respondents

⁶¹ These adjusted probabilities were taken from the tables in Chapters 4 and 5. They were created using the logistic regression models therein and the table presents only the results of those variables that were statistically significant.

more in 1993 than in 1989. In 1989, if a respondent lived in Manhattan, he or she had a nearly 42% adjusted probability of being pessimistic. By 1993, this adjusted probability had dropped to almost 37%. Correspondingly, the proportion of outer-borough respondents who were probably pessimists grew by four percentage points. This may have to do with Staten Island's desire to secede from New York City. On the 1993 ballot, there was a proposition for Staten Island to secede from the city of New York. Staten Island also had the highest proportion of pessimists in 1993, 62.6% (*New York Times/CBS News Polls* May 1993). While it is impossible, given the nature of the data, to draw a direct conclusion, it is reasonable to suspect that the desire to secede and higher levels of pessimism about the city's future are related.⁶²

A respondent's perception of race relations was the other variable that remained the same between the two equations. The adjusted probability of a respondent being a pessimist when he or she considered race relations generally good was remarkably similar from 1989 to 1993, at 40.10% and 40.38% respectively. This means that even though someone may have been an optimist about race relations, there still might have been other things that kept him or her a pessimist about New York City's future. The adjusted probability of being a pessimist if the respondent thought race relations were bad increased during the same period from 54.48% to 57.23%. In light of Dinkins' poor handling of the Korean store boycott and the Crown Heights incident, a four percentage point rise in pessimism toward race relations seems rather low.

⁶² The *New York Times/CBS News* polls did ask questions concerning the possibility of secession in a later survey (September 1993). However, they did not include in the survey a question regarding long-term outlook.

The other variables that appeared in 1989 that did not appear in 1993 related to demographics. It appeared that by 1993, demographics, aside from race and borough of residence, did not factor into the equation, as they were insignificant predictors in 1993. Pessimism became an overarching phenomenon, irrespective of age, political ideology or income level. One might think that given the nature of the economy in 1993 that perceptions of Dinkins' handling of New York City's economy would be closely linked to income class; however, income class and the perceptions surrounding Dinkins' handling of the economy turned out to be only very weakly associated.⁶³ Therefore, the assumptions of a class level phenomenon being masked by perceptions of how Dinkins handled the economy did not hold true.

In 1993, income class was not part of the exploration of the causes of pessimism, while the perception of what Dinkins did to the economy was a significant factor. Hypothesis 1a stated that race and income class were significant predictors of pessimism. In 1989, race was not a predictor of pessimism and in 1993, income class was not a predictor. This occurred even as groups where race and income class intersect were highly pessimistic. Middle class whites were the most pessimistic about the city's future in 1993. It could be that in 1989, income class overshadowed race, and the reverse occurred in 1993. This would make sense given the racial tension in New York City in 1993, as well as the racial tenor of the campaign. If people perceived the individual or party in power as hurting the economy, then they may have also thought the economy was

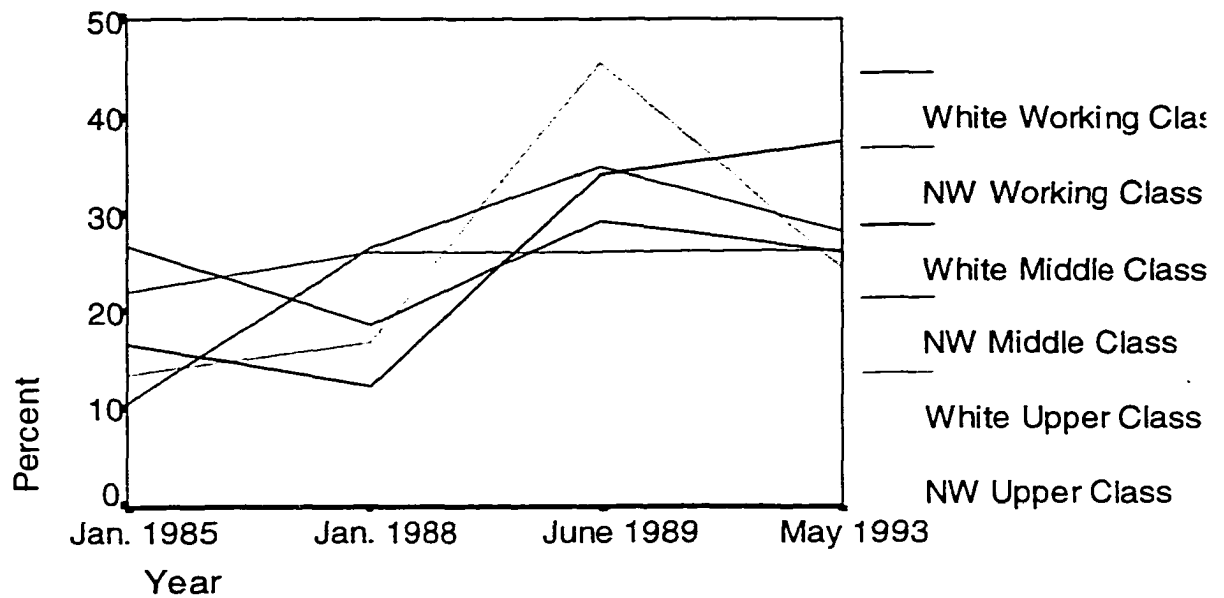
⁶³ The correlation between the two variables, while significant at the $p < 0.05$ level, was only .067.

worse and would be more anxious about the future. This anxiety could manifest itself in this survey as pessimism. Therefore, hypothesis 1a could not be confirmed.

The perception of Dinkins' actions regarding to the economy was a significant predictor of pessimism in 1993. Respondents who thought that Dinkins had helped the economy had an adjusted probability of 39.53% to be pessimistic, while respondents who thought that Dinkins had made no difference with the economy had an adjusted probability of 48.63% to be pessimistic. This indicates strongly that there were other motivations behind the rise of pessimism in New York City besides dissatisfaction with Dinkins' handling of the economy. The respondents who felt that Dinkins hurt the economy were 60% probable (adjusted) to be pessimists regardless of race or income class. Feeling that Dinkins hurt the economy is the single strongest predictor in 1993 of pessimism. The next section will examine whether people vote with their pocketbooks as well.

Race, while not a significant predictor in 1989, was a strong predictor in 1993. White respondents were more likely than nonwhite respondents or those who answered "don't know/not answered" to be pessimistic, with an adjusted probability of 53.80%. Nonwhite respondents were more likely to be not pessimistic about the city's future with an adjusted probability towards pessimism of 47.47%. This may be related to the high level of nonwhites that supported Dinkins in 1993. This "flip-flopping" between the two years of these factors suggests that it is perhaps the relationship between race and income class that is crucial.

Long-term outlook for New York City was not distributed equally throughout the population. Middle class white New Yorkers had the largest share of pessimistic outlook of all other racial and class groups (see Figure 6.1).



Source: NYT/CBS Polls 1985, 1988, 1989, 1993

Figure 6.1 Chart of Pessimism Broken Down by Race and Income Class

Figure 6.1 can perhaps be explained by the context of the 1993 election. By this point, the economy, at least for the wealthy, had improved, leading to the decrease in the percentage of upper class of all races that considered themselves pessimistic about New

York City's future. The stability of the nonwhite working class can be explained by the draw of David Dinkins in that community. Additionally, by 1993, only middle class whites increased their levels of pessimism. All other groups were more optimistic. This finding is even more interesting, given that income class was not among the significant predictors of pessimism in 1993.

Between the elections, there were only two significant variables that remained the same; the rest varied depending on the year. The next section will explore whether this pattern will be duplicated when the candidate preferred equations are compared.

Comparison Between 1989 and 1993 New York Times/CBS News Polls

Giuliani won by 97,000 total votes in the 1993 election in comparison to the 1989 election (Mollenkopf 1994). In a close election, one might expect to see similar causes behind the selection of one candidate over another with only small differences in the proportion of each variable in the support equation for either candidate. However, measuring the differing amounts of support for Giuliani and Dinkins, there are very few common causative factors. As such, rather than presenting a long series of adjusted probabilities detailing what was statistically significant and what was not; this chapter will only present what was statistically significant in both years. Then, the graphical constructs of the prime theoretical variables of race, income class and long-term outlook

will be contrasted. In the final portion of this section, the adjusted probabilities taken from the model with exit poll data from 1989 and 1993 will be compared.⁶⁴

⁶⁴ I realize that in this section I am comparing two different samples. However, adjusting the probabilities so that they represent what would be the average probability holding everything else constant provides a picture of what could happen.

Table 6.2 Adjusted Probabilities for Candidate Support for 1989 and 1993

<i>Variable</i>	<i>1989 Adjusted</i>	<i>1993 Adjusted</i>
	<i>(Recycled)</i>	<i>(Recycled)</i>
Liberal Dinkins	55.80%	58.95%
Liberal Giuliani	40.50%	36.09%
Liberal "Neither/No Vote"	3.68%	4.95%
Moderate Dinkins	43.98%	45.82%
Moderate Giuliani	50.89%	49.33%
Moderate "Neither/No Vote"	5.13%	4.84%
Conservative Dinkins	41.07%	35.54%
Conservative Giuliani	52.72%	61.76%
Conservative "Neither/No Vote"	6.19%	2.70%
Ideology DK Dinkins	49.20%	43.49%
Ideology DK Giuliani	45.14%	51.29%
Ideology DK "Neither/No Vote"	5.63%	5.21%
White Dinkins	31.62%	27.63%
White Giuliani	63.30%	67.56%
White "Neither/No Vote"	5.06%	4.80%
Nonwhite Dinkins	72.01%	75.61%
Nonwhite Giuliani	23.37%	21.17%
Nonwhite "Neither/No Vote"	4.61%	3.22%
Race DK Dinkins	49.07%	52.41%
Race DK Giuliani	50.92%	47.50%
Race DK "Neither/No Vote"	0%	0.00%
Outer Borough Dinkins	44.47%	44.19%
Outer Borough Giuliani	50.30%	51.56%
Outer Borough "Neither/No Vote"	5.22%	4.24%
Manhattan Dinkins	56.44%	58.54%
Manhattan Giuliani	39.35%	37.38%
Manhattan "Neither/No Vote"	4.20%	4.08%
Hispanic Dinkins	32.75%	29.99%
Hispanic Giuliani	59.50%	66.86%
Hispanic "Neither/No Vote"	7.74%	3.15%
Non-Hispanic Dinkins	47.69%	50.66%
Non-Hispanic Giuliani	48.27%	45.11%
Non-Hispanic "Neither/No Vote"	4.04%	4.22%

Political ideology was a factor in both election year equations. Between 1989 and 1993, the city became increasingly polarized along ideological lines; liberals increased their support of Dinkins, while conservatives increased their support of Giuliani even though he was a candidate for the Liberal Party in both 1989 and 1993. The adjusted probabilities for Dinkins among liberal respondents increased between 1989 and 1993 from 55.8% to 58.95%, while liberal respondent support for Giuliani dropped by close to 4 percentage points, from 40.5% to 36.09%. While these increases in support are more polarized between the candidates, the separation was not as extreme as it was for conservatives. Holding everything else constant, conservative respondents increased their support for Giuliani by almost 9 percentage points. Likewise, the percentage of conservative respondents who stated that they preferred “Neither/No Vote” also decreased dramatically from 6.19% to 2.70%. This decrease may indicate an acceptance of Giuliani as the only viable conservative candidate in New York City by 1993, although there was an even more conservative candidate running on the Right-to-Life ticket, George Marlin. If Marlin’s candidacy had been considered viable among conservative respondents, an increase in the proportion of conservatives who supported neither of the major candidates would be expected, rather than a decrease.

Race was one of the defining characteristics of both the 1989 and 1993 elections. Dinkins ran a deracialized campaign in 1989, yet his support was concentrated among nonwhites (Thompson 1996). This held true again for 1993, as the adjusted probable support for Dinkins among nonwhite respondents increased from 72.01% to 75.61%. Adjusted probable support for Dinkins dropped among white respondents by 4 percentage points. In 1989, Dinkins ran not only a deracialized campaign but positioned himself as a

racial peacemaker. It was only during the final month of the campaign that Giuliani was able to gain support through his thinly veiled race-based attacks (Thompson 1996). By 1993, Dinkins had failed as a racial conciliator; Giuliani was successfully able to paint him as a “puppet” of African American interests in New York City politics (Mollenkopf 1994). Given the heated rhetoric surrounding the campaign in 1993, the small drop in probable support among whites for Dinkins indicates not only the power of the liberal voting bloc within the white community, but also the failure of Giuliani’s race-baiting tactics to win over the entire community. Adjusted probable support for Giuliani among white respondents rose by the same approximate percentage as probable support for Dinkins dropped. The number of respondents who supported “Neither/No Vote” remained comparatively constant, hovering around 5% for whites, with a slight drop for nonwhites from an adjusted probability of 4.61% in 1989 to 3.22% in 1993.

Where a person lives can provide a context for candidate support during elections. The relative consistency of the adjusted probable support for each candidate when analyzed by borough of residence is surprising. The 1993 election saw a movement in Staten Island to opt for secession rather than remain a part of New York City. Staten Island is a mostly conservative, mostly white outer borough of the city whose residents are overwhelmingly more likely to support Giuliani than Dinkins. The Staten Island vote increased the probability of support for Giuliani by a substantial amount in 1993 by 1.2 percentage points from 50.3% in 1989 to 51.56% in 1993. Probable support for Dinkins in the outer boroughs remained even more consistent, with only a small drop of less than one percentage point between 1989 and 1993. Both candidates’ adjusted probable support remained consistent in Manhattan from 1989 to 1993. Dinkins experienced only a two

percentage point gain in probable support from Manhattanites, a rather low increase in light of the liberal tendencies of Manhattan residents. The adjusted probability of supporting Giuliani dropped by the same percentage as was gained by Dinkins, indicating a small switch at the margins rather than a wholesale defection to one of the candidates.

The final variable that appeared in both election year equations was Hispanic origin. Between 1989 and 1993, the percentage of Hispanics, controlling for race, who had an adjusted probability of support for Giuliani jumped from 59.5% to 66.86%. Therefore, Hispanics, when isolated from other nonwhite voters appear to be almost as strong Giuliani supports as whites. This is a much larger jump than found in any of the other variables. Additionally, the percentage of respondents who preferred “Neither/No Vote” dropped by almost the same amount as was gained by Giuliani. This indicates that the increase in probable support for Giuliani came not from Dinkins supporters, but from those who were undecided or did not plan on voting in 1989. The increased mobilization, as evidenced by the comparison of the adjusted probabilities, is due to both the support of Giuliani by many Hispanic leaders including Herman Badillo, as well as the seeming abandonment of Hispanic issues by Dinkins (NPR 1993).

The original model stated that the two largest predictors of candidate support in the *New York Times*/CBS News polls were a respondent’s race and class. These were then filtered by respondents’ long-term outlook. Figures 6.2 and 6.3 are the graphical representations of these variables in 1989 (figure 6.2) and 1993 (figure 6.3). As in Chapters 4 and 5, these figures graphically represent the discrete and relative coefficient changes in comparison to Giuliani. In other words, a multinomial logistic regression is essentially equivalent to a series of linked binary logistic regressions where the dependent

variable is scored either 0 or 1. In this situation, the 0 always equals Giuliani and the 1 is either Dinkins or “Neither/No Vote.” The size of the letters represents the discrete change and the distance between the letters the relative change (Long 1997). Where the letters are connected by a line, it means that the relationship between the variables is insignificant at $p > .05$.

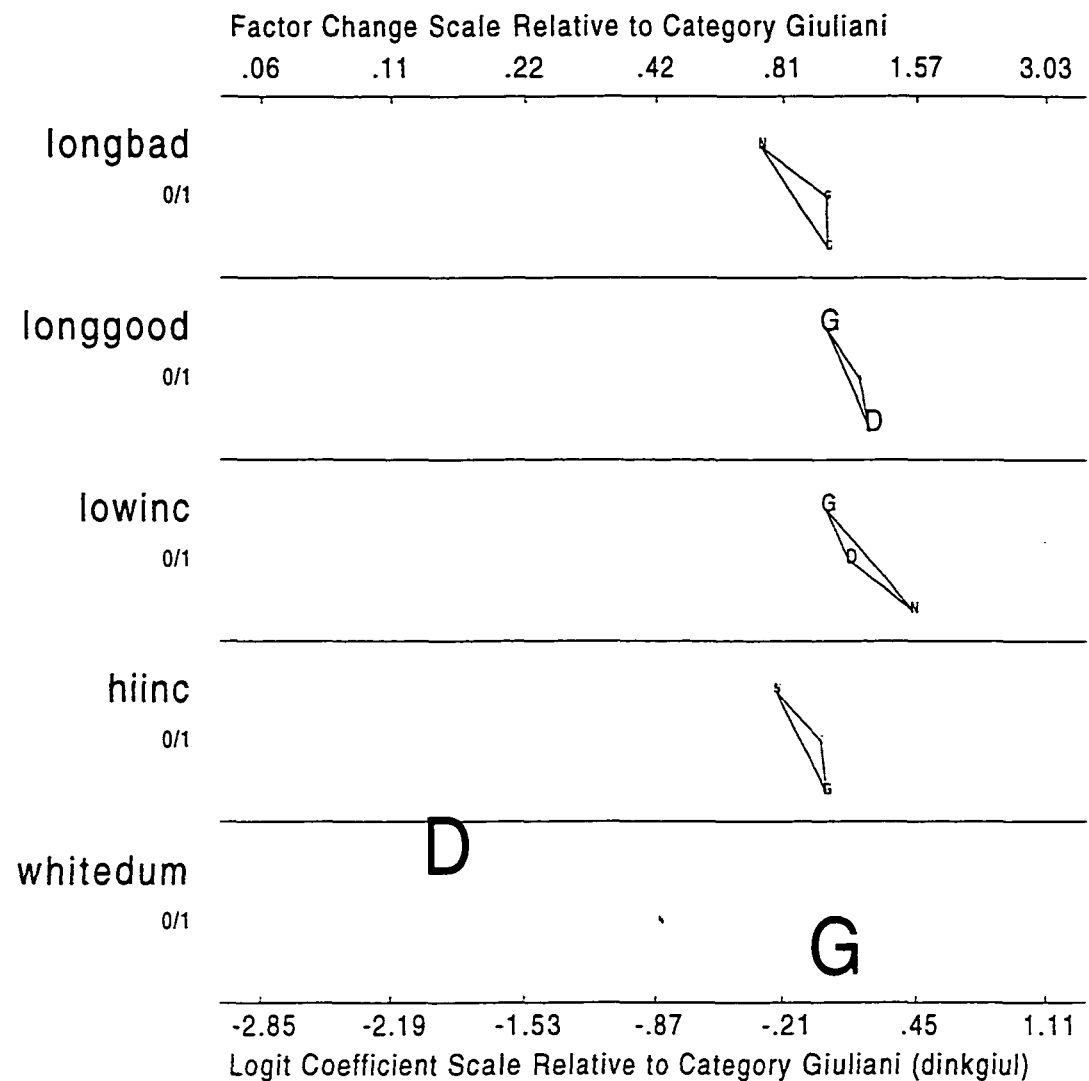


Figure 6.2 1989 Graphical Representations of Primary Theoretical Variables

Figure 6.2 shows the five dummy variables representing race (White versus Nonwhite), income class (Low Income versus Middle Income, and High Income versus Middle Income), and long-term outlook (Longgood – Optimist versus Stay Same, and Longbad – Pessimist versus Stay Same) in 1989. The dummies representing the “Don’t

know” options were eliminated from the figure, as they were insignificant in both years and did not contribute either graphically or theoretically. The only significant variable in 1989 is race. White respondents in 1989 were far less inclined to support Dinkins with an odds ratio of approximately .15. In other words, whites were .15 times more likely to support Dinkins than Giuliani. They were also .42 times as likely not to vote or prefer “Neither/No Vote” to Giuliani; however, they were slightly more likely to prefer “Neither/No Vote” to Dinkins.

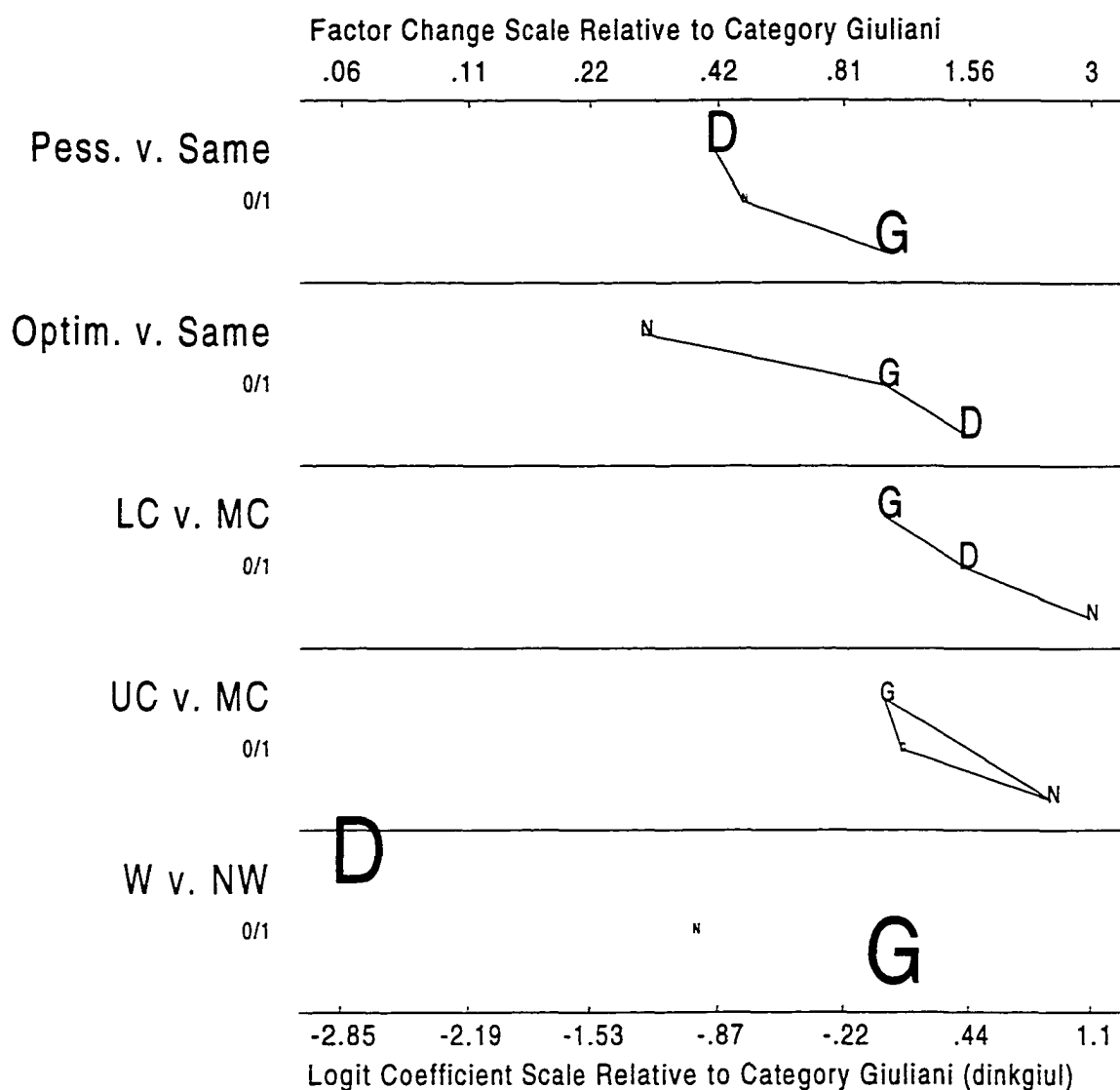


Figure 6.3 1993 Graphical Representations of Primary Theoretical Variables

In contrast, Figure 6.3 (1993) shows that all of the variables except for upper income versus middle income have significant relationships. These types of graphical representations provide a picture of all three relationships— Dinkins and Giuliani, Dinkins and “Neither/No Vote,” Giuliani and “Neither/No Vote”— when odds ratio

tables only show two. As in 1989, race is the largest predictor of candidate preference among the respondents. Both figures have the same scale, so it is apparent that whites were even less supportive of Dinkins in 1993 than in 1989. Income also plays a role in candidate support, or rather, lack of income, as low-income respondents are more likely to prefer “Neither/No Vote” to Giuliani. The relationship preferring Dinkins to “Neither/No Vote” or Giuliani is insignificant; however, these relationships are apparent from the odds ratio or relative risk ratio tables. What is not apparent is that the optimists, when given a choice between neither candidate, Giuliani or Dinkins, chose Dinkins over “Neither/No Vote” at all. One of the theories behind Dinkins’ loss in 1993 was that people did not turn out to vote in his key support groups. However, when the optimists were given a choice between neither candidate or Dinkins, they chose Dinkins. In pocketbook voting, if the country is perceived to be doing well, the incumbent will usually be reelected. Therefore, it makes sense that those respondents who are optimists and think the city will get better in the long run will prefer Dinkins and show their support by coming out to vote and not staying home.

Comparison with Exit Polls

This section will verify how well the adjusted probabilities or recycled predictors from the model fared when compared with the exit poll data. Exit poll data will be used rather than actual voting tallies, because the actual votes are tabulated for New York City by election district. Unfortunately, long-term outlook for New York City is not asked in the exit poll of either year. However, a proxy variable was created for long-term outlook

in 1993 (when it was a significant indicator in the model), which will be included within the comparison. The long-term outlook variable was created from two questions asked in the 1993 exit poll. The first is on perspectives on race relations and whether they are generally good or generally bad. In Chapter 5, perspective on race relations was a significant predictor of pessimism; therefore, its inclusion here is useful. The second variable is an attempt to include other factors that may influence a respondent's long-term outlook. The second question in the creation of long-term outlook for use with the exit poll is how the voter perceives the city's safety. Questions of this type were not included in the original model for long-term outlook in 1993 (see Chapter 5) because they did not appear on the original questionnaire.

Respondents who answered that the city was safer and race relations were better became optimists. Respondents who answered that the city was as safe and race relations were stable became those who thought that the city would stay the same; and those who thought that race relations were worse and the city was less safe became pessimists. This section will begin with a comparison of selected variables in common to both years with the exit poll. It will continue with an analysis of the variables specific to each year. Since exit polls are only conducted with those respondents who have just left the voting booth, within the analysis of the exit polls, those who did not give an answer as to who they voted for are compared with those who responded "neither/no vote" on the pre-election polls.

Table 6.3 Comparison of Recycled Predictors with Exit Polls 1989 and 1993

<i>Variable</i>	<i>1989 Adjusted</i>	<i>1989 Exit</i>	<i>1993 Adjusted</i>	<i>1993 Exit</i>
Liberal Dinkins	55.80%	68.90%	58.95%	63.50%
Liberal Giuliani	40.50%	29.90%	36.09%	33.10%
Liberal Neither/No Vote	3.68%	1.20%	4.95%	3.40%
Moderate Dinkins	43.98%	47.80%	45.82%	42.20%
Moderate Giuliani	50.89%	50.50%	49.33%	54.40%
Moderate Neither/No Vote	5.13%	1.70%	4.84%	3.50%
Conservative Dinkins	41.07%	32.30%	35.54%	33.50%
Conservative Giuliani	52.72%	64.70%	61.76%	61.20%
Conservative Neither/No Vote	6.19%	3.10%	2.70%	5.30%
White Dinkins	31.62%	26.30%	27.63%	20.70%
White Giuliani	63.30%	70.90%	67.56%	75.30%
White Neither/No Vote	5.06%	2.90%	4.80%	4.00%
Non-White Dinkins	72.01%	80.10%	75.61%	79.20%
Non-White Giuliani	23.37%	18.00%	21.17%	17.20%
Non-White Neither/No Vote	4.61%	1.90%	3.22%	3.60%
Hispanic Dinkins	32.75%	64.60%	29.99%	58.10%
Hispanic Giuliani	59.50%	34.60%	66.86%	36.60%
Hispanic Neither/No Vote	7.74%	0.80%	3.15%	5.30%
Non-Hispanic Dinkins	47.69%	47.80%	50.66%	45.10%
Non-Hispanic Giuliani	48.27%	49.50%	45.11%	51.20%
Non-Hispanic Neither/No Vote	4.04%	2.70%	4.22%	3.70%

As one can see from Table 6.3, the adjusted predictors largely predicted the scope and direction of the votes cast in the November elections within a reasonable margin. This is critical because the polls used in the adjusted predictor method were conducted in the spring of each election year, and there were approximately five months in between the survey and the election when the exit polls were conducted. The main demographic variable where there are substantial differences is within Hispanic preferences. While for many Hispanics, having an African American mayor was important, Dinkins alienated

many in the Latino community by seeming unresponsive to Hispanic issues (NPR 1993). Both pre-election surveys were conducted in the spring before the primaries. During this period there were many more candidates considering a run for mayor on the Democratic ticket, some were Hispanic. While this may have influenced some of the Hispanic respondents to not vote for Dinkins, it does not explain why so many of them stated that if Dinkins and Giuliani were the only two candidates, they would prefer Giuliani. These results were contradicted by the exit polls, where Hispanic respondents strongly preferred Dinkins to Giuliani or not voting.

Table 6.4 Long-Term Outlook Compared

<i>Variable</i>	<i>1993 Adjusted</i>	<i>1993 Exit</i>
Pessimistic Dinkins	39.00%	16%
Pessimistic Giuliani	56.63%	80.10%
Pessimistic "Neither/No Vote"	4.36%	3.80%
Stay Same Dinkins	51.93%	74.20%
Stay Same Giuliani	41.93%	19.80%
Stay Same "Neither/No Vote"	6.12%	6.00%
Optimistic Dinkins	60.97%	99%
Optimistic Giuliani	37.49%	0%
Optimistic "Neither/No Vote"	1.53%	1%
Don't Know Dinkins	57.09%	62.30%
Don't Know Giuliani	39.38%	34.20%
Don't Know "Neither/No Vote"	3.52%	3.50%

In Table 6.4, the exit polls show that in 1993, long-term outlook was an even more important indicator of voter preference. Approximately 80% of the pessimists preferred Giuliani according to the exit polls, thereby providing support for Hypothesis 1.

At the same time, 99% of all optimists were Dinkins supporters. The variable long-term outlook in the exit polls is a combination of two variables, opinion on race relations and on city safety. These are two areas where voters believe that the mayor has some control (see Chapter 3). Optimists feel that race relations are good and the city is safe; therefore, it follows that they will support the mayor. However, this is not a perfect match due to the construction of the long-term outlook variable from the exit polls, rather than having it be asked as an original question as it was in the 1993 pre-election survey. Therefore, it should not be taken as definitive proof of the strength of the model, instead all the factors should be considered together.

Table 6.5 Comparison of 1993 Recycled Probabilities and 1993 Exit Polls for Income Class and Race Relations

<i>Variable</i>	<i>1993 Adjusted</i>	<i>1993 Exit</i>
Low Income Dinkins	50.27%	58.10%
Low Income Giuliani	43.65%	36.60%
Low Income "Neither/No Vote"	6.08%	5.30%
Middle Income Dinkins	45.58%	42.10%
Middle Income Giuliani	51.94%	55.00%
Middle Income "Neither/No Vote"	2.57%	2.90%
High Income Dinkins	45.55%	33.80%
High Income Giuliani	48.71%	65.50%
High Income "Neither/No Vote"	5.73%	0.70%
Race Relations Good Dinkins	55.86%	84.20%
Race Relations Good Giuliani	42.18%	14.30%
Race Relations Good "Neither/No Vote"	1.96%	1.50%
Race Relations Bad Dinkins	41.62%	27.50%
Race Relations Bad Giuliani	52.78%	68.40%
Race Relations Bad "Neither/No Vote"	5.60%	4.10%

In 1993, the adjusted probabilities from the May survey provided a good indication of how each group would vote in November. However, for these groups of variables, the results were more polarized by Election Day. This may be due to the wording of the question on race relations on the 1993 exit poll, which states: “Over the last few years, have race relations in New York City: Gotten Better, Gotten Worse, Stayed the Same?” The question in the May of 1993 survey read: “Are race relations in New York City: Generally Good, or Generally Bad?” While one question is asking the respondent to consider race relations over a period of time, and the other is asking the respondent for their opinion at the moment, it is safe to compare the two as measures of perceptions of race relations in New York City during an election that turned on race.

Income class was a significant factor in only one of the comparisons within the 1993 multinomial logistic regression—“Neither/No Vote” and Giuliani. Table 6.5 illustrates the comparison between the exit polls and the 1993 pre-election survey for all three components of the multinomial logistic regression. In all three components, the exit polls showed a more polarized electorate than one would be led to believe based on the pre-election survey. This is not surprising given that the pre-election survey was conducted in May of 1993 before the primaries.

One variable that is not included in the multinomial logistic regressions for 1993 was how people voted in 1989. It was not included for two main reasons; first, when included in the calculations, it became the prime reason why people voted for a particular candidate (see Appendix 6.1); and second, including how people voted in 1989 as a predictor variable in 1993 substantially limited the comparability of the two equations. Table 6.7 shows the unadjusted and adjusted predictors based on how the respondent

reported their vote in 1989, compared with the exit poll conducted in 1993 by the same news organization. As one can see, the adjusted probability of voting for the same candidate in both elections is extremely high, approximately 80% for Dinkins in both years and 97% for Giuliani in both years. This points to one of the essential features of any electoral contest, mobilization. As discussed in the introduction, any candidate who hopes to win an election must be able not only to articulate the views of the majority of the electorate, but also to mobilize and ensure turnout of the majority of the electorate. Between 1989 and 1993, Giuliani was successfully able to mobilize and ensure turnout from enough voters from both his base and his swing categories to narrowly win the election. Table 6.7 indicates that there were approximately 16% of individuals predicted to vote for Giuliani who voted for Dinkins in 1989. This translated into approximately 22% in the actual election as shown by the exit polls. This is a critical group: without these individuals, Giuliani would have lost the election. The question remains, who are these voters, and why did they switch allegiance?

Table 6.6 Probabilities and Results for Voting in 1993 Based on 1989 Voting Behavior

	<i>New York Times/CBS Poll May 1993</i>		<i>Exit Poll Nov. 1993⁶⁵</i>
	<i>Unadjusted</i>	<i>Adjusted</i>	
	<i>(Cross Tabs)</i>	<i>(Recycled)</i>	
Dinkins 1989 Dinkins 1993	80.29%	80.29%	74.00%
Dinkins 1989 Giuliani 1993	16.76%	16.76%	22.60%
Dinkins 1989 "Neither/No Vote" 1993	2.94%	2.94%	3.40%
Giuliani 1989 Dinkins 1993	1.92%	1.92%	3.10%
Giuliani 1989 Giuliani 1993	97.12%	97.11%	95.50%
Giuliani 1989 "Neither/No Vote" 1993	0.96%	0.96%	1.40%
Won't Say 1989 Dinkins 1993	10%	16%	
Won't Say 1989 Giuliani 1993	50%	64%	
Won't Say 1989 "Neither/No Vote" 1993	40%	20%	
Didn't Vote 1989 Dinkins 1993	20%	41.80%	45%
Didn't Vote 1989 Giuliani 1993	73.33%	50.26%	51.10%
Didn't Vote 1989 "Neither/No Vote" 1993	6.67%	7.90%	3.90%

The "potential switchers" in 1993 from Dinkins to Giuliani have many uniform characteristics. Demographically, their characteristics were: mostly female, high school education or more, between 30 and 44 years old, middle class, white and outer-borough residents (See Appendix 6.2 for more detail). This profile resembles the "soccer mom" profile that journalists associated with the female voters who identified with Clinton. This switch from a liberal outlook with Dinkins to a conservative outlook with Giuliani is perhaps not as dramatic as it seems. Ideologically, the majority of the "potential

⁶⁵ The question in the exit poll for 1993 was worded somewhat differently from the question in the May of 1993 poll. The question in the exit poll asked specifically whether you voted for another candidate in the 1989 mayoral election, and did not include a "Won't Say" response category. For ease of comparison, I omitted the "other candidate" category from Table 6.7. To see the full results, please consult Appendix 6.1.

switchers” were moderate (36.84%) and pessimistic (66.67%), and thought race relations were generally bad (73.68%). These were all significant predictors of preference for Giuliani. However, had the majority of these “switchers” stated that they were conservative, had been crime victims or stated that they thought that Dinkins had hurt the economy, it might have indicated a more dramatic turn of events. Additionally, the only predictor of the switch was education, in particular *some* college education rather than a completed bachelors’ degree. Given that the predictive value of the data for the switch was relatively poor, a check of the exit poll data to see if the assumptions about the switchers were correct was warranted.⁶⁶

Approximately 11% of the voters in 1993 switched from their 1989 preference of Dinkins to support Giuliani (Voter News Survey Exit Poll 1993). Table 6.8 details a profile of the “switchers” taken from the 1993 exit poll frequencies and crosstabulations in comparison with the profile from the May of 1993 poll’s frequencies and crosstabulations. The demographic profile provides a clearer picture of the “switcher.” It is indeed overwhelmingly female, middle class, moderate, with some college or higher, and nonwhite. Of the nonwhite switchers, 44% were Hispanic indicating a greater propensity to switch among non-Hispanic nonwhites than Hispanic nonwhites. This results provides critical evidence as to the identity of the approximately 20% of nonwhites who supported Giuliani. Further evidence of switching will be explored in the ecological data analysis in Chapter 7.

⁶⁶ See Appendix 6.2 for the full detail of the model with the recycled predictors. In the equation, only education was a significant predictor.

The borough of residence of the “switchers” could not be calculated because the exit poll did not have sufficient cases for Staten Island. However, the weights were designed to compensate for this (VNS Poll Codebook 1993). The opinion portrait was slightly more difficult to create. The exit poll did not ask a question on long-term outlook, and had slightly different wording for its question on race relations. Therefore, a long term outlook variable was created, where those who answered that the city was safer and race relations were better became optimists; those who answered that the city was as safe and race relations were stable became those who thought that the city would stay the same; and those who thought that race relations were worse and the city was less safe became pessimists. As such, 89% of the “switchers” were pessimists in 1993. This is much higher than in the May of 1993 poll; thus, it can be concluded that many of the people who brought Giuliani to victory were pessimistic, middle class and nonwhite non-Hispanics.

Table 6.7 "Switcher" Profile from May 1993 Poll and November 1993 Exit Poll

	<i>May 1993 Poll</i>	<i>Exit Poll November 1993</i>
	<i>"Switcher"</i>	<i>"Switcher"</i>
Age 18-29	14.04%	8%
Age 30-44	42.11%	32.60%
Age 45-64	33.33%	24.80%
Age 65 and Over	10.53%	34.60%
LT HS	5.26%	4%
HS Grad	42.11%	26.90%
Some College	8.77%	21.40%
BA Plus	43.86%	47.70%
Jewish	19.30%	38.10%
Non-Jewish	80.70%	61.90%
Low Income	24.56%	28.50%
Middle Income	54.39%	46.50%
High Income	17.54%	16.40%
DK Income	3.51%	8.60%
Liberal	29.82%	28.50%
Moderate	36.84%	51%
Conservative	31.58%	16%
Nonwhite	64.91%	80.80%
White	33.33%	18.20%
DK Race	1.75%	1%
Pessimistic	66.67%	89%
Stay Same	21.05%	11%
Optimistic	12.28%	0%
Hispanic	19.30%	13.10%
Non-Hispanic	80.70%	86.90%

Conclusion

The essential theory behind Giuliani's 1993 victory was that race and class factors were filtered through long-term outlook, causing a shift in votes for Giuliani and away

from Dinkins. However, through the analysis of the pre-election survey polls in both 1989 and 1993, this original theory was not supported. In 1989, race was indeed a primary factor behind the election of David Dinkins as mayor. Whites tended to support Giuliani, and nonwhites overwhelmingly supported Dinkins. Neither income class nor long-term outlook were significant factors in the analysis of this election. By 1993, race continued to be a factor, income class was a factor in the choice between nonvoting and Giuliani, and long-term outlook had become a significant factor in the multinomial logistic regression analysis behind candidate support. Therefore, the original theory seems to have been flawed, as income class did *not* play a critical role in respondents' preference between Dinkins and Giuliani. What seemed to have mattered more were the respondent's long-term outlook and race.

Given the tenor of the campaign in 1993, it follows that long-term outlook and race would be critical factors, in some ways overshadowing class. Many of the problems Dinkins faced were race-based, including his problems with key support groups. Additionally, the 1989 to 1992 recession affected people of all classes, albeit some more than others (see Chapter 2), and many in the city acknowledged that national-level economic problems were beyond the mayor's control. Therefore, it is not surprising that class did not make an appearance in the comparison between Giuliani and Dinkins. What can be conclusively stated is that support for Giuliani did not necessarily make one a pessimist. The data in Table 6.3 shows that being a pessimist did not mean that a voter could not support Dinkins. Additionally, as shown in Table 6.8, even switching support from Dinkins to Giuliani did not equate with being a pessimist. Approximately 16% of

the “switchers” were optimists about New York City’s future. Therefore, while being a pessimist did indicate a level of support for Giuliani, it was not conclusive.

The analysis presented in Chapters 3 to 6 also provided support for three out of the four alternative hypotheses presented in the introduction. The first alternative hypothesis stated that African Americans would not support Dinkins to the same degree as in 1989. This hypothesis was not supported in the pre-election survey analysis. Non-white levels of support for Dinkins increased by 1993, and this was reinforced by the exit poll data. This hypothesis can be further tested in Chapter 7 with the ecological analysis of district voting data. The second, third, and fourth alternative hypothesis all found measures of support in the analysis presented in the previous four chapters. Jews did decrease their support of Dinkins overall, even though liberals did not. There were parts of the nonwhite community who seemed responsive to Giuliani’s message; this group seemed to be primarily Hispanic. We shall see whether these alternative hypotheses can be further supported in the next chapter.

The next chapter will examine election district data in order to elucidate demographic influences within election districts. Unfortunately, there is no attitudinal data in the dataset, so the influence of long-term outlook cannot be assessed. However, the alternative hypotheses can be investigated through the election district data in order to create a more accurate “switcher” profile.

*Chapter 7 Election District Analysis*⁶⁷

The same fundamental research question guides this chapter as guides the entire dissertation: why was Giuliani narrowly elected in 1993 when he lost in 1989? This dissertation has posited that Giuliani's victory was due to race- and class-based factors affected by long-term outlook, specifically, that middle class whites would be more likely to support Giuliani due to dissatisfaction with the status quo. The analysis presented in the previous chapters found that race and long-term outlook were significant factors in the multinomial logistic regression on candidate support while income class was not. Giuliani supporters tended to be mostly white, outer borough residents who were pessimistic about New York City's future. Dinkins supporters tended to be nonwhite Manhattanites optimistic about New York City's future. The analysis presented in this chapter illustrates how each major racial group in New York City voted in both the 1989 and 1993 contests. As the dataset does not contain attitudinal questions, the analysis will not focus on long-term outlook as a causative factor. The analysis will also attempt to gauge the influence of the percent of whites in an election district, the percent of middle class and upper class residents in an election district, and where the district was located on the estimated turnout and estimated percent of candidate support by race.

Analyzing the election district data through the methods presented in this chapter allows for testing of this dissertation's original thesis regarding the influence of race and class on candidate support. This chapter will take a different approach toward answering

⁶⁷ This chapter would not have been possible without the data compiled and made available by John Mollenkopf.

the fundamental question. The chapter presents an analysis of election district and demographic data as the third leg in a triangulation approach. The first leg was the analysis of Census data and cross-sectional survey data over time to establish the context for the two elections. Chapters 2 and 3 explored the contextual reasons behind the dissatisfaction. The in-depth analysis of the cross-sectional survey data in Chapters 4 through 6 provides the second leg of the triangle. This final leg, Chapter 7, will adapt certain aspects of the model created using the cross-sectional survey data and test it with actual election district data and US Census data.

The data in this chapter can be used to ascertain if race and class had an influence on candidate support. Giuliani and Dinkins were separated by a very small margin in 1993. This dissertation theorizes that the rising dissatisfaction with New York City's present and future direction caused an increase in mobilization of mostly middle class whites and a shift in turnout towards Giuliani among middle class whites. In other words, the key to Giuliani's election in 1993 can be found in the middle class white population, who were found to be the most dissatisfied with New York City's future prospects, and life in the city generally (Figure 6.1). Additionally, three out of the four alternative hypotheses can also be tested. The first alternative hypothesis to be tested is whether the decline in African American turnout hurt Dinkins' chances at reelection; the second alternative hypothesis is that there was a substantial portion of overall nonwhite voters who switched their allegiances from Dinkins to Giuliani. The third alternative hypothesis to be tested is whether Asians and/or Hispanics were more of a factor in the 1993 election than the 1989 election through increased turnout and increased levels of voting for Giuliani. Therefore, assuming no change in the racial or class composition of New York

City between the elections (1990 Census data was used in the dataset), two specific hypotheses arise.

Hypothesis 1: More whites in middle class election districts voted in 1993 than in 1989.

Hypothesis 2: The net shift in votes from Dinkins to Giuliani occurred specifically among white (mostly middle class) voters.

To test this theory, this chapter will examine the different measures of turnout for whites and nonwhites as a whole and broken down into racial groups, as well as the different measures of voter support for Giuliani by race. A description of the data used in this analysis will be followed by a discussion of the method of ecological inference first developed by Gary King (1997). Finally, a detailed report of the results will conclude the chapter.

The Dataset

While election district analysis is not as accurate as individual-level analysis because all individual-level claims are inferred from aggregate data, this level of analysis is necessary due to the nature of the dataset. This dataset pairs election district data with

1990 Census tract and block data (Olsen 1997, 236),⁶⁸ utilizing the 1993 redistricted election districts for the entire city (5,647). Each election district contains on average 1,391 people; 1,071 are of voting age, and 532 are registered (Olsen 1997, 236). The election district is matched with a Census tract or block group in an attempt to create a fuller picture of the election district and the neighborhood that contains it (Olsen 1997, 237).

The use of this dataset allows for turnout rate calculation on a very small scale for specific groups. Turnout is calculated as the votes cast divided by citizens of voting age within the population (Olsen 1997, 238). Two transformations have occurred during the construction of the dataset; first, New York City was redistricted in 1992 so that some of the election districts from the 1989 election were changed or eliminated due to shifting boundaries. The data in the pre-1992 election districts was transformed into the current election district units. Second, data in the 1990 Census tracts units was matched with the 1993 election district units, and then split accordingly.⁶⁹ The basic population data was taken from Summary Tape File 1 at the block level and allocated to the election districts whenever possible (Olsen 1997, 247). Where election districts split Census blocks, the parts of the block population were allocated to the respective election districts according

⁶⁸ The Census data initially matched with the election district was taken from Table P37 in Summary Tape File 3 (STF 3) 1990 Census of Population and Housing. Table P37 lists the number of individuals in the tract by age (under 18 and 18 and over) and by citizenship status (native born, foreign-born naturalized, or foreign born not a citizen) (STF3 Documentation 1990, 5-18).

⁶⁹ Census tracts are much larger than election districts as each contains approximately 5,000 people. The splitting of the tracts into election districts, as well as the re-creation of election districts with the new guidelines, was conducted using a "link" or equivalency file. This file lists every block and split block in New York City and states where it is located in the old election district system and the new election district system. These were then matched with Census blocks linked to tracts (Olsen 1997, 240-246). Census blocks are the smallest geographical unit containing Census data (STF 3 documentation 1990, a-3).

to their respective shares of the registered voters in the split block portions. All other demographic data (drawn from STF3 and STF4 tract level data) was then allocated to the election districts based on this underlying population count (Olsen 1997, 248). The data from these files was split into two groups, one for blocks and one for split blocks. The data was then weighted and divided according to the total population universe for that tract (Olsen 1997, 249). This chapter will present an analysis of the percentage of support for each candidate in both election years using the same independent variables in a linear regression. These variables detail both racial and class backgrounds and will be constructed using the EZI method developed by Gary King and discussed in the next section.

The Method

Analyzing election district data based on individual-level characteristics can result in an ecological fallacy. An ecological fallacy is “an error of reasoning committed by coming to conclusions about individuals based only on data about groups “ (Vogt 1999). For example, if car thefts were higher in areas with large numbers of pet owners, you could commit an ecological fallacy if you then stated that pet owners steal cars. That both exist in the same neighborhood is true; what is potentially false is the connection. While there have been a few statistical methods that have attempted to address this problem (for example, Goodman’s ecological regression) the method that comes closest to solving this problem (the method used in this dissertation), was developed by Gary King.

The method he proposes is an ecological inference model. Usually, when one cross tabulates a question such as vote or not vote by a variable such as white versus nonwhite, one deduces only the marginal results. For example, Table 7.1 shows a cross tabulation from a mythical election precinct with potential marginals.

Table 7.1 — Mythical Precinct Outcome

	Giuliani	Dinkins
White VAP	3000	?
Nonwhite VAP	3000	?
	2500	3500

It would be tempting to assume that the “Giuliani vote” is split evenly between white and nonwhite, but this would be incorrect. It could be split along any proportion between 0 and 2500. The actual numbers of whites who voted is unknown, and statistical methods to measure this are inaccurate at best, due to aggregation bias and other statistical problems such as heteroskedasticity (King 1997). A method statisticians commonly use to try to infer the proportions is the method of bounds, and in more complicated cases, Goodman’s model, which is based on weighted least squares regression procedures and assumes constant quantities of interest across all precincts (King 1997). For example, a researcher may assume that the variance in people voting yes on a measure (from Table 7.1) is dependent on the number of whites in a district. It holds only if the probabilities of whites

voting are constant. If another factor, such as mobilization efforts or campaign slogans, influenced the variance in the number of whites voting yes, then impossible results may occur, i.e. that 300% of the whites voted yes on a proposition (King 1997).

The goal of ecological inference is “to learn about the quantities within the body of the table on the basis of the information in the margins” (King 1997, 31). King’s method adapts the method of bounds to create a statistical model of the estimate of a particular cell in a potential cross-tabulation weighted by the aggregate across districts of a particular characteristic. To do this, one creates the proportion of interest—the estimated proportion of whites that voted at all—and then weights it by the total voting age population in the district using King’s EZI program.⁷⁰

Once this is created, one then multiplies the proportion of white turnout by the white voting age population in the district, thereby creating an estimate of white voters ($\text{White turnout} \times \text{White VAP} = \text{Estimated White Voters}$). The estimate of white voters in that district is then divided by the total number of votes cast in that election district to create an estimated proportion of white voters, or a truer estimate of white turnout. King’s program also creates the opposite proportion at the same time, in this case the proportion of nonwhite voters. It is certainly possible to stop at this point; however, in order to see how whites and nonwhites voted for a particular candidate, the program was rerun using the total number of votes as a weight or N , and the proportion of votes for Dinkins (an example) as the turnout or T , then the proportion of white voters as the proportion of interest or X (King 1997). The results represented the proportions of white Dinkins voters

⁷⁰ There are ways that one can do this by hand, but Gary King developed a computer program that performs the necessary math. It is downloadable from <http://www.gking.harvard.edu>.

and nonwhite Dinkins voters by district. This set of analyses was then repeated for the other major racial groups in New York City (African American, Asian and Hispanic) and for each candidate (Dinkins and Giuliani) in an effort to provide the fullest picture possible of New York City's voting behavior during this period.

Preliminary Results

The 1989 and 1993 elections were extremely close. The mean turnout as shown in Table 7.2 varied by only one hundredth of a point, while the 1993 election between Dinkins and Giuliani was almost too close to call. In contrast, the 1989 election had a much clearer outcome.

Table 7.2 Basic Election Statistics⁷¹

1989	Mean	N	1993	Mean	N ⁷²
Total Vote 89	334.5869	5256	Total Vote 93	335.4519	5256
Turnout 89	0.32.975	5256	Turnout 93	0.33.629	5256
Percent Dinkins 89	0.517	5256	Percent Dinkins 93	0.4997	5256
Percent Giuliani 89	0.481	5256	Percent Giuliani93	0.5003	5256

⁷¹ The N of 5,256 represents all election districts in New York City for which there were turnout variables and census variables available for both election years. This accounts for some of the inflation of the 1993 turnout figures, as there was more accurate census data available.

⁷² The number of election districts used for the analysis corresponds to the number of election districts with data for both the 1989 election, the 1990 Census and the 1993 election.

The EZI method was in hopes of determining what proportion of whites and the various nonwhite groups voted for each candidate in each district. Income class was not a major contributing factor in the final cross-sectional survey model; however, its influence on turnout and candidate support will be examined here, due to its primacy in the original model.

Table 7.3 presents the mean figures for both New York City as a whole and by borough.

Table 7.3 Mean Estimated Turnout Figures by Borough and for New York City

	Whites	Blacks	Hispanics	Asians	Overall
Bronx 1989	40.07%	32.04%	17.70%	33.70%	32.27%
Brooklyn 1989	37.30%	34.70%	13.19%	31.40%	31.20%
Manhattan 1989	39.44%	35.20%	16.55%	32.70%	34.92%
Queens 1989	38.21%	36.20%	12.70%	30.63%	32.46%
Staten Island 1989	43.15%	41.10%	14.82%	36.57%	41.05%
NYC 1989	38.70%	35.10%	14.50%	32.10%	32.9%
Bronx 1993	41.13%	27.90%	15.22%	40.40%	31.40%
Brooklyn 1993	39.18%	30.16%	12.14%	37.49%	32.23%
Manhattan 1993	40.70%	29.17%	14.37%	40.19%	34.96%
Queens 1993	38.76%	30.60%	11.41%	36.42%	32.44%
Staten Island 1993	51.90%	34.62%	19.58%	44.11%	49.40%
NYC 1993	40.37%	29.98%	13.27%	38.56%	33.6%

In 1993, turnout for whites overall rose slightly; for nonwhites, turnout dropped slightly. The jump in turnout for Staten Island was caused by the presence on the ballot of a highly publicized secession initiative proposing that Staten Island secede from New York City to

form its own entity. African American turnout decreased dramatically from 1989 to 1993. This provided initial support for the alternative hypothesis that Dinkins lost the election due to declines in African American support. Additionally, Hispanic turnout dropped, except for in Staten Island, presumably because of the presence of the secession measure on the ballot. The largest increase in turnout was in the Asian population. This is a critical finding because the estimated turnout figures were created with a constant population figure taken from the 1990 Census. The increased turnout indicates an increased possible mobilization within the Asian community (see Appendix 7.1 for the complete tables including standard deviations).

Table 7.4 shows the changes in estimated turnout for each racial group and the overall estimated turnout change for each neighborhood in New York City.

Table 7.4 -- Turnout Change from 1989 to 1993 by Neighborhood

Neighborhood	White Turnout Change	Black Turnout Change	Hispanic Turnout Change	Asian Turnout Change	Overall Turnout Change
Astoria	-0.10%	-5.64%	0.40%	5.91%	-0.10%
Battery Park	3.63%	-2.63%	-7.09%	12.96%	3.51%
Bay Ridge	0.90%	-4.00%	-1.60%	5.60%	0.80%
Baychester	0.10%	-1.00%	-6.00%	6.00%	-1.50%
Bedford Styvesant	3.20%	-7.27%	-0.70%	7.40%	0.30%
Bensonhurst	1.40%	-4.20%	-1.00%	3.99%	1.31%
Boro Park	1.23%	-5.53%	3.64%	6.36%	0.70%
Canarsie	-0.08%	-4.07%	-1.75%	5.43%	-0.30%
Chinatown	1.60%	-6.99%	-4.57%	6.31%	1.14%
Coney Island	2.96%	-4.69%	-0.70%	8.50%	2.12%
Coop City	-0.50%	-1.00%	1.11%	4.97%	-4.69%
Corona	0.40%	-6.50%	1.16%	8.00%	-1.07%
Crown Heights	2.71%	-6.34%	-3.65%	6.80%	0.93%
East Harlem	1.40%	-7.67%	9.12%	13.61%	-2.72%
East Midtown	0.86%	-5.55%	-2.50%	5.48%	0.66%
East New York	2.35%	-4.22%	-1.83%	6.70%	1.43%
East Village	0.84%	-6.14%	-1.43%	5.45%	0.16%
Flatbush	2.00%	-4.68%	-3.96%	7.13%	1.17%
Flushing	1.37%	-7.00%	-0.83%	6.12%	1.32%
Forest Hills	0.35%	-5.67%	-1.68%	6.18%	0.17%
Fort Greene	1.86%	-5.84%	-0.65%	6.66%	-1.18%
Greenpoint	0.22%	-6.28%	-0.84%	6.07%	0.15%
Harlem	2.27%	-6.25%	-4.88%	10.48%	-2.61%
Howard Beach	-0.21%	-4.10%	-1.52%	5.63%	-0.16%
Inwood	-1.08%	-6.63%	-4.03%	4.27%	-1.87%
Jackson Heights	-2.00%	-4.64%	-3.42%	5.70%	-1.03%
Lubavitchers	3.90%	-4.12%	-0.98%	7.35%	3.70%
Middle Village	0.90%	-5.51%	-0.13%	5.61%	0.47%
Mott Haven	2.66%	-6.67%	6.40%	6.11%	0.37%
North Shore	3.90%	-3.39%	0.62%	8.25%	3.02%
Park Slope	1.42%	-2.77%	0.35%	5.26%	0.67%
Pelham Bay	1.16%	-4.11%	-2.29%	6.44%	-0.80%
Queens Village	0.66%	-6.75%	-3.13%	4.90%	0.13%
Riverdale	-0.18%	-0.90%	-2.30%	6.27%	-0.85%
Rockaways	0.10%	-5.00%	-0.78%	4.90%	-0.39%

Satmar	16.18%	-2.14%	10.56%	5.40%	16.43%
Sheepshead Bay	0.79%	-3.52%	-0.70%	6.21%	0.61%
SouthEast Queens	2.19%	-5.50%	-1.50%	6.19%	-0.90%
Staten Island	9.55%	-6.93%	5.34%	7.40%	9.10%
Styvesant Town	-0.15%	-7.30%	5.40%	8.71%	-1.68%
Sunset Park	0.14%	-3.35%	-1.08%	5.67%	-0.68%
Tremont	0.99%	-5.94%	-4.72%	7.84%	-0.80%
Upper East Side	2.41%	-6.17%	-1.00%	6.08%	2.21%
Upper West Side	2.03%	-6.25%	-2.68%	8.84%	1.20%
Washington Heights	-1.33%	-4.90%	-7.84%	5.32%	-2.70%
West Midtown	1.05%	-5.16%	-5.34%	7.13%	0.81%
West Village	0.41%	-5.48%	1.15%	4.87%	0.12%
Windsor	3.77%	-3.90%	-1.00%	5.58%	3.81%

As shown in the breakdown by borough, African American estimated turnout dropped across the neighborhoods, while Asian estimated turnout uniformly increased. However, there was some variation within the white and Hispanic communities. The two largest increases in white turnout were on Staten Island (presumably due to the secession ballot measure) and in the Satmar community in Brooklyn. The Satmar are a sect of ultra-orthodox Jews who were courted heavily by Giuliani during the 1993 campaign (Tabor 1993). The increase in Satmar turnout may be related to the increase in estimated Hispanic turnout for that neighborhood, suggesting a neighborhood effect. Hispanics living in the Satmar neighborhood had the second largest Hispanic turnout change, while Sheepshead Bay had the largest. Traditionally Hispanic neighborhoods, such as East Harlem, had mixed turnout levels, as did traditionally white communities. This may be due more to the individual characteristics of the community or to individual voters rather than to any “neighborhood effect.”

The next step was to estimate the numbers of white and nonwhite voters based on the turnout estimates multiplied by the total voting age population for that racial group. The proportion of voters from the total voting age population is the traditional measure of turnout, although it does not consider citizenship status. This was a factor in some election districts, due to a high proportion of immigrants in those districts. The final step was to use EZI to estimate the proportion of white, African American, Hispanic and Asian voters who voted for the two major candidates in each election. The white group and each group in the nonwhite voting age population multiplied by the turnout estimates by race created new estimates of the numbers of actual voters. These estimates of the amount of actual voters by race in each district were then divided by the total turnout from each election year to create an estimated proportion of actual voters by race from that election.

The results in Tables 7.4 and 7.5 were created using the final estimated proportion of white and all nonwhite voter groups into EZI with the total percentage of the vote for each candidate, and then weighted by total number of votes. Table 7.4 shows the mean percentage of vote for each candidate by borough and for the city as a whole in 1989.

Table 7.4 EZI Estimated Votes by Race and Borough in 1989

	Giuliani 1989		Dinkins 1989	
	Whites	Nonwhites	Whites	Nonwhites
Bronx	0.77	0.14	0.22	0.85
Brooklyn	0.72	0.13	0.26	0.87
Manhattan	0.58	0.13	0.42	0.87
Queens	0.80	0.20	0.20	0.79
SI	0.87	0.15	0.13	0.84
NYC	0.73	0.15	0.26	0.84

Table 7.5 Breakdown of Nonwhite Estimated Votes

	Giuliani 1989			Dinkins 1989		
	Afr. Amer.	Asian	Hispanic	Afr. Amer.	Asian	Hispanic
Bronx	0.05	0.47	0.11	0.72	0.39	0.83
Brooklyn	0.05	0.46	0.11	0.78	0.38	0.84
Manhattan	0.05	0.49	0.11	0.76	0.38	0.82
Queens	0.06	0.49	0.11	0.75	0.37	0.85
SI	0.04	0.53	0.11	0.84	0.39	0.84
NYC	0.05	0.48	0.11	0.76	0.38	0.84

Tables 7.4 and 7.5 detail second-stage estimates generated from the first stage EZI estimates of turnout by race (Table 7.3). Each estimate was created as a proportion of the racial group of interest, for example, Asians, with a reference group, Non-Asians, created at the same time. Only the particular racial estimates are shown here (for a fuller depiction of the estimates of racial group behavior please see Appendix 7.1). The results show the racial divide that characterized the elections between Dinkins and Giuliani. The only borough where Dinkins won a large percentage of the white vote was Manhattan, where he had previously served as Borough president. When the estimated nonwhite voters are broken out, the estimated African American votes for Dinkins are lower than expected. The pressure within the African American community to elect one of their own during this period was high. The high estimated levels of support for Dinkins among Hispanics also bear watching as they are the only estimate of support that increase between 1989 and 1993.

It was expected that these estimates would change somewhat in 1993. The 1993 election was even more racially polarized than the 1989 election; Dinkins had failed in

his promise to act as a racial reconciliator (Thompson 1996; McNickle 1993). Therefore, a widespread shift in the estimated proportion of whites voting for Dinkins to Giuliani was expected. Alternative hypothesis two states that overall nonwhite voters switched their allegiance from Dinkins to Giuliani. Table 7.5 shows a two point drop overall from 1989 contributing to support for this alternative hypothesis. Additionally, the drop appears to be highest in the African American estimated support for Giuliani.

Table 7.6 EZI Estimated Votes for Candidate by Race and Borough in 1993

	Giuliani 1993		Dinkins 1993	
	Whites	Nonwhites	Whites	Nonwhites
Bronx	0.77	0.16	0.22	0.84
Brooklyn	0.74	0.17	0.25	0.83
Manhattan	0.59	0.15	0.41	0.85
Queens	0.82	0.24	0.17	0.76
SI	0.91	0.22	0.09	0.79
NYC	0.74	0.18	0.25	0.82

Table 7.7 Breakdown of Estimated Nonwhite Support for the Candidates

	Giuliani 1993			Dinkins 1993		
	Afr. Amer.	Asian	Hispanic	Afr. Amer.	Asian	Hispanic
Bronx	0.06	0.55	0.14	0.7	0.31	0.86
Brooklyn	0.06	0.54	0.15	0.77	0.3	0.85
Manhattan	0.07	0.57	0.14	0.75	0.29	0.86
Queens	0.07	0.58	0.16	0.74	0.3	0.86
SI	0.05	0.63	0.15	0.82	0.32	0.84
NYC	0.06	0.56	0.15	0.75	0.3	0.86

Surprisingly, such a widespread shift did not occur; the estimated proportions remained very close to the 1989 estimates, except for the slight decline in Dinkins' estimated support and increase in Giuliani's estimated support. This shift amounted to fewer than 100,000 votes, so the small percentage changes are not surprising. The higher percentage of white voters for Giuliani in Staten Island was due primarily to the secession vote and the mutual support between those politicians who supported the secession measure and Giuliani than to any increased desire to vote for or support a particular candidate.

The primary hypothesis for this dissertation stated that middle class whites would increase support for Giuliani such that he would win the election. According to this hypothesis, increased votes for Giuliani can be the result of two things: increased turnout among whites (who were overwhelmingly predisposed to support Giuliani) or switchers from the middle class white community who moved their support from Dinkins to Giuliani. As table 7.4 states, turnout among whites was relatively stable, a small increase in Staten Island and in the ultra-Orthodox Jewish community. Both of these communities

had strong amounts of support for Giuliani in 1989. Therefore, perhaps Giuliani's victory was more a move away from Dinkins than a move towards Giuliani.

Table 7.8 displays the percent change in estimated support for Dinkins broken down by neighborhood.

Table 7.8 -- Change in EZI Estimated Support for Dinkins by Neighborhood

Neighborhood	White Dinkins Change	Black Dinkins Change	Hispanic Dinkins Change	Asian Dinkins Change	Overall Dinkins Change
Astoria	-1.00%	-0.01%	1.60%	-7.80%	-1.50%
Battery Park	1.39%	-0.43%	-10.20%	-7.10%	0.65%
Bay Ridge	-2.08%	-3.00%	2.97%	-7.64%	-2.67%
Baychester	5.40%	-2.22%	1.24%	-9.10%	2.40%
Bedford Styvesant	-6.70%	-1.22%	2.20%	-8.64%	2.24%
Bensonhurst	-2.38%	-0.14%	1.15%	-7.07%	-3.02%
Boro Park	2.87%	-0.90%	-0.70%	-7.08%	0.25%
Canarsie	0.36%	-1.55%	2.65%	-7.17%	-0.33%
Chinatown	-3.02%	-0.75%	-0.98%	-6.87%	-8.19%
Coney Island	-1.38%	0.48%	4.92%	-8.82%	-2.88%
Coop City	8.63%	-0.67%	0.98%	-11.29%	2.88%
Corona	-6.05%	-5.49%	2.35%	-7.30%	-1.81%
Crown Heights	1.65%	-1.17%	1.60%	-6.74%	0.02%
East Harlem	-2.50%	-3.12%	4.89%	-8.44%	-0.02%
East Midtown	1.12%	-1.23%	6.72%	-9.35%	0.69%
East New York	-1.06%	-0.70%	1.62%	-7.96%	0.43%
East Village	-3.06%	-2.74%	1.07%	-9.56%	-2.57%
Flatbush	-3.07%	-2.74%	1.07%	-9.55%	3.66%
Flushing	-1.33%	-0.65%	1.43%	-7.72%	-3.13%
Forest Hills	-2.02%	-2.22%	0.70%	-7.98%	-3.10%
Fort Greene	-0.33%	-0.88%	0.26%	-8.62%	-0.46%
Greenpoint	-1.57%	-1.89%	-2.26%	-9.83%	-3.09%
Harlem	2.09%	-1.26%	3.45%	-7.77%	0.10%
Howard Beach	-0.56%	-0.66%	0.84%	-7.12%	0.14%
Inwood	1.23%	-2.73%	3.94%	-8.66%	-1.03%
Jackson Heights	0.64%	-0.83%	3.40%	-8.06%	-1.72%

Lubavitchers	-27.11%	-0.70%	4.02%	-7.59%	-13.81%
Middle Village	-0.75%	-0.12%	1.95%	-7.82%	-2.69%
Mott Haven	-1.70%	-0.57%	5.48%	-7.44%	-1.17%
North Shore	-3.10%	-1.24%	0.46%	-8.48%	-1.99%
Park Slope	0.66%	-1.19%	0.13%	7.59%	-0.42%
Pelham Bay	-0.01%	-1.54%	3.19%	8.78%	-0.82%
Queens Village	-1.29%	-1.56%	1.68%	-8.64%	-2.45%
Riverdale	-2.56%	-2.01%	1.62%	-9.84%	-3.58%
Rockaways	3.90%	-0.87%	0.60%	-7.25%	0.09%
Satmar	-28.57%	-0.57%	-2.63%	-6.43%	-28.56%
Sheepshead Bay	-6.50%	-0.60%	0.56%	-7.83%	-7.05%
SouthEast Queens	-8.40%	-1.53%	1.46%	-6.67%	0.84%
Staten Island	-3.60%	-1.54%	-0.01%	-7.43%	-3.99%
Styvesant Town	1.62%	-0.90%	0.62%	-9.70%	0.73%
Sunset Park	0.09%	0.38%	2.15%	-7.25%	-5.97%
Tremont	-0.97%	-1.72%	3.82%	-7.70%	-1.25%
Upper East Side	-0.55%	-2.22%	4.65%	-9.18%	-0.76%
Upper West Side	-2.05%	-1.99%	4.38%	-7.63%	-2.29%
Washington Heights	1.45%	-0.19%	4.36%	-7.34%	0.95%
West Midtown	-1.08%	-1.64%	0.98%	-9.43%	-1.18%
West Village	-3.29%	-0.45%	1.87%	-10.27%	-3.31%
Windsor	-1.25%	0.57%	-1.75%	-5.74%	-6.96%

The areas with the largest changes in the white community were those that were primarily identified as Jewish, specifically ultra-Orthodox. This is not surprising given the hostility toward Dinkins after Crown Heights combined with Giuliani's active courting of the community (Tabor 1993; Thompson 1996; McNickle 1993). However, there were two other troubling trends for Dinkins (both of which were hinted at in Table 7.6). One was that in mixed neighborhoods such as Sheepshead Bay, Corona, and Riverdale, support for Dinkins dropped by two to three percentage points. This may be indicative of more widespread dissatisfaction with Dinkins' tenure than previously believed. These neighborhoods contain about 40 percent middle class households and a

variety of ethnic groups, indicating a possible growth in middle class dissatisfaction with Dinkins. The other trend was that Dinkins lost support in traditionally liberal neighborhoods such as the West Village and the Upper West Side. Both of these neighborhoods provided heavy white liberal support in 1989; in 1993, however, Dinkins lost over 2 percentage points in each neighborhood, indicating a possible liberal defection.

Interestingly, Dinkins' levels of estimated voters did increase among Hispanics with some heavily Hispanic neighborhoods increasing estimated votes by over 4 percentage points. This contradicts the model created in Chapters 4 to 6 from the pre-election surveys. The pre-election survey model stated that Hispanic ethnicity was a prime feature of voters who switched their support from Dinkins to Giuliani. Hypothesis two of this chapter states that the net shift in votes occurred specifically among white voters. Therefore, one should expect that white estimated votes for Dinkins would decrease uniformly, while white support for Giuliani would increase in the same fashion.

As table 7.8 shows, this was not the case. Support for Dinkins did not decrease in all neighborhoods among estimated white voters. Concurrently, support for Giuliani did not increase uniformly in all neighborhoods among estimated white voters. Data on several mixed neighborhoods showed white support for Giuliani down by one to two percentage points while support for Giuliani did increase among nonwhites.⁷³ This finding occurred particularly in middle class neighborhoods such as Park Slope, the Upper West Side, Stuyvesant Town, and Forest Hills.

⁷³ A mixed neighborhood is one where a single ethnic group does not have over 70% of the population.

Within the nonwhite community, Asian voters showed the largest increases in overall estimated turnout and votes for Giuliani. There were no decreases in estimated votes for Giuliani among Asians and, interestingly, Hispanics. The Hispanic finding is unusual because among Hispanics, support for both Dinkins and Giuliani increased in some neighborhoods. This indicates variations within the election districts in regards to candidate choice. More importantly, this finding indicates the variations inherent in the EZI method. EZI creates the best possible estimate for each election district given the percentages of interest. When these election-district estimates are aggregated to the neighborhood level, it becomes possible to have both an increase in support for both candidates and a decrease in turnout. This is because within the aggregation, it is impossible to know which district has the increase in candidate support and which has turnout decreases. It may be that one district has an increase in support for Dinkins with a turnout decrease while the other has an increase in support for Giuliani with a turnout increase. Therefore, the findings presented here should be seen as estimates of possible candidate support breakdowns by race, rather than as the true racial breakdowns of the vote.

The areas with the smallest increases in estimated support for Giuliani among Hispanics were in heavily Hispanic/African American neighborhoods such as East Harlem. For African Americans, there were some increases in estimated votes for Giuliani but they were very small. The overall increases in support for Giuliani in communities of color provide support for Hypothesis 3.

Table 7.9 Change in EZI Estimates for Giuliani Support by Neighborhood

Neighborhood	White Giuliani Change	Black Giuliani Change	Hispanic Giuliani Change	Asian Giuliani Change	Overall Giuliani Change
Astoria	0.90%	2.54%	4.00%	6.50%	1.90%
Battery Park	-0.76%	0.28%	3.10%	2.70%	-0.05%
Bay Ridge	2.07%	1.28%	2.62%	8.70%	2.80%
Baychester	-5.60%	0.50%	3.70%	8.10%	-2.30%
Bedford Styvesant	7.30%	-0.50%	2.70%	8.90%	-0.19%
Bensonhurst	2.37%	1.27%	3.92%	9.86%	3.10%
Boro Park	-2.45%	-0.04%	4.60%	8.37%	0.04%
Canarsie	-0.40%	0.51%	3.17%	9.60%	0.35%
Chinatown	3.00%	2.49%	3.70%	9.40%	8.56%
Coney Island	1.92%	6.47%	7.22%	9.33%	3.27%
Coop City	-8.42%	0.05%	4.30%	8.91%	-2.62%
Corona	4.27%	1.46%	1.75%	7.29%	1.81%
Crown Heights	-1.01%	0.34%	1.32%	5.80%	0.06%
East Harlem	1.11%	1.67%	0.20%	6.60%	2.00%
East Midtown	-0.88%	2.32%	3.89%	8.81%	-0.30%
East New York	0.63%	0.82%	2.92%	6.91%	-0.38%
East Village	4.03%	1.65%	2.57%	5.93%	3.31%
Flatbush	-8.17%	-2.28%	3.29%	6.36%	-3.57%
Flushing	1.09%	1.98%	4.48%	8.38%	3.22%
Forest Hills	1.90%	1.27%	4.56%	9.94%	3.27%
Fort Greene	-0.13%	0.58%	3.93%	5.33%	0.58%
Greenpoint	1.31%	1.21%	6.09%	9.53%	3.14%
Harlem	-0.05%	0.46%	0.98%	5.24%	0.03%
Howard Beach	0.25%	1.30%	1.91%	9.40%	-0.11%
Inwood	-1.14%	1.38%	6.56%	8.71%	1.37%
Jackson Heights	-1.00%	4.70%	8.67%	5.52%	1.90%
Lubavitchers	25.46%	2.15%	-1.78%	4.81%	13.86%
Middle Village	0.56%	1.51%	5.18%	7.98%	2.76%
Mott Haven	0.73%	1.30%	2.37%	5.66%	1.56%
North Shore	2.81%	1.74%	3.58%	8.46%	2.06%
Park Slope	0.03%	1.38%	4.08%	7.39%	0.98%
Pelham Bay	-0.16%	1.14%	3.71%	8.60%	1.00%
Queens Village	1.16%	0.87%	4.19%	8.66%	2.49%
Riverdale	2.48%	1.98%	5.03%	10.50%	3.80%
Rockaways	-3.60%	3.80%	5.66%	11.21%	-0.04%

Satmar	28.62%	1.25%	12.13%	7.48%	28.78%
Sheepshead Bay	6.55%	1.55%	3.97%	10.14%	7.27%
SouthEast Queens	8.32%	-1.18%	4.12%	13.08%	-0.79%
Staten Island	3.50%	1.04%	3.54%	10.09%	4.00%
Styvesant Town	-1.37%	1.93%	4.02%	10.80%	-0.32%
Sunset Park	-0.35%	1.52%	3.38%	7.00%	6.02%
Tremont	0.84%	1.15%	2.22%	7.49%	1.37%
Upper East Side	0.87%	1.15%	3.85%	8.89%	1.10%
Upper West Side	2.72%	1.41%	4.40%	8.04%	2.88%
Washington Heights	-1.93%	1.74%	3.98%	8.46%	-0.77%
West Midtown	1.73%	1.39%	4.25%	8.83%	1.74%
West Village	3.87%	1.37%	3.90%	7.76%	3.91%
Windsor	1.14%	2.63%	5.39%	9.19%	4.78%

Overall, the model taken from the pre-election survey model matched what was found in the examination of election district data. Whites preferred Giuliani while nonwhites preferred Dinkins. However, when nonwhite support was broken out into its composite groups—African American, Asian and Hispanic—a new story began to emerge. African Americans still preferred Dinkins, while Asians and Hispanics began to prefer Giuliani. In 1993 there was an increase in estimated votes for Giuliani among Asians and Hispanics, providing support for Alternative Hypothesis Three, which states that support among Asians and Hispanics was a deciding factor in the 1993 election. The next two sections are an exploration of the possible different reasons behind the estimated results. Using the percentage of white residents, the percentage of middle class and upper class households of an election district, and the location of the election district within the five boroughs as independent variables, the regression analysis which follows is an attempt to discover what features from my original hypothesis accounted for these differences in turnout and support.

It would be possible to stop here and simply say that the reason why Giuliani won was the difference in the voting patterns; however, the more interesting question is, why did the changes occur? The EZI-generated estimates from each election can serve as variables in subsequent analyses (King 1997). By placing the estimated turnout rates by race, the estimated votes for each candidate by race in each year, along with the differences in votes and turnout by race as dependent variables in a regression, it is possible to test for racial, class and turnout/mobilization causes behind candidate preference. Were more whites prompted to vote in one election or another? From Tables 7.6 and 7.7, it seems that that was indeed the case, as the estimated proportion of whites voting for Giuliani rose. Alternatively, was there a neighborhood effect, as Carsey predicted? Areas with large numbers of nonwhite residents might force the remaining white residents to “circle the wagons”, support a white candidate, and vote more heavily for Giuliani (Carsey 1995). Additionally, this analysis will allow testing for the influence of class on candidate choice so that it can be definitively excluded.

Mobilization Model

Mobilization of voters or a “get out the vote” strategy is one method of trying to ensure victory for a particular candidate, the theory being that once voters are motivated to come to the polls, it then becomes easier to sway them towards a particular candidate. The regression models shown in table 7.10 are an analysis of what was behind turnout for a particular group of voters. The independent variables for the model are taken from the original theory on race and class and their influence on voters.

Table 7.10 Regression Models for Race-Based EZI Estimated Turnout

	White Turnout 1989	White Turnout 1993	White Turnout Change	Afr. Amer. Turnout 1989	Afr. Amer. Turnout 1993	Afr. Amer. Turnout Change
% White	-0.0313*	-0.044*	-0.0128*	-0.031*	-0.0163*	0.0147*
% MC	-0.0387*	-0.0742*	-0.0355*	-0.0436*	-0.0159	0.0277*
% UC	0.1737*	0.228*	0.0542*	0.0142	0.011	-0.013
Bronx Dummy	0.0263*	0.0176*	-0.0086*	-0.033*	-0.0255*	0.0074*
Manhattan Dummy	0.0055	-0.0043	-0.0098*	0.0056	-0.0087	-0.0143*
Queens Dummy	-0.0047	-0.0195*	-0.0148*	0.0184*	0.0066	-0.0118*
SI Dummy	0.0247*	0.0853*	0.0606*	0.072*	0.0507*	-0.0213*
Constant	0.3758911	0.4046228	0.0287317	0.3758327	0.3147877	-0.061045
Adj. R2	0.076	0.1352	0.0964	0.0253	0.0147	0.0155
N	5256	5256	5256	5256	5256	5256

	Asian Turnout 1989	Asian Turnout 1993	Asian Turnout Change	Hispanic Turnout 1989	Hispanic Turnout 1993	Hispanic Turnout Change
% White	-0.018*	-0.0346*	-0.0166*	-0.0149*	0.0078*	0.0226*
% MC	0.0051	-0.0003	-0.00533*	-0.0301*	-0.1468*	-0.117*
% UC	-0.0054	-0.0084	-0.00294*	0.0418*	0.0511*	0.0104
Bronx Dummy	0.0201*	0.0235*	0.0033*	0.0433*	0.0312*	-0.0117*
Manhattan Dummy	0.0155*	0.0315*	0.016*	0.0302*	0.0141*	-0.0161*
Queens Dummy	-0.0061	-0.0068	-0.00072	-0.00571	-0.0037	0.0021
SI Dummy	0.0598*	0.0817*	0.0219*	0.0115*	0.06*	0.0486*
Constant	0.3211972	0.3918145	0.0706174	0.1434646	0.1645652	0.0207869
Adj. R2	0.0221	0.0296	0.0275	0.0576	0.1027	0.0314
N	5256	5256	5256	5256	5256	5256

*Indicates Significance at .05. Brooklyn, Percent Nonwhite, and Percent Low Income Class are Reference Categories

The percentage white of an election district was the single variable that was significant across all the models. However, its impact was not unidirectional. For whites, African Americans and Asians, an increase in the percentage white of an election district had a negative impact, while for Hispanics, it increased turnout. In 1989, borough of residence was an indeterminate factor in white turnout as both the dummies for Queens and Manhattan were insignificant. Both Queens and Manhattan have areas of upper-income

residents where, given the significance and direction of upper income class on the dependent variable, one would expect a stronger showing of the borough-level dummies. By 1993, however, borough of residence had a significant impact, both positive and negative. Living in the Bronx or Staten Island encouraged turnout as compared with Brooklyn, while living in Manhattan or Queens depressed turnout as compared with Brooklyn. Additionally, the percentage white of the voting age population (VAP) in a district had a negative impact on turnout, as did the percentage of middle class households. This is the opposite of what had been expected, that the percentage of white VAP in a district would have a positive impact on turnout, as whites tend to vote at higher rates.

For communities of color, the model was not as strong as it was for whites with generally low R-squared values. As R-squared represents the percent of the variance in the dependent variable explained by the model, the low values indicate other factors not included in the model that must account for the changes in estimated turnout. The percent middle class of an election district had a mixed effect on the model. For most dependent variables, when the variable was significant, it had a negative effect. However, for African Americans' change in estimated turnout it had a positive effect. This may indicate an increased tendency towards turnout in mixed middle class neighborhoods as examined in Table 7.4. Yet, these results seem inconclusive, as the amount of variance explained by the models is low.

Shift in Support?

A shift in support from one candidate to another is a typical factor in a candidate's victory. When the difference in votes from one election to another is so small, as in the mayoral elections of 1989 and 1993, examining the reasons behind the shift is critical to making sense of the change. Was the change the result of a defection from one candidate to another based on racial factors, income factors or other factors? Table 7.9 presents the regression coefficients from twelve different regressions with the dependent variables representing the estimated amount of support Giuliani received in both elections by race, and the change from 1989 to 1993 by race.

Table 7.11 OLS Regression Coefficients from Estimated Support for Giuliani Models by Race and Year

	White Giuliani 1989	White Giuliani 1993	White Giuliani Change	Afr. Amer. Giuliani 1989	Afr. Amer. Giuliani 1993	Afr. Amer. Giuliani Change
% White	0.2694*	0.2863*	0.01693*	-0.0029	0.0201*	0.02298*
% MC	-0.0868*	-0.19*	-0.0821*	0.0555*	0.0039	-0.0515*
% UC	-0.2467*	-0.2702*	-0.0235	0.003	-0.0524*	-0.05548*
Bronx Dummy	0.0904*	0.0743*	-0.0161*	0.0003	0.005255	0.0049*
Manhattan Dummy	-0.1497*	-0.152*	-0.0023	0.0017	0.0103*	0.0086*
Queens Dummy	0.0923*	0.1039*	0.0116*	0.0029	0.0181*	0.01513*
SI Dummy	0.1138*	0.1343*	0.0204*	-0.0076*	0.0021	0.0097*
Constant	0.6700504	0.7109467	0.0408964	0.0313249	0.0565907	0.0252658
Adj. R2	0.2724	0.3127	0.0064	0.0116	0.0135	0.0144
N	5256	5256	5256	5256	5256	5256

	Asian Giuliani 1989	Asian Giuliani 1993	Asian Giuliani Change	Hispanic Giuliani 1989	Hispanic Giuliani 1993	Hispanic Giuliani Change
% White	0.1068*	0.119*	0.01224*	0.0106*	0.196*	0.0089*
% MC	0.333*	0.347*	0.0139	-0.0053	-0.0122	-0.0068
% UC	-0.060*2	-0.0243	0.0359*	-0.006	0.01584*	0.0228*
Bronx Dummy	0.0398*	0.0445*	0.0047	-0.0011	-0.0031	-0.00171
Manhattan Dummy	0.0315*	0.0257*	-0.0058	-0.004	-0.0092*	-0.005
Queens Dummy	0.007	0.01366	0.0067	0.0443	0.0125*	0.0078*
SI Dummy	0.049*	0.0536*	0.0046	0.0012	-0.0091*	-0.0103
Constant	0.2928572	0.3567173	0.0638601	0.1087325	0.140678	0.0315048
Adj. R2	0.0683	0.0666	0.0114	0.0041	0.0276	0.0062
N	5256	5256	5256	5256	5256	5256

* Indicates Significance at .05. Brooklyn, Percent Nonwhite, and Percent Low Income are Reference Categories

Perhaps the biggest difference between the regression models for candidate choice and turnout is the significant impact of the percentage white voting age population on supporting Giuliani for a particular election district. It is the strongest determinant of support for whites in both 1993 and 1989, as well as the strongest determinant of selecting Giuliani among nonwhites in 1993. It seems that the percentage of white VAP

in a district made a positive difference in selecting Giuliani in contrast to its impact on turnout. This provides an interesting contextual or neighborhood effect because as the percentage of white VAP in a district increases, so does the percentage of votes for Giuliani. This was expected among white voters, but not among nonwhite voters.

As with turnout, the percentage middle class of an election district has a deterring effect on whites and Hispanics supporting Giuliani. In fact, when examining factors surrounding the change in votes from 1989 to 1993, an increase in a percentage middle class has a deterrent effect on the model with a beta of $-.8121$ for whites and $-.0068$ for nonwhites. This means that in districts where the percentage of middle class households are high, the level of support for Giuliani among whites and Hispanics *decreased* rather than increased, as had been expected. For Asians, however, the reverse was true. An increase in the percentage of an election district that was middle class meant an increase in Giuliani support. For African Americans, the percent middle class of an election district had an inconsistent effect on the models. This pattern of decreasing impact on a model for percent middle class of an election district speaks to Giuliani's efforts to enlist support for cuts in city government. From his loss in 1989, Giuliani advocated large cuts in city services as a way to balance the budget. This put him in direct conflict with communities of color, and in particular African Americans. Many African Americans entered the middle class through the civil service. When Giuliani threatened those jobs, it makes sense that the percent middle class of an election district would have a declining impact on support for Giuliani.

Borough of residence was also a significant factor in support for Giuliani in some of the regression models, with the pattern corresponding to the model in Chapters 4

through 6. In the cross sectional survey model, those who lived in the outer boroughs of New York City were more likely to support Giuliani, while those who lived in Manhattan were more likely to support Dinkins. This has held true throughout the analysis presented in this chapter. As a whole, there was only one regression equation where all the dummy variables for borough of residence had a significant effect, the model of change in estimated African American support for Giuliani. However, the total variance explained by the model was so small as to render the equation virtually unimportant.

Conclusion

The results of this analysis have shown that both original hypotheses were incorrect. Not only did turnout among middle class whites not increase, but the percentage of middle class whites who supported Giuliani decreased. This remained true even as the overall percentage of whites that supported Giuliani remained stable. Although this analysis has focused on finding the reasons behind a small number of absolute votes changing direction from one candidate to another, it cannot be overemphasized that the results of this election changed the face of New York City politics and policies. One may generalize by observing that New York City metamorphosed from a bastion of liberalism to a conservative, quasi-suburban place to live and work due to this small percentage shift. That this transformation apparently came about due to a shift in nonwhite voter support was unforeseen in the previous analysis.

The EZI estimates presented support the alternative hypotheses more than the original theory. Alternative hypothesis 1 stated that African American turnout dropped

and that this would impact support for Dinkins in that community. As shown in tables 7.3, 7.5 and 7.6, estimated turnout among African Americans did drop, as did support for Dinkins. The second alternative hypothesis posited that the majority of the switchers to Giuliani would be nonwhite. This chapter's analysis appears to support this hypothesis. White support for Giuliani remained stable from 1989 to 1993, while Asian and Hispanic support for Giuliani grew. This finding also gives support to alternative hypothesis 3, which stated that Asians and Hispanics would be the prime movers to Giuliani's camp.

The lack of support for the original hypothesis was not completely unexpected given the finding in Chapters 4 and 5 that income class was not a factor, and that Hispanics in the pre-election survey supported Giuliani over Dinkins. Yet, the degree to which Asians, and to some degree Hispanics, moved towards supporting Giuliani indicates that looking at New York City politics simply in terms of black and white is over. The emergence of Asians and Hispanics as possible swing voters in tight elections signals the emergence of New York City as a multicultural, multiethnic political entity.

Chapter 8 Concluding Thoughts About the Research Question

Although this analysis has focused on finding the reasons behind a small number of absolute votes changing direction from one candidate to another, it cannot be overemphasized that the outcome of this election changed the face of New York City politics and policies. One may generalize by observing that New York City metamorphosed from a bastion of liberalism to a conservative, quasi-suburban place to live and work due to this small percentage shift. That this transformation apparently came about due to a shift in nonwhite voter support was unforeseen.

The original model for this dissertation was that middle class whites were the reason behind Giuliani's victory in 1993, due to the dramatic shifts in their economic fortunes, paralleling unsteady middle class fortunes on the national level (Newman 1993; Ehrenreich 1990; Greenberg 1995; Tolchin 1994; Hochschild 1995; Bartlett and Steele 1996). National level middle class pessimism or anxiety was translated into a long-term pessimistic outlook about New York City's future. This pessimism's impact on the 1993 election was tempered by dramatic economic shifts. Giuliani's ability to address this pervasive middle class dissatisfaction and other broader quality of life issues theoretically would have mobilized larger numbers of middle class white voters, thereby winning the election. However, a problem arose when assessing statistical reasons behind small shifts (a net difference of 97,000 votes.) Often, the reason a researcher originally suspects to find behind the small shifts turns out to be false. In fact, the national phenomenon of middle class white dissatisfaction did not translate to the local level. Throughout this

dissertation, three different datasets were used to determine the impact of middle class whites and their dissatisfaction on the 1993 election. Although the analyses did not confirm the original hypothesis, they did provide valuable new information about life in New York City during this period.

Chapter 2 explored the economics behind the middle class pessimism discussed in Chapters 4 through 6. The economic fortunes of the middle class changed only slightly between the elections (1989 to 1993); therefore, an economic basis for the pessimism permeating the city could not be established. This is an important and surprising finding independent of the main focus of this dissertation. The recession in New York City began later than in the rest of the nation and lasted longer. Much of the analysis of the recessionary impacts has focused on the middle class and their subsequent hardships. Failing to find a severe drop in income or earnings among the middle class buttresses Angelo's and others' theory that the recessionary effect on New York City may not have been as severe as first imagined.

The cross-sectional survey data in Chapters 4 through 6 was used to arrive at a model that would hold when used with the actual voting returns, which would affirm the original thesis that race and class filtered by long-term outlook were behind candidate support. Race was a factor in pessimistic behavior and candidate selection, while income class was not a factor in pessimistic behavior in 1993 or in candidate selection in either election year. This analysis yielded important albeit unforeseen results. The first result was the numerical evidence behind the impact of liberal and Jewish voters in the 1989 election of David Dinkins. In Chapter 4, being liberal and being Jewish were found to be the two most important factors besides being nonwhite behind supporting David Dinkins.

These two factors later diminished in importance; the significance of being Jewish disappeared altogether in the 1993 equation, pointing to a possible demoralization and definitive demobilization of support among one of Dinkins' key support groups, Jewish liberals. However, the lack of critical associations with the Jewish variable did not signify a change towards supporting Giuliani; rather it may have started a trend towards nonvoting among members of the Jewish community in New York City. This is a facet of the elections that will be explored in a later work.

While the final resultant model seemed to agree with the exit poll data (see Chapter 6), when the actual votes in each election district were estimated for each candidate and each ethnic group, Asians, and not whites, as previously hypothesized, showed the largest overall mean change. Estimated white votes for Giuliani fluctuated between 1989 and 1993. Some election districts showed a positive change, while some changed in a negative direction. In contrast, the estimated Asian votes for Giuliani uniformly increased from 1989 to 1993. The uneven nature of the estimated white vote over time contradicts the overwhelmingly positive model for the probability of white votes for Giuliani presented in Chapters 4 to 6. It also points to the possibility that Asians and not whites were the "essential force" behind Giuliani's victory. In addition, when broken down by neighborhood, the strongly Jewish neighborhoods had some of the largest shifts in estimated support for Giuliani, which was contraindicated in the pre-election survey model. The analysis presented in the final chapter points towards major shifts in the New York City political scene. Not only were voting patterns becoming less "black versus white," but traditional support groups for each candidate were shifting slowly into new, unexplored territory.

So, was the entire thesis wrong? The intersection of race and class was not as important to either long-term pessimism or candidate support, although race alone still played a role in both elections, as posited in the original theory. The main difference between the end result and the original theory was the inability of class based factors to explain the 1993 election; the analysis of Census data did not show an economic reason behind middle class dissatisfaction with New York City. It was predicted that the shrinking middle class in New York City would have shrunk during this period, and that this would have placed increased pressure on those who remained to hold onto what they had, hence the title, “circling the wagons.” That this did not occur was the first indication that reliance on class was misplaced. Between 1987 and 1996, there was a slight gain in both personal and household income in the middle class, as well as a relatively *stable* proportion of total middle class households. These two factors contradict what this dissertation had predicted, based on national-level scholarship. The national-level scholarship predicted that the middle class would shrink in size during this period due to the recession (Barlett and Steele 1996; Duncan, Smeedling and Rodgers 1997).

The second indication came from the cross-sectional survey model presented in Chapters 4 through 6. While Chapter 3 showed that middle class whites were the most pessimistic towards New York City’s future, being middle class did not have an influence on either a pessimistic outlook or candidate selection. In fact, income class was an insignificant variable in both candidate choice models. Instead, *race* was the most important factor in choosing a candidate with whites preferring Giuliani and nonwhites preferring Dinkins in both elections years. Long-term outlook was indeed an important factor in the 1993 model, as originally predicted, but since income class was not a

predictor of pessimism in 1993, it is impossible to determine if an individual respondent's race and class were filtered by long-term outlook when choosing between Dinkins and Giuliani. In truth, the income class of an individual simply did not matter in the cross-sectional survey models.

What was completely surprising was that middle classness would have a negative effect on the change in percentage voting for Giuliani (Chapter 7.) The original hypothesis was based on the national-level phenomenon of "middle class anxiety" that had been well documented in the scholarship surrounding President Clinton's first election in 1992. The scholarly literature hypothesized that middle class whites were feeling neglected by Washington and squeezed out of existence by the increasing amounts of both wealthy and poor people, and that they would vote out the incumbent out of anger (Newman 1993; Ehrenreich 1990; Greenberg 1995; Tolchin 1994; Hochschild 1995; Bartlett and Steele 1996). The initial hypothesis posited that Giuliani would receive more votes from the middle class not only because he represented a "cure" for some of the quality of life issues that had been plaguing the city, but also because he stood for the anti-establishment vote. According to the dictums of pocketbook voting and middle class anxiety, if voters are anxious about the future, they will vote out the incumbent. This was, however, not the case in New York City. As stated in Chapters 4 through 6, income class had no effect on either individual long-term outlook for the city or candidate preference. However, income class did affect the percentage change in votes for Giuliani from 1989 to 1993; having larger numbers of middle class households in an election district meant that Giuliani received fewer votes in that district, (Chapter 7) contrary to both the indications of the national-level literature and this dissertation's original hypotheses.

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The change in the estimated percentage of nonwhite voters who supported Giuliani was a surprise. Both estimated white turnout and estimated white votes for Giuliani increased from 1989 to 1993. Estimated nonwhite turnout decreased overall from 1989 to 1993, and the expectation was that they would not vote for Giuliani given the cross-sectional survey model and conventional wisdom. However, when examined individually, estimated Asian turnout instead *rose* dramatically. Estimated Asian turnout rose more than estimated white turnout, signaling a greater mobilization on the part of Asians. The Asian population in New York City has had historically low turnout; therefore, it is highly significant that Giuliani was able to motivate large numbers to come to the polls. When examining the votes for each candidate, the estimated white vote for Giuliani went up overall, as expected, which alone could explain his victory, given the small margins. However, the dramatic increase in Asian votes for Giuliani gives greater credence to the alternative hypothesis that it was the Asian vote that granted Giuliani the victory. Consequently, in the final analysis, when analyzing small differences it does not matter how good your model is, because changes at the margins happen for a variety of reasons.

What did the two elections mean for New York City? The 1989 election has been characterized as a “last stand” for middle class whites in New York City. Middle class whites should have and did to some degree “circle the wagons” around a candidate (Giuliani) who seemed to represent their interests. The city was majority nonwhite, and middle class whites lost a portion of their economic position over the 1980s. Dinkins’ 1989 victory promised to usher in a new era of racial reconciliation and inclusiveness for all New Yorkers. Yet, Dinkins instead came to represent the “last stand” of the New York

liberal establishment. His inability to satisfy his core constituency and failure to control a burgeoning budget deficit paved the way for Giuliani's candidacy and eventual victory.

However, the 1993 election was also not the "last stand" of middle class whites in New York City. There are fewer whites in New York City now than there were at the start of the decade. Additionally, being middle class in New York City means enduring high rents and mediocre public schools. Nevertheless, it seems that middle class whites' desire to have their voices heard by electing Giuliani worked in their favor. Giuliani tackled many of the "quality of life" issues that bothered New Yorkers, and in conjunction with a booming economy, raised the living standards of many middle class New Yorkers such that they could now afford to leave if they so desired. Giuliani was also able to capitalize on Dinkins' faults, articulating a vision of New York City that was cleaner, shinier and happier. This appealed to enough voters (white and nonwhite, middle class and non-middle class) to elect him by a small margin. By 1997, it was enough to elect him by a landslide over a candidate from the "old-school" liberal establishment. The result, having begun as "circling the wagons" around a middle class white candidate against "incoming forces," became the adoption and inclusion of the "enemy" to create the New York City of today.

Appendix A
Dataset descriptions

HOUSING AND VACANCY SURVEY

The sampling frame and the questionnaire for the Housing and Vacancy Survey were consistent over the four surveys conducted in 1978, 1981, 1984 and 1987 with the major changes coming between the 1987 and 1991 surveys and further changes between the 1991 and 1993 surveys. The 1978 to 1987 surveys will be discussed first, then the surveys in the 1990s.

The sampling frame for the 1978 to 1987 Housing and Vacancy Survey was taken from four different sources: the housing units in existence from the 1970 Census; all housing units constructed since 1970 with a certificate of occupancy no later than one year prior to the survey; all housing units constructed under the supervision of the New York State Urban Development Corporation; and those units that at the time of the 1970 Census were under the J-51 Tax Exemption and Tax Abatement program.¹ The sampling probability from 1978 to 1987 was one out of every 167 housing units (Housing and Vacancy Survey Documentation 1987). Transient hotels, lodging and boarding houses, institutions, military housing and other large group quarters such as dormitories are excluded. The instrument from 1978 to 1987 consisted of two sets of questions; one for occupied units consisting of descriptions of the housing unit, the household occupying the housing unit, and a few individual-level questions. The second set of questions concerned vacant housing quality. Many of the questions follow the 1970 Census questionnaire in terms of wording and reliability. Questions on race, ethnicity and income are only asked at the household level. Individual-level characteristics of each member of the household are addressed only in terms of gender, age, relationship to householder and education. While it is possible to compare questions over the 1978 to 1987 period, comparing actual numbers and questions between 1978 and 1996, for example, is very difficult due to the changes in the nature of the instrument. As such, only percentages will be reported; areas where possible discrepancies may exist will be identified.

The sample design and questionnaire wording are all similar in the 1991, 1993 and 1996 surveys. They are all based on the 1990 Census sampling frame, have demographic questions that are asked of all members of the household, and have substantial increases in the number of questions asked about income, occupation and labor force participation. Due to these changes, the survey has been separated into three files: occupied housing unit that contains information about the head of household and the unit itself,

person-level record that contains information about each individual in the household, and vacant unit that contains information only about the housing unit. The exclusions from the sampling frame are similar to the exclusions in the 1978 to 1987 surveys. Three out of the four possible sampling frames were the same as in previous years. However in the fourth frame, IN-REM housing units was added.² The new section added in 1991, the person-level file is based on the 1990 Census questionnaire. Detailed questions on race and ethnicity, income, occupation and labor force participation were added in an effort to increase the accuracy of tracking demographic shifts within the city. The questionnaire is essentially the same for all three instances during the 1990s. The main exception is that in 1996 and 1993, adjustments were made to the race/ethnicity categories and the income categories to account for non-responses.

The sample from 1991 onward was taken from the 1990 Census and new construction Certificates of Occupancy from April to December of 1990 (Housing and Vacancy Survey Codebook 1991, 2-1). The total number of housing units in New York City increased from 2,840,256 to 2,980,763 from 1987 to 1991. This change was due to the new sampling protocol (Housing and Vacancy Survey Codebook 1991, 2-4). The Census Bureau recommends using percentages to compare across years; this is how data will be presented in this section (Housing and Vacancy Survey Codebook 1991, 2-4).

New York Times/CBS News Surveys

The *New York Times/CBS News* surveys are conducted on a periodic basis to monitor the thoughts and feelings of New York City residents. The surveys asked a battery of questions on the upcoming elections, life in New York City, and on specific timely topics. The samples were generated from a sampling frame of all New York City residents aged 18 and over. A stratified random digit dialing method was used and calls were made over a four-day period. Table A.1 lists the basic demographic features in the two main datasets used, June 1989 and May 1993. In both years, the percentage in each category remains very close to one another, so comparison should not pose any difficulty.

Table A2 Basic demographics from the 1989 *New York Times*/CBS News survey and the 1993 *New York Times*/CBS News Survey

	1989	1993
<i>Gender</i>		
Male	46.20%	46.30%
Female	53.80%	53.70%
<i>Religion</i>		
Protestant	21.60%	24.40%
Catholic	45.20%	41.90%
Jewish	11.80%	12.80%
Other	7.80%	5.80%
None	11.10%	12.60%
<i>Register to Vote</i>		
Yes	65.20%	66.40%
None	34.60%	33.60%
<i>Race</i>		
White	54.60%	52.70%
Black	25.50%	25.80%
Other	18.90%	19.80%
DK/NA	1%	1.70%
<i>Income Class</i>		
Lower	36.20%	37.80%
Middle	37.20%	43.40%
Upper	17.30%	10.80%
DK/NA	9.40%	8%
<i>Hispanic Origin</i>		
Yes	21.80%	19.40%
No	77.20%	79.70%
DK/NA	1%	1%
<i>Educational Attainment</i>		
Not HS Grad	16.30%	13.60%
HS Grad	32.60%	29.20%
Some College	21.60%	23.90%
BA	28.80%	33.00%
DK/NA	0.80%	0.30%

Appendix 4.1

Variable	Obs	Mean	Std. Dev.	Min	Max
sex	1461	.4099932	.4920005	0	1
longbad	1461	.4928131	.5001195	0	1
longgood	1461	.2217659	.4155767	0	1
longdk	1461	.0663929	.2490529	0	1
whitedum	1461	.5770021	.4942043	0	1
racedk	1461	.0130048	.1133334	0	1
lowinc	1461	.3785079	.4851812	0	1
hiinc	1461	.1683778	.3743296	0	1
incdk	1461	.0869268	.2818242	0	1
crimedum	1461	.192334	.394269	0	1
racegood	1461	.2689938	.4435886	0	1
dkracrel	1461	.1266256	.332667	0	1
outerdum	1461	.8104038	.3921157	0	1
jewish	1461	.1341547	.3409351	0	1
lthsdk	1461	.3687766	.1622177	0	1
somecol	1461	.2142368	.4104323	0	1
hsgrad	1461	.3258042	.468835	0	1
hispdum	1461	.1998631	.4000342	0	1

. *I will now tabulate my single-level variables

Jewish	Freq.	Percent	Cum.
Not Jewish	1265	86.58	86.58
Jewish	196	13.42	100.00
Total	1461	100.00	

. tab outerdum

outerdum	Freq.	Percent	Cum.
Manhattan	277	18.96	18.96
Outer Borough	1184	81.04	100.00
Total	1461	100.00	

. tab crime

crime	Freq.	Percent	Cum.
Victim	281	21.16	21.16
No Victim	953	71.76	92.92
NA	94	7.08	100.00
Total	1328	100.00	

. tab hispanic

hispanic	Freq.	Percent	Cum.
Hispanic	292	19.99	19.99

Non-Hispanic	1152	78.85	98.84
NA	17	1.16	100.00
-----+-----			
Total	1461	100.00	

. tab race relations (racerela)

racerela	Freq.	Percent	Cum.
-----+-----			
Good	393	26.90	26.90
Bad	883	60.44	87.34
NA	185	12.66	100.00
-----+-----			
Total	1461	100.00	

. tab incclass

incclass	Freq.	Percent	Cum.
-----+-----			
Low	553	37.85	37.85
Middle	535	36.62	74.47
High	246	16.84	91.31
NA	127	8.69	100.00
-----+-----			
Total	1461	100.00	

. tab newrace

newrace	Freq.	Percent	Cum.
White	843	57.70	57.70
Non-White	599	41.00	98.70
NA	19	1.30	100.00
Total	1461	100.00	

. tab agecat

agecat	Freq.	Percent	Cum.
18-29	361	24.71	24.71
30-44	481	32.92	57.63
45-64	325	22.25	79.88
65 Plus	294	20.12	100.00
Total	1461	100.00	

. tab educ

educ	Freq.	Percent	Cum.
LT HS	237	16.22	16.22
HS Grad	476	32.58	48.80
Some Col	313	21.42	70.23
BA Plus	421	28.82	99.04
NA	14	0.96	100.00
Total	1461	100.00	

. tab sex

sex	Freq.	Percent	Cum.
Female	862	59.00	59.00
Male	599	41.00	100.00
Total	1461	100.00	

. tab longterm

Long Term Outlook for NYC	Freq.	Percent	Cum.
optimist	324	22.18	22.18
stay same	320	21.90	44.08
pessimist	720	49.28	93.36
DK/NA	97	6.64	100.00
Total	1461	100.00	

. tab register

register	Freq.	Percent	Cum.
Yes	986	67.49	67.49
No	471	32.24	99.73
NA	4	0.27	100.00
Total	1461	100.00	

. tab polviews

polviews	Freq.	Percent	Cum.
Liberal	418	28.61	28.61
Moderate	536	36.69	65.30
Conserv.	390	26.69	91.99
NA	117	8.01	100.00
Total	1461	100.00	

. **I am now going to do my cross tabs of each variable by longbad

. tab longbad sex, col chi2

		sex		Total
longbad		Female	Male	
0		423	318	741
		49.07	53.09	50.72
1		439	281	720
		50.93	46.91	49.28
Total		862	599	1461
		100.00	100.00	100.00

Pearson chi2(1) = 2.2811 Pr = 0.131

. tab longbad polviews, col chi2

		polviews				Total
longbad		Lib.	Mod.	Con.	DK/NA	
0		242	274	162	63	741
		57.89	51.12	41.54	53.85	50.72
1		176	262	228	54	720
		42.11	48.88	58.46	46.15	49.28
Total		418	536	390	117	1461
		100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 22.2540 Pr = 0.000

. tab longbad educ, col chi2

		educ						Total
longbad		LT	HS	HS Grad	Some Col.	BA Plus	DK/NA	
0		117	248	147	221	8	741	
		49.37	52.10	46.96	52.49	57.14	50.72	
1		120	228	166	200	6	720	
		50.63	47.90	53.04	47.51	42.86	49.28	
Total		237	476	313	421	14	1461	
		100.00	100.00	100.00	100.00	100.00	100.00	

Pearson chi2(4) = 3.0637 Pr = 0.547

. tab longbad agecat, col chi2

		agecat				Total
longbad		18-29	30-44	45-64	65 plus	
0		191	223	150	177	741
		52.91	46.36	46.15	60.20	50.72
1		170	258	175	117	720
		47.09	53.64	53.85	39.80	49.28
Total		361	481	325	294	1461
		100.00	100.00	100.00	100.00	100.00

Pearson $\chi^2(3) = 17.6382$ Pr = 0.001

. tab longbad newrace, col chi2

newrace				
longbad	White	Non-white	DK/NA	Total
-----+				
0	442	288	11	741
	52.43	48.08	57.89	50.72
-----+				
1	401	311	8	720
	47.57	51.92	42.11	49.28
-----+				
Total	843	599	19	1461
	100.00	100.00	100.00	100.00

Pearson $\chi^2(2) = 3.0497$ Pr = 0.218

```
. tab longbad incclass, col chi2
```

	incclass				
longbad	Low	Mid.	High	DK/NA	Total
0	293	247	135	66	741
	52.98	46.17	54.88	51.97	50.72
1	260	288	111	61	720
	47.02	53.83	45.12	48.03	49.28
Total	553	535	246	127	1461
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 7.3493 Pr = 0.062

```
. tab longbad racerela, col chi2
```

	racerela			
longbad	Good	Bad	DK/NA	Total
0	237	398	106	741
	60.31	45.07	57.30	50.72
1	156	485	79	720
	39.69	54.93	42.70	49.28
Total	393	883	185	1461
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 28.9112 Pr = 0.000

. tab longbad hispanic, col chi2

hispanic				
longbad	Hispanic	Non-Hisp.	DK/NA	Total
0	129	602	10	741
	44.18	52.26	58.82	50.72
1	163	550	7	720
	55.82	47.74	41.18	49.28
Total	292	1152	17	1461
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 6.5350 Pr = 0.038

. tab longbad crime, col chi2

crime				
longbad	Victim	No Victim	DK/NA	Total
0	144	469	53	666
	51.25	49.21	56.38	50.15
1	137	484	41	662
	48.75	50.79	43.62	49.85
Total	281	953	94	1328
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 1.9304 Pr = 0.381

. tab longbad outerdum, col chi2

outerdum			
longbad	Manhattan	Outer	Total
0	166	575	741
	59.93	48.56	50.72
1	111	609	720
	40.07	51.44	49.28
Total	277	1184	1461
	100.00	100.00	100.00

Pearson chi2(1) = 11.5975 Pr = 0.001

. tab longbad jewish, col chi2

jewish			
longbad	Non-Jewish	Jewish	Total
0	637	104	741
	50.36	53.06	50.72
1	628	92	720
	49.64	46.94	49.28
Total	1265	196	1461
	100.00	100.00	100.00

Pearson chi2(1) = 0.4970 Pr = 0.481

.

**Now I can run my logistic regression, with all possible theoretical reasons as to why someone may be a pessimist including demographics

```

Logit Estimates                               Number of obs = 1461
chi2(20)   = 86.89
Prob > chi2 = 0.0000
Log Likelihood = -969.09236                    Pseudo R2   = 0.0429

```

longbad	Odds Ratio	SE.	z	P> z	[95% CI]
age64up	.5908332	.0993684	-3.129	0.002	.4249197 .821529
age4564	.9919646	.149177	-0.054	0.957	.7387337 1.332001
age1829	.7161143	.1038321	-2.303	0.021	.5389686 .9514835
hispdum	1.235753	.1796359	1.456	0.145	.9293864 1.643112
hsgrad	.9526593	.1398566	-0.130	0.741	.7144564 1.27028
somecol	1.194513	.1863696	1.139	0.255	.879803 1.621797
lthsdum	1.18321	.2235849	0.890	0.373	.8169863 1.713598
jewish	1.104965	.1915088	0.576	0.565	.7867218 1.551943
outerdum	1.498634	.2168086	2.796	0.005	1.12863 1.989938
dkracrel	.6405624	.1089233	-2.619	0.009	.4590082 .8939278
racegood	.5471057	.0695241	-4.746	0.000	.4264851 .7018408
crimedum	.8775524	.1228325	-0.933	0.351	.6670047 1.154562
incdk	.9610883	.2098344	-0.182	0.856	.6264991 1.474369
hiinc	.718325	.1186315	-2.003	0.045	.5196907 .9928806
lowinc	.7938158	.1082797	-1.693	0.090	.6075925 1.037115
racedk	.802953	.4014611	-0.439	0.661	.3013739 2.139314
whitedum	.9167481	.1121688	-0.710	0.477	.7212755 1.165196
ideodk	.8825318	.1938094	-0.569	0.569	.5738538 1.357249
condummy	1.352171	.187264	2.179	0.029	1.030737 1.773846
libdummy	.7733436	.1054062	-1.886	0.059	.5920445 1.010161

*Based on the above I can drop Hispanic, education, Jewish, crime, and race dummies. But first I want to run it as a lstat, (A test) and then as a logit just to make sure.

*

Logistic model for longbad

Classified	True		Total
	D	~D	
+	430	277	707
-	290	464	754
Total	720	741	1461

Classified + if predicted $\Pr(D) \geq .5$

True D defined as longbad $\sim = 0$

Sensitivity	$\Pr(+ D)$	59.72%
Specificity	$\Pr(- \sim D)$	62.62%
Positive predictive value	$\Pr(D +)$	60.82%
Negative predictive value	$\Pr(\sim D -)$	61.54%
False + rate for true ~D	$\Pr(+ \sim D)$	37.38%
False - rate for true D	$\Pr(- D)$	40.28%
False + rate for classified +	$\Pr(\sim D +)$	39.18%
False - rate for classified -	$\Pr(D -)$	38.46%
Correctly classified		61.19%

. *So, only 61% were correctly classified. Not very good.

```
Iteration 0: Log Likelihood =-1012.5371
Iteration 1: Log Likelihood =-969.20329
Iteration 2: Log Likelihood =-969.09236
Iteration 3: Log Likelihood =-969.09236
```

```

Logit Estimates                                Number of obs =   1461
chi2(20)    = 86.89
Prob > chi2  = 0.0000
Log Likelihood = -969.09236                    Pseudo R2      = 0.0429

```

Coef.	SE	z	P> z	[95% CI]	Longbad
age64up	-.5262215	.1681835	-3.129	0.002	-.8558551 -.196588
age4564	-.0080678	.1503854	-0.054	0.957	-.3028178 .2866822
age1829	-.3339155	.1449938	-2.303	0.021	-.618098 -.0497329
hispdum	.2116805	.1453655	1.456	0.145	-.0732307 .4965917
hsgrad	-.0484979	.1468065	-0.330	0.741	-.3362333 .2392375
somocol	.1777389	.1560213	1.139	0.255	-.1280572 .4835351
lthsdum	.168231	.1889647	0.890	0.373	-.202133 .538595
jewish	.0998137	.1733166	0.576	0.565	-.2398805 .439508
outerdum	.4045541	.1446708	2.796	0.005	.1210045 .6881036
dkracrel	-.4454088	.1700432	-2.619	0.009	-.7786872-.1121303
racegood	-.6031133	.1270761	-4.746	0.000	-.8521779-.3540486
crimedum	-.1306186	.1399717	-0.933	0.351	-.4049581 .143721
incdk	-.039689	.21833	-0.182	0.856	-.4676079 .38823
hiinc	-.3308332	.1651501	-2.003	0.045	-.6545215-.0071449
lowinc	-.2309038	.136404	-1.693	0.090	-.4982509 .0364432
racedk	-.2194592	.4999808	-0.439	0.661	-1.199404 .7604852
whitedum	-.0869226	.1223551	-0.710	0.477	-.3267341 .152889
ideodk	-.1249604	.2196061	-0.569	0.569	-.5553805 .3054597
condummy	.3017118	.1384913	2.179	0.029	.0302738 .5731498
libdummy	-.2570318	.1362993	-1.886	0.059	-.5241735 .0101099
_cons	.1714715	.2141649	0.801	0.423	-.248284 .591227

Ok, so now I am going to drop what I had said I would, and re-run the pessimism without the insignificant variables.

```

Logit Estimates                                Number of obs = 1461
chi2(12)    = 79.03
Prob > chi2  = 0.0000
Log Likelihood = -973.02023                    Pseudo R2    = 0.0390

```

```

-----longbad |
Odds Ratio   SE      z      P>|z|    [95% CI]
-----+-----
age64up | .5656649   .0912359  -3.532  0.000   .412353   .7759778
age4564 | .9810363   .1454892  -0.129  0.897   .7335853  1.311957
age1829 | .7210028   .1038252  -2.272  0.023   .5437046  .9561166
outerdum| 1.482773   .2096566  2.786  0.005   1.123878  1.956276
dkracrel| .6445283   .1089668  -2.598  0.009   .4627369  .8977386
racegood|.5479421   .0689692  -4.779  0.000   .4281484  .7012534
  incdk | 1.003424   .212798   0.016  0.987   .6621686  1.520549
  hiinc | .716394   .1144084  -2.088  0.037   .5238593  .9796911
  lowinc|.8466507   .1086427  -1.297  0.195   .6583814  1.088757
  ideodk|.937917   .2018833  -0.298  0.766   .6151008  1.430153
condummy| 1.389538   .1905479  2.399  0.016   1.062049  1.818009
libdummy|.7875601   .1067037  -1.763  0.078   .6038894  1.027093
-----+-----

```

```
. lstat
```

```
Logistic model for longbad
```

```

----- True -----
Classified |      D      ~D      Total
-----+-----
+ |      399      256 |      655
- |      321      485 |      806
-----+-----
Total |      720      741 |      1461

```

```

Classified + if predicted Pr(D) >= .5
True D defined as longbad ~= 0

```

```

-----
Sensitivity          Pr( + | D)   55.42%
Specificity          Pr( - | ~D)   65.45%
Positive predictive value  Pr( D | +)   60.92%
Negative predictive value  Pr( ~D | -)   60.17%
-----
False + rate for true ~D   Pr( + | ~D)   34.55%
False - rate for true D    Pr( - | D)    44.58%
False + rate for classified + Pr( ~D | +)   39.08%
False - rate for classified - Pr( D | -)    39.83%
-----
Correctly classified          60.51%
-----

```

```
. *Ack that is worse.
```

```
.
```

```

Iteration 0: Log Likelihood = -1012.5371
Iteration 1: Log Likelihood = -973.10066
Iteration 2: Log Likelihood = -973.02024
Iteration 3: Log Likelihood = -973.02023

```

```

Logit Estimates                                Number of obs = 1461
chi2(12)    = 79.03

```

```

Prob > chi2 = 0.0000
Log Likelihood = -973.02023          Pseudo R2 = 0.0390

```

```

-----
longbad | Coef.   Std. Err. z  P>|z|   [95% CI]
-----+-----
age64up | -.5697534 .1612897 -3.532 0.000  -.8858754 -.2536313
age4564 | -.0191458 .1483015 -0.129 0.897  -.3098115 .2715198
age1829 | -.3271122 .1440011 -2.272 0.023  -.6093491 -.0448754
outerdum | .3939139 .1413949 2.786 0.005  .1167849 .6710429
dkracrel | -.4392365 .1690644 -2.598 0.009  -.7705966 -.1078764
racegood | -.6015857 .1258695 -4.779 0.000  -.8482854 -.354886
  incdk | .0034182 .2120719 0.016 0.987  -.4122351 .4190715
  hiinc | -.3335251 .1597004 -2.088 0.037  -.6465321 -.020518
  lowinc | -.166467 .1283206 -1.297 0.195  -.4179708 .0850368
  ideodk | -.0640938 .2152465 -0.298 0.766  -.4859691 .3577815
condummy | .3289711 .1371304 2.399 0.016  .0602004 .5977418
libdummy | -.2388156 .1354865 -1.763 0.078  -.5043642 .026733
  _cons | .1703092 .1860796 0.915 0.360  -.1944001 .5350186
-----

```

```

. *Now I can do a log likelihood test

. lrtest, saving(0)

. quietly logit longbad agecat polviews outerdum racerela incclass

. lrtest
Logit: likelihood-ratio test          chi2(7)   =   63.33
Prob > chi2 =   0.0000

. *Now I will drop incclass
.
. quietly logit longbad agecat polviews outerdum racerela

. lrtest
Logit: likelihood-ratio test          chi2(8)   =   63.33
Prob > chi2 =   0.0000

. *Wow no real difference.....
.
. *NOW I will drop racerela
. quietly logit longbad agecat polviews outerdum

. lrtest
Logit: likelihood-ratio test          chi2(9)   =   64.12
Prob > chi2 =   0.0000

. *Bigger difference..... but still not great
.
. *Now I will drop outerdum
.
. quietly logit longbad agecat polviews

. lrtest
Logit: likelihood-ratio test
chi2(10) =   74.68
Prob > chi2 =   0.0000

. *HUGE difference....
.

```

```
. *Now I will drop polviews
. quietly logit longbad agecat
```

```
. lrtest
Logit: likelihood-ratio test
chi2(11)    =   76.39
Prob > chi2 =   0.0000
```

```
. *Not as big.
```

```
.
. *Just to make sure I am going to drop all of it, and then add them
back in
. quietly logit longbad
```

```
. lrtest
Logit: likelihood-ratio test
chi2(12)    =   79.03
Prob > chi2 =   0.0000
```

I will now re-add in the variables I just took out.

```
.
. *Now adding in outerdum
. quietly logit longbad outerdum
```

```
. lrtest
Logit: likelihood-ratio test                chi2(11)    =   67.37
Prob > chi2 =   0.0000
```

```
. *Huge difference, makes sense because its the largest predictor.....
```

```
.
. *Now adding in polviews
. quietly logit longbad outerdum polviews
```

```
. lrtest
Logit: likelihood-ratio test
chi2(10)    =   66.88
Prob > chi2 =   0.0000
```

```
.
. *Not as big a difference
```

```
.
. *Now adding in race relations
. quietly logit longbad outerdum polviews racerela
```

```
. lrtest
Logit: likelihood-ratio test
chi2(9)     =   65.82
Prob > chi2 =   0.0000
```

```
.
. *Now adding in incclass
. quietly logit longbad outerdum polviews racerela incclass
```

```
. lrtest
Logit: likelihood-ratio test
chi2(8)     =   65.82
Prob > chi2 =   0.0000
```

. *Income class makes no real contribution, but I will calculate it anyway. *Now adding in age category

. quietly logit longbad outerdum polviews racerela incclass agecat

. lrtest

Logit: likelihood-ratio test

chi2(7) = 63.33

Prob > chi2 = 0.0000

. *Small contribution.

.

. **So my model is:

. **Pr(y=1) = $1/(1+\exp(-(.1703092+-.2388156*\text{libdummy}+-$
 $.3289711*\text{condummy}+- .064098*\text{ideodk}+- .116467*\text{lowinc}+$
 $-.3335251*\text{hiinc}+.0034182*\text{incdk}+- .6015857*\text{racegood}+$
 $-.4392365*\text{dkracrel}+.3939139*\text{outerdum}+- .3271122*\text{age1829}+$
 $-.0191458*\text{age4564}+- .56977534*\text{age64up}$

.

.

.

Recycled Predictors!

```
. *Now what if everyone lived in the outer boroughs
. replace outerdum=1
(277 real changes made)
```

```
. predict youter
```

```
. *now what if everyone lived in manhattan
. predict ymanhat
```

```
. sum youter ymanhat
```

Variable	Obs	Mean	Std. Dev.	Min	Max
youter	1461	.5104058	.1071106	.2351499	.7102529
ymanhat	1461	.5104058	.1071106	.2351499	.7102529

```
. drop ymanhat
```

```
. replace outerdum=0
(1461 real changes made)
```

```
. predict ymanhat
```

```
. sum youter ymanhat
```

Variable	Obs	Mean	Std. Dev.	Min	Max
youter	1461	.5104058	.1071106	.2351499	.7102529
ymanhat	1461	.4171599	.1037488	.1717364	.6230933

```
. **So if you lived in the outerboros you were 51% probable to be a
pessimist.
```

```
.
. replace outerdum=outerbk
(1184 real changes made)
```

```
. **Now what if everyone was low income
. replace lowincome=1
lowincom not found
r(111);
```

```
. replace lowinc=1
(908 real changes made)
```

```
. replace hiinc=0
(246 real changes made)
```

```
. replace incdk=0
(127 real changes made)
```

```
. predict ylowinc
```

```
. *now middle income
. replace lowinc=0
(1461 real changes made)
```

```
. predict ymidinc
```

```
. *now high income
```

```
.
```

```

. replace hiinc=1
(1461 real changes made)

. predict yhiinc

. *now incdk
. replace hiinc=0
(1461 real changes made)

. replace incdk=1
(1461 real changes made)

. predict yincdk

. sum ylowinc ymidinc yhiinc yincdk

Variable | Obs      Mean   Std. Dev.   Min      Max
-----+-----
ylowinc  | 1461   .4814306   .1111171   .1968163   .6740867
ymidinc  | 1461   .5209615   .1114319   .2244629   .7095489
yhiinc   | 1461   .4419685   .10949    .1717364   .636376
yincdk   | 1461   .5217721   .1114245   .2250585   .7102529

. *Middle income and those who did not state their income were more
likely to be pessimists
.
. replace lowinc= lowincbk
(553 real changes made)

. replace hiinc= hiincbk
(246 real changes made)

. replace incdk= incdkbk
(1334 real changes made)

Now what if everyone was liberal
. replace libdummy=1
(1043 real changes made)

. replace condummy=0
(390 real changes made)

. replace ideodk=0
(117 real changes made)

. predict yliberal

.
. *Now what if everyone was a moderate
.
. replace libdummy=0
(1461 real changes made)

. predict ymoderate
ymoderate invalid name
r(198);

. predict ymoderate
ymoderate invalid name
r(198);

```



```

. predict ymoderat

. *Now what if everyone was a conservative
.
. replace condummy=1
(1461 real changes made)

. predict yconserv

. *now what if everyone didnt know
. replace condummy=0
(1461 real changes made)

. replace ideodk=1
(1461 real changes made)

. predict yideodk

. sum yliberal ymoderat yconserv yideodk

```

Variable	Obs	Mean	Std. Dev.	Min	Max
yliberal	1461	.4323455	.0963077	.1717364	.5814736
ymoderat	1461	.489337	.0987762	.2084069	.6382188
yconserv	1461	.5679252	.0981636	.267845	.7102529
yideodk	1461	.4739588	.0983488	.1980306	.6232927

```

. *So, if you were a conservative you were most likely to be pessimist.
Makes sense, given the nature of the times.

. replace libdummy= libbk
(418 real changes made)

. replace condummy= conbk
(390 real changes made)

. replace ideodk= ideobk
(1344 real changes made)

. *Now, what about race relations
. replace racegood=1
(1068 real changes made)

. replace dkracrel=0
(185 real changes made)

. predict yracgood

. *now race relations are generally bad
. replace racegood=0
(1461 real changes made)

. predict yracbad

. replace dkracrel=0
(0 real changes made)

. replace dkracrel=1
(1461 real changes made)

```

```

. predict ydkrace

. sum yracgood yracbad ydkrace

Variable | Obs      Mean   Std. Dev.    Min      Max
-----+-----
yracgood | 1461   .4009889   .0888035   .1717364   .5732263
yracbad  | 1461   .5448177   .0924565   .2745249   .7102529
ydkrace  | 1461   .4392012   .0912017   .196073    .6123915

. *If you thought that race relations were bad, then you tended to be
more pessimistic
.
. replace racegood= racegdbk
(393 real changes made)

. replace dkracrel= dkrelbk
(1276 real changes made)

. *Now only age is left
.
. replace age1829=1
(1100 real changes made)

. replace age4564=0
(325 real changes made)

. replace age64up=0
(294 real changes made)

. predict yage1829

. replace age1829=0
(1461 real changes made)

. predict yage3044

. replace age4564=1
(1461 real changes made)

. predict yage4564

. replace age64up=1
(1461 real changes made)

. replace age4564=0
(1461 real changes made)
. predict yage64up

. sum yage1829 yage3044 yage4564 yage64up

Variable | Obs      Mean   Std. Dev.    Min      Max
-----+-----
yage1829 | 1461   .4621878   .1014469   .2090387   .6386479
yage3044 | 1461   .5403871   .1020629   .2682309   .7102529
yage4564 | 1461   .535828    .1021587   .2644896   .706297
yage64up | 1461   .4050877   .0979916   .1717364   .580995

. *Interesting, those aged 30-45 (peak earning years) were most likely
to be pessimistic, followed by those who were in the later part of being
middle aged

```

```
. replace age1829= age18bk
(361 real changes made)
```

```
. replace age4564= age45bk
(325 real changes made)
```

```
. replace age64up= age64bk
(1167 real changes made)
```

Recycled Predictors for All Variables in Model B

Variable	Obs	Mean	Std. Dev.	Min	Max
youter	1461	.5104058	.1071106	.2351499	.7102529
ymanhat	1461	.4171599	.1037488	.1717364	.6230933
ylowinc	1461	.4814306	.1111171	.1968163	.6740867
ymidinc	1461	.5209615	.1114319	.2244629	.7095489
yhiinc	1461	.4419685	.10949	.1717364	.636376
yincdk	1461	.5217721	.1114245	.2250585	.7102529
yliberal	1461	.4323455	.0963077	.1717364	.5814736
ymoderat	1461	.489337	.0987762	.2084069	.6382188
yconserv	1461	.5679252	.0981636	.267845	.7102529
yvideodk	1461	.4739588	.0983488	.1980306	.6232927
yragood	1461	.4009889	.0888035	.1717364	.5732263
yragbad	1461	.5448177	.0924565	.2745249	.7102529
ydkrace	1461	.4392012	.0912017	.196073	.6123915
yage1829	1461	.4621878	.1014469	.2090387	.6386479
yage3044	1461	.5403871	.1020629	.2682309	.7102529
yage4564	1461	.535828	.1021587	.2644896	.706297
yage64up	1461	.4050877	.0979916	.1717364	.580995

Appendix 4.2

*I will now start doing the recycled predictions for Dinkgiul 1989 using the recycled predictions or adjusted probability method. The N here is for all registered respondents in the *New York Times/CBS News Poll* taken in June of 1989.

*First the single level frequencies

. Tab sex

Sex	Freq.	Percent	Cum.
Female	495	59.07	59.07
Male	343	40.93	100.00
Total	838	100.00	

. tab longterm

Long Term Outlook for NYC	Freq.	Percent	Cum.
optimist	180	21.48	21.48
stay same	187	22.32	43.79
pessimist	425	50.72	94.51
DK/NA	46	5.49	100.00
Total	838	100.00	

. tab borough

borough	Freq.	Percent	Cum.
Bronx	290	34.61	34.61
Brooklyn	117	13.96	48.57
Manhattan	167	19.93	68.50
Queens	215	25.66	94.15
SI	46	5.49	99.64
NA	3	0.36	100.00
Total	838	100.00	

. tab polviews

polviews	Freq.	Percent	Cum.
Liberal	247	29.47	29.47
Moderate	332	39.62	69.09
Conservative	229	27.33	96.42
NA	30	3.58	100.00
Total	838	100.00	

. tab education

Education	Freq.	Percent	Cum.

LT HS	111	13.25	13.25
HS Grad	259	30.91	44.15
Some Col	194	23.15	67.30
BA Plus	269	32.10	99.40
NA	5	0.60	100.00
-----+-----			
Total	838	100.00	

. tab age category

Age category	Freq.	Percent	Cum.
-----+-----			
18-29	177	21.12	21.12
30-44	275	32.82	53.94
45-64	199	23.75	77.68
65 plus	187	22.32	100.00
-----+-----			
Total	838	100.00	

. tab newrace

newrace	Freq.	Percent	Cum.
-----+-----			
White	520	62.05	62.05
Non-White	309	36.87	98.93
NA	9	1.07	100.00
-----+-----			
Total	838	100.00	

. tab incclass

incclass	Freq.	Percent	Cum.
Lower	282	33.65	33.65
Middle	334	39.86	73.51
Upper	170	20.29	93.79
NA	52	6.21	100.00
Total	838	100.00	

. tab race relations

race relations	Freq.	Percent	Cum.
Good	228	27.21	27.21
Bad	534	63.72	90.93
NA	76	9.07	100.00
Total	838	100.00	

. tab outerdum

outerdum	Freq.	Percent	Cum.
Manhattan	167	19.93	19.93
Outer Borough	671	80.07	100.00
Total	838	100.00	

. tab Jewish

Jewish	Freq.	Percent	Cum.
Non-Jewish	710	84.73	84.73
Jewish	128	15.27	100.00
Total	838	100.00	

.

* I will now start with my cross tabulations.
 . tab dinkgiul sex, col chi2

		sex		
dinkgiul		Female	Male	Total
-----+-----				
Dinkins		246	147	393
		49.70	42.86	46.90
-----+-----				
Giuliani		221	182	403
		44.65	53.06	48.09
-----+-----				
Neither/NoVote		28	14	42
		5.66	4.08	5.01
-----+-----				
Total		495	343	838
		100.00	100.00	100.00

Pearson chi2(2) = 6.0070 Pr = 0.050

. tab dinkgiul longterm, col chi2

		Long Term Outlook for NYC				
dinkgiul		optimist	stay same	pessimist	DK/NA	Total
-----+-----						
Dinkins		89	85	192	27	393
		49.44	45.45	45.18	58.70	46.90
-----+-----						
Giuliani		81	93	214	15	403
		45.00	49.73	50.35	32.61	48.09
-----+-----						
Neither/NV		10	9	19	4	42
		5.56	4.81	4.47	8.70	5.01
-----+-----						
Total		180	187	425	46	838
		100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 6.7880 Pr = 0.341

. *Very interesting that long-term outlook has no relationship at this point with preference for either Dinkins or Giuliani.
 . *

```
. tab dinkgiul polviews, col chi2
```

	polviews				
dinkgiul	Liberal	Moderate	Conser.	DK	Total
Dinkins	145	141	92	15	393
	58.70	42.47	40.17	50.00	46.90
Giuliani	93	175	122	13	403
	37.65	52.71	53.28	43.33	48.09
Neither/NV	9	16	15	2	42
	3.64	4.82	6.55	6.67	5.01
Total	247	332	229	30	838
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 21.6823 Pr = 0.001

```
. *Political ideology has a relationship with preference.
```

```
. *
```

```
. tab dinkgiul education, col chi2
```

	education					
dinkgiul	LT HS	HS Grad	Some Col.	BA Plus	NA	Total
Dinkins	46	117	98	131	1	393
	41.44	45.17	50.52	48.70	20.00	46.90
Giuliani	51	131	92	125	4	403
	45.95	50.58	47.42	46.47	80.00	48.09
Neither/NV	14	11	4	13	0	42
	12.61	4.25	2.06	4.83	0.00	5.01
Total	111	259	194	269	5	838
	100.00	100.00	100.00	100.00	100.00	100.00

Pearson chi2(8) = 20.7645 Pr = 0.008

```
. *Education has an influence on candidate support in 1989.
```

```
.
```


. tab dinkgiul age category, col chi2

Age category					
dinkgiul	18-29	30-44	45-64	65 plus	Total
-----+					
Dinkins	72	136	100	85	393
	40.68	49.45	50.25	45.45	46.90
-----+					
Giuliani	99	126	86	92	403
	55.93	45.82	43.22	49.20	48.09
-----+					
Neither/NV	6	13	13	10	42
	3.39	4.73	6.53	5.35	5.01
-----+					
Total	177	275	199	187	838
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 7.9270 Pr = 0.243

. *Age category does not have a relationship in 1989.

. tab dinkgiul newrace, col chi2

newrace				
dinkgiul	White	Non-white	NA	Total
-----+				
Dinkins	177	212	4	393
	34.04	68.61	44.44	46.90
-----+				
Giuliani	316	82	5	403
	60.77	26.54	55.56	48.09
-----+				
Neither/NV	27	15	0	42
	5.19	4.85	0.00	5.01
-----+				
Total	520	309	9	838
	100.00	100.00	100.00	100.00

Pearson chi2(4) = 97.2385 Pr = 0.000

. *Race has a relationship with candidate support.

```
. tab dinkgiul incclass, col chi2
```

	incclass				
dinkgiul	Lower	Middle	Upper	NA	Total
-----+-----					
Dinkins	140	154	73	26	393
	49.65	46.11	42.94	50.00	46.90
-----+-----					
Giuliani	125	166	91	21	403
	44.33	49.70	53.53	40.38	48.09
-----+-----					
Neither/NV	17	14	6	5	42
	6.03	4.19	3.53	9.62	5.01
-----+-----					
Total	282	334	170	52	838
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 7.8453 Pr = 0.250

```
. *No relationship between income class and candidate support.
```

```
. tab dinkgiul race relations, col chi2
```

	Race relations			
dinkgiul	Good	Bad	NA	Total
-----+-----				
Dinkins	89	268	36	393
	39.04	50.19	47.37	46.90
-----+-----				
Giuliani	123	244	36	403
	53.95	45.69	47.37	48.09
-----+-----				
Neither/NV	16	22	4	42
	7.02	4.12	5.26	5.01
-----+-----				
Total	228	534	76	838
	100.00	100.00	100.00	100.00

Pearson chi2(4) = 9.2015 Pr = 0.056

```
. *Slightly insignificant relationship here. Interesting.
```

```
.
```

```
. tab dinkgiul Hispanic, col chi2
```

	Hispanic			
dinkgiul	Hispanic	Non-Hispanic	NA	Total
Dinkins	57	333	3	393
	41.61	47.91	50.00	46.90
Giuliani	69	331	3	403
	50.36	47.63	50.00	48.09
Neither/NV	11	31	0	42
	8.03	4.46	0.00	5.01
Total	137	695	6	838
	100.00	100.00	100.00	100.00

```
Pearson chi2(4) = 4.3775 Pr = 0.357
```

```
. *No significant relationship in 1989 between Hispanic origin and  
candidate support.
```

```
.  
.
```

```
tab dinkgiul outerdum, col chi2
```

	outerdum		
dinkgiul	Manhat.	Outer B.	Total
Dinkins	96	297	393
	57.49	44.26	46.90
Giuliani	64	339	403
	38.32	50.52	48.09
Neither/NV	7	35	42
	4.19	5.22	5.01
Total	167	671	838
	100.00	100.00	100.00

```
Pearson chi2(2) = 9.4027 Pr = 0.009
```

```
. tab dinkgiul Jewish, col chi2
```

	Jewish		
dinkgiul	Non-Jewish	Jewish	Total
Dinkins	333	60	393
	46.90	46.88	46.90
Giuliani	343	60	403
	48.31	46.88	48.09
Neither/NV	34	8	42
	4.79	6.25	5.01
Total	710	128	838
	100.00	100.00	100.00

```
Pearson chi2(2) = 0.5085 Pr = 0.776
```

```
. * Outerdum, the dummy for outer borough versus Manhattan is
significant. Jewish versus non-Jewish is not.
```

```
. *Ok based on my crosstabs I suspect that political views, outer
borough and the dummy for white versus non-white will be significant.
```

```
.
```

First Logistic Regression ----- Saturated Model

Multinomial regression Number of obs = 838
 Chi2(48) = 200.24
 Prob > chi2 = 0.0000
 Log Likelihood = -618.21466 Pseudo R2 = 0.1394

```
-----
-----
dinkgiul |Coef.  Std. Err.   z  P>|z|  [95% CI]
-----+-----
Dinkins |
  sex | -.2071611 .1649021 -1.256 0.209 -.5303632 .1160411
  longbad | -.0316936 .2062122 -0.154 0.878 -.4358621 .3724748
  longgood | .2064631 .2420499 0.853 0.394 -.2679459 .6808721
  longdk | .4137713 .3986905 1.038 0.299 -.3676477 1.19519
  libdummy | .5230859 .195258 2.679 0.007 .1403872 .9057845
  condommy | -.1261298 .2007355 -0.628 0.530 -.5195642 .2673046
  ideodk | .2747945 .4568297 0.602 0.547 -.6205752 1.170164
  whitedum | -1.941919 .1923513 -10.1 0.000 -2.31892 -1.564917
  racedk | -1.312987 .7711795 -1.703 0.089 -2.824471 .1984974
  lowinc | .1431806 .2038877 0.702 0.483 -.256432 .5427932
  hiinc | .0311835 .2237993 0.139 0.889 -.407455 .469822
  incdk | .266505 .3838638 0.694 0.488 -.4858542 1.018864
  crimedum | .2079783 .2042992 1.018 0.309 -.1924408 .6083975
  racegood | -.3314908 .1884964 -1.759 0.079 -.700937 .0379553
  dkracrel | -.1407648 .2818747 -0.499 0.618 -.6932292 .4116995
  outerdum | -.5539004 .2049995 -2.702 0.007 -.955692 -.1521089
  Jewish | .5557494 .2286283 2.431 0.015 .1076462 1.003853
  lthsdum | -.0775027 .3006872 -0.258 0.797 -.6668388 .5118333
  somecol | .0590833 .2181449 0.271 0.787 -.3684728 .4866393
  hsgrad | -.146327 .2166308 -0.675 0.499 -.5709155 .2782615
  hispdum | -.7237419 .2384007 -3.036 0.002 -1.19099 -.2564851
  age1829 | -.5163597 .2242284 -2.303 0.021 -.9558393 -.0768802
  age4564 | .3034331 .220204 1.378 0.168 -.1281588 .735025
  age64up | -.1204961 .2460573 -0.490 0.624 -.6027595 .3617674
  _cons | 1.675371 .3616138 4.633 0.000 .9666211 2.384121
-----+-----
neither |
  sex | -.5106345 .3666636 -1.393 0.164 -1.229282 .208013
  longbad | -.3934767 .4515702 -0.871 0.384 -1.278538 .4915846
  longgood | .1451447 .5065653 0.287 0.774 -.8477051 1.137995
  longdk | .6299791 .708341 0.889 0.374 -.7583437 2.018302
  libdummy | -.1656353 .4605178 -0.360 0.719 -1.068234 .7369631
  condommy | .2328862 .4001857 0.582 0.56 -.5514633 1.017236
  ideodk | -.3626949 .896552 -0.405 0.686 -2.119904 1.394515
  whitedum | -.9399405 .403248 -2.331 0.020 -1.730292 -.149589
  racedk | -40.38546 7.05e+08 0.000 1.000 -1.38e+09 1.38e+09
  lowinc | .2896628 .44078 0.657 0.511 -.5742502 1.153576
  hiinc | -.2342481 .5364828 -0.437 0.662 -1.285735 .8172389
  incdk | .9165244 .6449408 1.421 0.155 -.3475363 2.180585
  crimedum | .2462323 .4222096 0.583 0.560 -.5812832 1.073748
  racegood | .4807933 .3725897 1.290 0.197 -.2494691 1.211056
  dkracrel | .0554129 .6028707 0.092 0.927 -1.126192 1.237018
  outerdum | .1052553 .4626102 0.228 0.820 -.801444 1.011955
  Jewish | .9376243 .4875214 1.923 0.054 -.0179 1.893149
  lthsdum | .8329561 .5289984 1.575 0.115 -.203861 1.869774
  somecol | -.9554445 .6034082 -1.583 0.113 -2.138103 .2272138
  hsgrad | -.3722278 .4763497 -0.781 0.435 -1.305856 .5614004
```

```

hispdum | .1724536 .4531467 0.381 0.704 -.7156976 1.060605
age1829 | -.6656303 .528898 -1.259 0.208 -1.702251 .3709907
age4564 | .109074 .4611588 0.237 0.813 -.7947807 1.012929
age64up | -.6121776 .5379195 -1.138 0.255 -1.66648 .4421252
_cons | -1.59525 .7939854 -2.009 0.045 -3.15143 -.0390671
-----

```

(Outcome dinkgiul==Giuliani is the comparison group)

. * Ok, so based on this, I can drop longterm outlook, income class,
crime, race relations, and education.

Logistic Regression - Final Model --- Model B

Multinomial regression Number of obs = 838
 chi2(22) = 168.18
 Prob > chi2 = 0.0000
 Log Likelihood = -634.24287 Pseudo R2 = 0.1171

```
-----
dinkgiul| Coef.   Std. Err.   z    P>|z|   [95% CI]   -----
```

Dinkins v. Giuliani

```
Libdummy|.5547117 .1924342 2.883 0.004 .1775477 .9318757
condummy|-.1240839 .1978284 -0.627 0.531 -.5118205 .2636527
ideodk|.2765227 .4453955 0.621 0.535 -.5964364 1.149482
whitedum| -1.966217 .1879982 -10.459 0.000 -2.334686 -1.597747
racedk| -1.249091 .7266426 -1.719 0.086 -2.673284 .1751021
outerdum| -.5821224 .198784 -2.928 0.003 -.9717319 -.192513
Jewish|.5716952 .2230611 2.563 0.010 .1345035 1.008887
hispdum| -.727759 .2310481 -3.150 0.002 -1.180605 -.274913
age1829| -.497267 .2212688 -2.247 0.025 -.930946 -.0635881
age4564|.3348125 .2135073 1.568 0.117 -.0836541 .7532791
age64up| -.0034273 .2188425 -0.016 0.988 -.4323507 .4254961
_cons| 1.596947 .2753424 5.800 0.000 1.057286 2.136609
-----+-----
```

Neither/No Vote v. Giuliani

```
libdummy| -.0671933 .4457734 -0.151 0.880 -.9408931 .8065066
condummy|.1454803 .3875582 0.375 0.707 -.6141199 .9050804
ideodk|.2336761 .8262915 0.283 0.777 -1.3858251 .853178
whitedum| -.9405399 .3895287 -2.415 0.016 -1.704002 -.1770778
racedk| -31.59225 7923449 0.000 1.000 -1.55e+07 1.55e+07
outerdum| -.0668951 .4435677 -0.151 0.880 -.9362719 .8024816
Jewish|.6458409 .4589099 1.407 0.159 -.253606 1.545288
hispdum|.3923264 .4183897 0.938 0.348 -.4277023 1.212355
age1829| -.5683728 .5164827 -1.100 0.271 -1.58066 .4439147
age4564|.4672519 .4271298 1.094 0.274 -.3699071 1.304411
age64up|.1977632 .4529027 0.437 0.662 -.6899098 1.085436
_cons| -1.812167 .6028995 -3.006 0.003 -2.993828 -.6305059
-----+-----
```

(Outcome dinkgiul==Giuliani is the comparison group)

. *Its interesting here that being Jewish was significant when its not in the crosstabulations.

. *Ok now I am going to do recycled predictions for political ideology

. *What if everyone was liberal?

. replace libdummy=1
(591 real changes made)

. replace condummy=0
(229 real changes made)

. replace ideodk=0
(30 real changes made)

. predict libdink, outcome(Dinkins)

. predict libgiul, outcome(Giuliani)

. predict libnv, outcome(3)

. sum libdink libgiul libnv

Variable	Obs	Mean	Std. Dev.	Min	Max
libdink	838	.5579	.1926795	.1587711	.9062291
libgiul	838	.4052957	.1889818	.075401	.8036544
libnv	838	.0368042	.0154975	8.38e-16	.0830549

. *So, as I suspected if everyone was liberal there would be a probability of 56% of voting for Dinkins, 41% of voting for Giuliani, and 3.6% of not voting

. *now, what if everyone was moderate

. replace libdummy=0
(838 real changes made)

. predict moddink, outcome(1)

. predict modgiul, outcome(2)

. predict modnv, outcome(3)

. sum moddink modgiul modnv

Variable	Obs	Mean	Std. Dev.	Min	Max
moddink	838	.4398336	.1968458	.0975092	.8455611
modgiul	838	.5088587	.1961421	.1225159	.8595116
modnv	838	.0513077	.0206684	1.11e-15	.1119324

. *Interesting, if everyone was moderate, you would have a probability of 44% for supporting Dinkins, but a probability of 51% of supporting Giuliani and 5% for neither/no vote.

Does this mean that Giuliani garnered increased support among moderates in 1989????

. *What if everyone was conservative?

. replace condummy=1
(838 real changes made)


```
. predict condink, outcome(1)
. predict congiul, outcome(2)
. predict connv, outcome(3)
. sum condink congiul connv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
condink	838	.4107987	.1937573	.0865327	.8240835
congiul	838	.527277	.1941282	.1351785	.8635257
connv	838	.0619243	.0246237	1.34e-15	.1362598

. *What I find interesting here is that if you are conservative you only have a likelihood of 53% of supporting Giuliani, I would have thought it would have been much higher.

. *Plus, there is a probability of 41% of support for Dinkins??? Who were the conservatives who liked him?

```
.
. *Now what if everyone didn't know?
. replace condommy=0
(838 real changes made)
```

```
. replace ideodk=1
(838 real changes made)
```

```
. predict iddkdink, outcome(1)
. predict iddkgiul, outcome(2)
. predict iddknv, outcome(3)
. sum iddkdink iddkgiul iddknv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
iddkdink	838	.4921862	.1955312	.1233429	.8725551
iddkgiul	838	.4514885	.1923356	.0958844	.8245713
iddknv	838	.0563253	.0227292	1.27e-15	.1169311

. *As I suspected, the outcome is pretty evenly split.

```
. *Now I am going to look at race
```

```
.
. *Whites
. replace whitedum=1
(318 real changes made)
```

```
. replace racedk=0
(9 real changes made)
```

```
. predict wdink, outcome(1)
. predict wgiul, outcome(2)
. predict wnv, outcome(3)
```

```
. sum wdink wgiul wnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
wdink	838	.3162665	.1268717	.0865327	.716103
wgiul	838	.6330453	.12586	.2402966	.8635257
wnv	838	.0506882	.0207233	.0191219	.1169338

```
. *If everyone was white there would be a 63% probability of supporting Giuliani in 1989, and a 32% probability of supporting Dinkins.
```

```
.
```

```
. *Non-whites
```

```
. replace whitedum=0
```

```
(838 real changes made)
```

```
. predict nwdink, outcome(1)
```

```
. predict nwgiul, outcome(2)
```

```
. predict nwnv, outcome(3)
```

```
. sum nwdink nwgiul nwnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
nwdink	838	.7201418	.1134217	.3840426	.9356248
nwgiul	838	.2337537	.099972	.0439498	.536485
nwnv	838	.0461044	.0240759	.0136929	.1362598

```
. *WOW, a 72% probability of being non-white and voting for Dinkins. Fascinating!!!
```

```
.
```

```
. *What if everyone didn't know his or her race
```

```
. replace racedk=1
```

```
(838 real changes made)
```

```
. predict racdkdin, outcome(1)
```

```
. predict racdkgiu, outcome(2)
```

```
. predict racdknv, outcome(3)
```

```
. sum racdkdin racdkgiu racdknv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
racdkdin	838	.4907741	.1445063	.1703179	.8592501
racdkgiu	838	.5092259	.1445063	.1407499	.8296821
racdknv	838	1.98e-15	9.24e-16	6.59e-16	5.40e-15

```
. *Too close to call
```

```
. *
```

```
. replace whitedum=whitebk
```

```
(520 real changes made)
```

```
. replace racedk=racedkbk
```

```
(829 real changes made)
```

```
. *Now, I am going to do the outer boroughs
```

```
. replace outerdum=1
```

```
(167 real changes made)
```

```
. predict outdink, outcome(1)
. predict outgiul, outcome(2)
. predict outnv, outcome(3)
. sum outdink outgiul outnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
outdink	838	.4447317	.2030823	.0865327	.8454136
outgiul	838	.503028	.20027	.1258986	.8635257
outnv	838	.0522403	.0239646	1.11e-15	.1362598

*So, outer boro means a 50% probability of supporting G, it also means a 50% probability of not supporting G

```
.
. replace outerdum=0
(838 real changes made)
. predict mandink, outcome(1)
. predict mangiul, outcome(2)
. predict mannv, outcome(3)
. sum mandink mangiul mannv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
mandink	838	.5643877	.196837	.1445035	.9062291
mangiul	838	.3935213	.1906657	.075401	.8056769
mannv	838	.042091	.0203552	9.46e-16	.1098004

. *But, if you lived in Manhattan that means that you had a 56% probability of supporting Dinkins... Interesting

```
. *I am going to continue by looking at Jewish v non-Jewish
. replace Jewish=1
(710 real changes made)
. predict jewdink, outcome(1)
. predict jewgiul, outcome(2)
. predict jewnv, outcome(3)
. sum jewdink jewgiul jewnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
jewdink	838	.5516814	.2012668	.1378267	.9356248
jewgiul	838	.3826295	.189622	.0439498	.7765055
jewnv	838	.0656892	.0317965	1.26e-15	.1808197

. *Still even though its significant, being Jewish meant that you had a strong probability that you would vote for Dinkins

```
.
. replace Jewish=0
(838 real changes made)
```

```

. predict nojewdin, outcome(1)

. predict nojewgiu, outcome(2)

. predict nojewnv, outcome(3)

. sum nojewdin nojewgiu nojewnv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
nojewdin	838	.4511038	.2123494	.0865327	.9062291
nojewgiu	838	.5018047	.2087486	.075401	.8635257
nojewnv	838	.0470915	.0222514	1.02e-15	.1362598

```

. *If you were non-Jewish it was pretty evenly split between the
candidates with a slight probability towards Giuliani

. replace jewbk=Jewish
(128 real changes made)

. *Now hispanics
. replace hispdum=1
(701 real changes made)

. predict hispdink, outcome(1)

. predict hispgiul, outcome(2)

. predict hispnv, outcome(3)

. sum hispdink hispgiul hispnv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
hispdink	838	.3275172	.1991158	.0865327	.8101112
hispgiul	838	.5950176	.2020753	.139555	.8635257
hispnv	838	.0774653	.0249326	1.98e-15	.1362598

```

. *Hispanics here have a strong probability to support Giuliani 60%.

. replace hispdum=0
(838 real changes made)

. predict nohispd, outcome(1)

. predict nohispg, outcome(2)

. predict nohispnv, outcome(3)

. sum nohispd nohispg nohispnv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
nohispd	838	.4768848	.2184935	.1664408	.9062291
nohispg	838	.4827521	.2143144	.075401	.8022195
nohispnv	838	.040363	.0140913	1.02e-15	.0693481

```

. *Non-hispanics were evenly split between the two
. replace hispdum=hispbk
(137 real changes made)

```

```

.
. *Now by age
. replace age1829=1
(661 real changes made)

. predict dink1829, outcome(1)

. predict giul1829, outcome(2)

. predict nv1829, outcome(3)

. sum dink1829 giul1829 nv1829

```

Variable	Obs	Mean	Std. Dev.	Min	Max
dink1829	838	.3678575	.2091744	.0865327	.8279888
giul1829	838	.6008949	.2090204	.1583183	.8635257
nv1829	838	.0312476	.013497	6.59e-16	.0794724

```

. *Wow, the younger generation is strongly probable to support Giuliani.

. *Now for 30-45
. replace age1829=0
(838 real changes made)

. predict dink3045, outcome(1)

. predict giul3045, outcome(2)

. predict nv3045, outcome(3)

. sum dink3045 giul3045 nv3045

```

Variable	Obs	Mean	Std. Dev.	Min	Max
dink3045	838	.4570958	.2130215	.1300572	.8817974
giul3045	838	.498768	.2086354	.1025452	.7893496
nv3045	838	.0441362	.0186542	8.39e-16	.1072436

```

. *Still support for Giuliani is more probable but not by as much.

. *now for 45 to 64
. replace age4564=1
(838 real changes made)

. predict dink4564, outcome(1)

. predict giul4564, outcome(2)

. predict nv4564, outcome(3)

. sum dink4564 giul4564 nv4564

```

Variable	Obs	Mean	Std. Dev.	Min	Max
dink4564	838	.5149403	.2067319	.1652946	.9062291
giul4564	838	.4262576	.1970414	.075401	.7177716
nv4564	838	.0588021	.025018	1.04e-15	.1362598

. *So, it seems that the older you are the more likely you are to support Dinkins

.
 . replace age4564=0
 (838 real changes made)

. replace age64up=1
 (838 real changes made)

. predict dink64up, outcome(1)

. predict giul64up, outcome(2)

. predict nv64up, outcome(3)

. sum dink64up giul64up nv64up

Variable	Obs	Mean	Std. Dev.	Min	Max
dink64up	838	.452274	.2116553	.1274233	.878423
giul64up	838	.4944641	.2064091	.1025035	.7760187
nv64up	838	.0532619	.0222031	1.02e-15	.1279067

. *Once again, there is greater support for Giuliani.

Table of recycled predictions

Variable	Obs	Mean	Std. Dev.	Min	Max
libdink	838	.5579	.1926795	.1587711	.9062291
libgiul	838	.4052957	.1889818	.075401	.8036544
libnv	838	.0368042	.0154975	8.38e-16	.0830549
moddink	838	.4398336	.1968458	.0975092	.8455611
modgiul	838	.5088587	.1961421	.1225159	.8595116
modnv	838	.0513077	.0206684	1.11e-15	.1119324
condink	838	.4107987	.1937573	.0865327	.8240835
congiul	838	.527277	.1941282	.1351785	.8635257
connv	838	.0619243	.0246237	1.34e-15	.1362598
iddkdink	838	.4921862	.1955312	.1233429	.8725551
iddkgiul	838	.4514885	.1923356	.0958844	.8245713
iddknv	838	.0563253	.0227292	1.27e-15	.1169311
wdink	838	.3162665	.1268717	.0865327	.716103
wgiul	838	.6330453	.12586	.2402966	.8635257
wnv	838	.0506882	.0207233	.0191219	.1169338
nwdink	838	.7201418	.1134217	.3840426	.9356248
nwgiul	838	.2337537	.099972	.0439498	.536485
nwnv	838	.0461044	.0240759	.0136929	.1362598
racdkdin	838	.4907741	.1445063	.1703179	.8592501
racdkgiu	838	.5092259	.1445063	.1407499	.8296821
racdknv	838	1.98e-15	9.24e-16	6.59e-16	5.40e-15
outdink	838	.4447317	.2030823	.0865327	.8454136
outgiul	838	.503028	.20027	.1258986	.8635257
outnv	838	.0522403	.0239646	1.11e-15	.1362598
mandink	838	.5643877	.196837	.1445035	.9062291
mangiul	838	.3935213	.1906657	.075401	.8056769
mannv	838	.042091	.0203552	9.46e-16	.1098004
jewdink	838	.5516814	.2012668	.1378267	.9356248
jewgiul	838	.3826295	.189622	.0439498	.7765055
jewnv	838	.0656892	.0317965	1.26e-15	.1808197
nojewdin	838	.4511038	.2123494	.0865327	.9062291
nojewgiu	838	.5018047	.2087486	.075401	.8635257
nojewnv	838	.0470915	.0222514	1.02e-15	.1362598
hispdink	838	.3275172	.1991158	.0865327	.8101112
hispgiul	838	.5950176	.2020753	.139555	.8635257
hispnv	838	.0774653	.0249326	1.98e-15	.1362598
nohispd	838	.4768848	.2184935	.1664408	.9062291
nohispg	838	.4827521	.2143144	.075401	.8022195
nohispnv	838	.040363	.0140913	1.02e-15	.0693481
dink1829	838	.3678575	.2091744	.0865327	.8279888
giul1829	838	.6008949	.2090204	.1583183	.8635257
nv1829	838	.0312476	.013497	6.59e-16	.0794724
dink3045	838	.4570958	.2130215	.1300572	.8817974
giul3045	838	.498768	.2086354	.1025452	.7893496
nv3045	838	.0441362	.0186542	8.39e-16	.1072436
dink4564	838				
.5149403		.2067319	.1652946	.9062291	
giul4564	838	.4262576	.1970414	.075401	.7177716
nv4564	838	.0588021	.025018	1.04e-15	.1362598
dink64up	838	.452274	.2116553	.1274233	.878423
giul64up	838	.4944641	.2064091	.1025035	.7760187
nv64up	838	.0532619	.0222031	1.02e-15	.1279067

Appendix 5.1

```
. tab longbad decon4yr, col chi2
```

DECON4YR					
LongBAD	Helped	No Diff.	Hurt	DK/NA	Total
Else	105	383	85	40	613
	48.17	51.69	40.87	54.05	49.40
Pessimist	113	358	123	34	628
	51.83	48.31	59.13	45.95	50.60
Total	218	741	208	74	1241
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 8.3857 Pr = 0.039

```
. tab longbad race relations, col chi2
```

RACERELA				
LongBAD	Good	Bad	DK/NA	Total
Else	196	318	99	613
	61.06	41.95	61.11	49.40
Pessimist	125	440	63	628
	38.94	58.05	38.89	50.60
Total	321	758	162	1241
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 43.1649 Pr = 0.000


```
. tab longbad newrace, col chi2
```

NEWRACE				
Longbad	White	Non-White	DK/NA	Total
Else	304	295	14	613
	46.34	52.30	66.67	49.40
Pessimist	352	269	7	628
	53.66	47.70	33.33	50.60
Total	656	564	21	1241
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 6.8638 Pr = 0.032

```
. tab longbad outerdum, col chi2
```

outerdum			
Longbad	Manhattan	Outer boro	Total
Else	154	459	613
	64.17	45.85	49.40
Pessimist	86	542	628
	35.83	54.15	50.60
Total	240	1001	1241
	100.00	100.00	

Pearson chi2(1) = 25.9713 Pr = 0.000

Full Model for Pessimism in 1993

Iteration 0: Log Likelihood = -860.105
 Iteration 1: Log Likelihood = -814.50636
 Iteration 2: Log Likelihood = -814.33955
 Iteration 3: Log Likelihood = -814.33952

Logit Estimates
 chi2(20) = 91.53
 Prob > chi2 = 0.0000
 Log Likelihood = -814.33952
 Number of obs = 1241
 Pseudo R2 = 0.0532

longbad	Coef.	Std. Err.	z	P> z	[95% CI]
libdum	-.2230556	.148802	-1.499	0.134	-.514702 .06859
consdum	.2174775	.151023	1.440	0.150	-.078522 .5134767
dkideodu	.0836173	.266855	0.313	0.754	-.439409 .6066434
whitedum	.3032304	.136425	2.223	0.026	.035843 .570618
dkracedu	-.592758	.489344	-1.211	0.226	-1.55186 .3663394
loincdum	.0284641	.1405936	0.202	0.840	-.247094 .3040224
hiincdum	-.092885	.2136407	-0.435	0.664	-.511613 .3258426
dkincdum	-.1066504	.2494905	-0.427	0.669	-.595643 .382342
racegood	-.6819085	.1408919	-4.840	0.000	-.958052-.4057655
racedk	-.749832	.1837729	-4.080	0.000	-1.1100 -.3896438
crimedum	-.204335	.1445159	-1.414	0.157	-.487581 .0789111
outerdum	.710017	.1598242	4.442	0.000	.396767 1.023267
lthsdum	-.255419	.2149531	-1.188	0.235	-.6767198 .165881
somecoll	-.034977	.1686155	-0.207	0.836	-.3654575 .295503
hsgradum	-.111182	.1628426	-0.683	0.495	-.4303478 .2079835
decong	.1179545	.1615405	0.730	0.465	-.198659 .4345681
deconhrt	.4388969	.1646743	2.665	0.008	.116141 .7616527
decondk	-.1387987	.2550367	-0.544	0.586	-.638662 .361064
jewish	.0046266	.1920415	0.024	0.981	-.371768 .3810211
hispdum	.1209757	.1631497	0.742	0.458	-.198792 .4407432
_cons	-.4188746	.223961	-1.870	0.061	-.857830 .0200809

Parsimonious Model in 1993 for Pessimism

Logit Estimates Number of obs = 1241
 Chi2(8) = 80.17
 Prob > chi2 = 0.0000
 Log Likelihood = -820.01901 Pseudo R2 = 0.0466

longbad	OR	Std. Err.	z	P> z	[95% CI]	
decong	1.106696	.1763283	0.636	0.525	.809856	1.512339
deconhrt	1.565502	.2568426	2.732	0.006	1.13502	2.159261
decondk	.8660317	.2178022	-0.572	0.567	.529007	1.417772
outerdum	2.081937	.32089	4.758	0.000	1.53912	2.816202
racegood	.4954907	.0687084	-5.064	0.000	.377574	.6502337
racedk	.4779392	.0861549	-4.096	0.000	.335685	.6804764
whitedum	1.3096	.1566166	2.255	0.024	1.03596	1.655522
dkracedu	.562388	.2745234	-1.179	0.238	.216039	1.463998

The logit procedure produces the coefficients needed to create the adjusted probabilities.

. logit

```
Logit Estimates                               Number of obs = 1241
Chi2(8)      = 80.17
Prob > chi2   = 0.0000
Log Likelihood = -820.01901                    Pseudo R2   = 0.0466
```

	longbad	Coef.	Std. Err.	z	P> z	[95% CI]
decong	.1013793	.1593285	0.636	0.525	-.2108988	.4136575
deconhrt	.4482065	.1640641	2.732	0.006	.1266468	.7697661
decondk	-.143834	.2514944	-0.572	0.567	-.6367538	.3490863
outerdum	.7332988	.1541305	4.758	0.000	.4312087	1.035389
racegood	-.702207	.1386674	-5.064	0.000	-.97399	-.4304235
racedk	-.738272	.1802633	-4.096	0.000	-1.09158	-.3849622
whitedum	.2697217	.1195912	2.255	0.024	.0353273	.5041162
dkracedu	-.575563	.4881388	-1.179	0.238	-1.532298	.3811711
_cons	-.510448	.1741512	-2.931	0.003	-.851778	-.1691181

I am now going to start to create the adjusted predictors.

```
. *What if everyone was white?
. replace whitedum=1
(585 real changes made)
```

```
. replace dkracedu=0
(21 real changes made)
```

```
. predict ywhite
```

```
. *What if everyone was non-white?
. replace whitedum=0
(1241 real changes made)
```

```
. predict ynonwhit
```

```
. *What if everyone did not know their race?
. replace dkracedu=1
(1241 real changes made)
```

```
. predict ydkrace
```

```
. sum ywhite ynonwhite ydkrace (Racial Responses)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ywhite	1241	.5381764	.1206635	.2454864	.7192569
ynonwhit	1241	.4747449	.119229	.1990004	.6617398
ydkrace	1241	.3439053	.105101	.1225913	.5238553

```
. *What if everyone lived in Manhattan?
. Replace outerdum=0
(1001 real changes made)
```

```
. Predict ymanhat
```

```
. *What if everyone lived in the Outer Boroughs?
. Replace outerdum=1
(1241 real changes made)
```

```
. Predict youter
```

```
. Sum ymanhat youter (Borough of Residence)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ymanhat	1241	.3668683	.0958564	.1225913	.5516847
youter	1241	.539062	.1042048	.2253393	.7192569

```
. *What if everyone thought race relations were good?
. replace racegood=1
(920 real changes made)
```

```
. replace racedk=0
(162 real changes made)
```

```
. predict yracgood
```

```
. replace racegood=0
(1241 real changes made)
```

```
. *What if everyone thought that race relations were bad?
. predict yracebad
```

```
. *What if everyone did not know how race relations were?
. replace racedk=1
(1241 real changes made)
```

```
. predict yracedk
```

```
. sum yracgood yracebad yracedk (Race Relations)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yracgood	1241	.4037878	.0826279	.1432913	.5593618
yracebad	1241	.5723335	.0869484	.2523701	.7192569
yracedk	1241	.3953795	.081939	.1389207	.5504545

```
. *What if everyone thought that Dinkins had helped the economy?
. replace decongnd=1
(1023 real changes made)
```

```
. replace deconhrt=0
(208 real changes made)
```

```
. replace decondk=0
(74 real changes made)
```

```
. predict ydecogd
```

```
*What if everyone thought that Dinkins made no difference with the
economy?
```

```

. replace decong=0
(1241 real changes made)

. predict ydecosam

. replace deconhrt=1
(1241 real changes made)

. *What if everyone thought that Dinkins had hurt the economy?
. predict ydecohrt

. replace decohrt=0
decohrt not found
r(111);

. replace deconhrt=0
(1241 real changes made)
. *What if people didn't know the effect Dinkins had on the economy?

. replace decondk=1
(1241 real changes made)

. predict ydecondk

. sum ydecogd ydecosam ydecohrt ydecondk (Dinkins' effect on the
economy)

```

Variable	Obs	Mean	Std. Dev.	Min	Max
ydecogd	1241	.510192	.1195491	.1514975	.6442714
ydecosam	1241	.4862914	.1187517	.1389207	.6207122
ydecohrt	1241	.5908717	.1183488	.2016398	.7192569
ydecondk	1241	.4524773	.1167513	.1225913	.5863117

```

. sum ywhite ynonwhit ydkrace ymanhat youter yracgood yracebad yracedk
ydecogd ydecosam ydecohrt ydecondk (All of the adjusted probabilities)

```

Variable	Obs	Mean	Std. Dev.	Min	Max
ywhite	1241	.5381764	.1206635	.2454864	.7192569
ynonwhit	1241	.4747449	.119229	.1990004	.6617398
ydkrace	1241	.3439053	.105101	.1225913	.5238553
ymanhat	1241	.3668683	.0958564	.1225913	.5516847
youter	1241	.539062	.1042048	.2253393	.7192569
yracgood	1241	.4037878	.0826279	.1432913	.5593618
yracebad	1241	.5723335	.0869484	.2523701	.7192569
yracedk	1241	.3953795	.081939	.1389207	.5504545
ydecogd	1241	.510192	.1195491	.1514975	.6442714
ydecosam	1241	.4862914	.1187517	.1389207	.6207122
ydecohrt	1241	.5908717	.1183488	.2016398	.7192569
ydecondk	1241	.4524773	.1167513	.1225913	.5863117

Appendix 5.2

```
. *
. *First I will run single variable frequencies
. tab rsex
```

RSEX	Freq.	Percent	Cum.
Male	341	44.75	44.75
Female	421	55.25	100.00
Total	762	100.00	

```
. tab longterm
```

LONGTERM	Freq.	Percent	Cum.
Better P	152	19.95	19.95
About th	183	24.02	43.96
Worse Pl	399	52.36	96.33
DK/NA	28	3.67	100.00
Total	762	100.00	

```
. tab boro
```

BORO	Freq.	Percent	Cum.
Brooklyn	101	13.25	13.25
Bronx	256	33.60	46.85
Manhattan	150	19.69	66.54
Queens	194	25.46	91.99
SI	61	8.01	100.00
Total	762	100.00	

```
. tab register
```

REGISTER	Freq.	Percent	Cum.
Register	762	100.00	100.00
Total	762	100.00	

```
. tab polviews
```

POLVIEWS	Freq.	Percent	Cum.
Liberal	229	30.05	30.05
Moderate	298	39.11	69.16
Conserva	210	27.56	96.72
DK/NA	25	3.28	100.00
Total	762	100.00	

```
. tab educ
```

EDUC	Freq.	Percent	Cum.
LT HS	72	9.45	9.45

HS Grad	223	29.27	38.71
Some Col	175	22.97	61.68
BA	292	38.32	100.00
-----+			
Total	762	100.00	

. tab agecat

AGECAT	Freq.	Percent	Cum.
-----+			
18-29	185	24.28	24.28
30-44	269	35.30	59.58
45-64	212	27.82	87.40
65 and o	96	12.60	100.00
-----+			
Total	762	100.00	

. tab newrace

NEWRACE	Freq.	Percent	Cum.
-----+			
White	444	58.27	58.27
Non-Whit	310	40.68	98.95
DK/NA	8	1.05	100.00
-----+			
Total	762	100.00	

.

tab incclass

INCCLASS	Freq.	Percent	Cum.
Lower	262	34.38	34.38
Middle	360	47.24	81.63
Upper	97	12.73	94.36
DK/NA	43	5.64	100.00
Total	762	100.00	

. tab dinkgiul

DINKGIUL	Freq.	Percent	Cum.
Dinkins	360	47.24	47.24
Giuliani	370	48.56	95.80
Neither/	32	4.20	100.00
Total	762	100.00	

. tab race relations

RACERELA	Freq.	Percent	Cum.
Good	209	27.43	27.43
Bad	471	61.81	89.24
DK/NA	82	10.76	100.00
Total	762	100.00	

. tab Hispanic

HISPANIC	Freq.	Percent	Cum.
Hispanic	107	14.04	14.04
Non-Hisp	650	85.30	99.34
DK/NA	5	0.66	100.00
Total	762	100.00	

tab crime

crime	Freq.	Percent	Cum.
Victim	166	21.78	21.78
No Victi	542	71.13	92.91
DK/NA	54	7.09	100.00
Total	762	100.00	

. tab outerdum

outerdum	Freq.	Percent	Cum.
Else	150	19.69	19.69
Outer bo	612	80.31	100.00
Total	762	100.00	

. tab jewish

jewish	Freq.	Percent	Cum.
Not Jewish	651	85.43	85.43
Jewish	111	14.57	100.00
Total	762	100.00	

. tab dinkgiul

DINKGIUL	Freq.	Percent	Cum.
Dinkins	360	47.24	47.24
Giuliani	370	48.56	95.80
Neither/	32	4.20	100.00
Total	762	100.00	

.

*Now I will work on my cross tabs
 . tab dinkgiul rsex, col chi2

	RSEX		
DINKGIUL	Male	Female	Total
Dinkins	161	199	360
	47.21	47.27	47.24
Giuliani	164	206	370
	48.09	48.93	48.56
Neither/ No Vote	16	16	32
	4.69	3.80	4.20
Total	341	421	762
	100.00	100.00	100.00

Pearson chi2(2) = 0.3840 Pr = 0.825

. tab dinkgiul longterm, col chi2

	LONGTERM				
DINKGIUL	Optimist	Stay Same	Pessimist	DK/NA	Total
Dinkins	103	101	139	17	360
	67.76	55.19	34.84	60.71	47.24
Giuliani	47	71	242	10	370
	30.92	38.80	60.65	35.71	48.56
Neither/ No Vote	2	11	18	1	32
	1.32	6.01	4.51	3.57	4.20
Total	152	183	399	28	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 60.9238 Pr = 0.000

. tab dinkgiul polviews, col chi2

POLVIEWS					
DINKGIUL	Liberal	Moderate	Conservative	DK/NA	Total
Dinkins	141	138	67	14	360
	61.57	46.31	31.90	56.00	47.24
Giuliani	77	146	137	10	370
	33.62	48.99	65.24	40.00	48.56
Neither/ No Vote	11	14	6	1	32
	4.80	4.70	2.86	4.00	4.20
Total	229	298	210	25	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 45.0884 Pr = 0.000

. tab dinkgiul educ, col chi2

EDUC					
DINKGIUL	LT HS	HS Grad	Some Col	BA	Total
Dinkins	41	100	88	131	360
	56.94	44.84	50.29	44.86	47.24
Giuliani	27	115	79	149	370
	37.50	51.57	45.14	51.03	48.56
Neither/ No Vote	4	8	8	12	32
	5.56	3.59	4.57	4.11	4.20
Total	72	223	175	292	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 5.9935 Pr = 0.424

.

```
tab dinkgiul agecat, col chi2
```

	AGECAT				
DINKGIUL	18-29	30-44	45-64	65 plus	Total
Dinkins	97	129	95	39	360
	52.43	47.96	44.81	40.62	47.24
Giuliani	83	127	107	53	370
	44.86	47.21	50.47	55.21	48.56
Neither/ No Vote	5	13	10	4	32
	2.70	4.83	4.72	4.17	4.20
Total	185	269	212	96	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 5.2723 Pr = 0.509

. *Based on the above cross tabs, I suspect that only long term outlook and political viewpoints would be significant in the mlogit

```
. tab dinkgiul newrace, col chi2
```

	NEWRACE			
DINKGIUL	White	Non-Whit	DK/NA	Total
Dinkins	127	229	4	360
	28.60	73.87	50.00	47.24
Giuliani	295	71	4	370
	66.44	22.90	50.00	48.56
Neither/ No Vote	22	10	0	32
	4.95	3.23	0.00	4.20
Total	444	310	8	762
	100.00	100.00	100.00	100.00

Pearson chi2(4) = 152.0958 Pr = 0.000

```
. tab dinkgiul incclass, col chi2
```

	INCCCLASS				
DINKGIUL	Lower	Middle	Upper	DK/NA	Total
Dinkins	146	155	39	20	360
	55.73	43.06	40.21	46.51	47.24
Giuliani	102	195	52	21	370
	38.93	54.17	53.61	48.84	48.56
Neither/ No Vote	14	10	6	2	32
	5.34	2.78	6.19	4.65	4.20
Total	262	360	97	43	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(6) = 17.6718 Pr = 0.007

. *
 . *Based on the above I would hope that both race and income class would
 be significant in the mlogit

. tab dinkgiul racerela, col chi2

	RACE RELATION			
DINKGIUL	Good	Bad	DK/NA	Total
Dinkins	132	177	51	360
	63.16	37.58	62.20	47.24
Giuliani	73	268	29	370
	34.93	56.90	35.37	48.56
Neither/	4	26	2	32
	1.91	5.52	2.44	4.20
Total	209	471	82	762
	100.00	100.00	100.00	100.00

Pearson chi2(4) = 47.2417 Pr = 0.000

tab dinkgiul Hispanic, col chi2

	HISPANIC			
DINKGIUL	Hispanic	Non-Hisp	DK/NA	Total
Dinkins	49	308	3	360
	45.79	47.38	60.00	47.24
Giuliani	54	314	2	370
	50.47	48.31	40.00	48.56
Neither/	4	28	0	32
	3.74	4.31	0.00	4.20
Total	107	650	5	762
	100.00	100.00	100.00	100.00

Pearson chi2(4) = 0.6689 Pr = 0.955

. tab dinkgiul crime, col chi2

	crime			
DINKGIUL	Victim	No Victim	DK/NA	Total
Dinkins	77	257	26	360
	46.39	47.42	48.15	47.24
Giuliani	86	259	25	370
	51.81	47.79	46.30	48.56

Neither/		3	26	3		32
		1.81	4.80	5.56		4.20
-----+-----+-----						
Total		166	542	54		762
		100.00	100.00	100.00		100.00
Pearson chi2(4) = 3.4825 Pr = 0.481						

```
. tab dinkgiul outerdum, col chi2
```

	outerdum		
DINKGIUL	Manhattan	Outer boro	Total

Dinkins	95	265	360
	63.33	43.30	47.24

Giuliani	49	321	370
	32.67	52.45	48.56

Neither/	6	26	32
	4.00	4.25	4.20

Total	150	612	762
	100.00	100.00	100.00

Pearson chi2(2) = 19.9625 Pr = 0.000

```
. tab dinkgiul jewish, col chi2
```

	Jewish		
DINKGIUL	Not Jewish	Jewish	Total

Dinkins	324	36	360
	49.77	32.43	47.24

Giuliani	305	65	370
	46.85	58.56	48.56

Neither/	22	10	32
	3.38	9.01	4.20

Total	651	111	762
	100.00	100.00	100.00

Pearson chi2(2) = 15.8669 Pr = 0.000

. *Ok based on the above I would suspect that being Jewish and outer borough residence are significant factors in the selection process of one who is going to support Giuliani.

. *But, neither Hispanic nor being a crime victim are factors.

*Ok, now onto the mlogit

Fully Saturated Model

```
Iteration 0: Log Likelihood =-638.69416
Iteration 1: Log Likelihood =-468.74633
Iteration 2: Log Likelihood =-455.04368
Iteration 3: Log Likelihood =-454.44166
Iteration 4: Log Likelihood =-454.42533
Iteration 5: Log Likelihood =-454.42004
Iteration 6: Log Likelihood =-454.41809
Iteration 7: Log Likelihood =-454.41738
Iteration 8: Log Likelihood =-454.41712
Iteration 9: Log Likelihood =-454.41702
Iteration 10: Log Likelihood =-454.41698
```



```

Iteration 11: Log Likelihood =-454.41697
Iteration 12: Log Likelihood =-454.41697
Iteration 13: Log Likelihood =-454.41696
Iteration 14: Log Likelihood =-454.41696
Iteration 15: Log Likelihood =-454.41696
Iteration 16: Log Likelihood =-454.41696
Iteration 17: Log Likelihood =-454.41696
Iteration 18: Log Likelihood =-454.41696
Iteration 19: Log Likelihood =-454.41696
Iteration 20: Log Likelihood =-454.41696
Iteration 21: Log Likelihood =-454.41696
Iteration 22: Log Likelihood =-454.41696
Iteration 23: Log Likelihood =-454.41696
Iteration 24: Log Likelihood =-454.41696
Iteration 25: Log Likelihood =-454.41696
Iteration 26: Log Likelihood =-454.41696
Iteration 27: Log Likelihood =-454.41696
Iteration 28: Log Likelihood =-454.41696
Iteration 29: Log Likelihood =-454.41696
Iteration 30: Log Likelihood =-454.41696
Iteration 31: Log Likelihood =-454.41696

```

```

Multinomial regression          Number of obs = 762
chi2(48) = 368.55
Prob > chi2 = 0.0000
Log Likelihood = -454.41696      Pseudo R2 = 0.2885

```

```

-----dinkgiul |
Coef. Std. Err. z P>|z| [95% CI]
-----+-----

```

Dinkins v. Giuliani

```

hispdum | -1.540504 .2927181 -5.263 0.000 -2.114221 -.9667875
jewish | .2056188 .2839771 0.724 0.469 -.3509662 .7622037
somecoll | .2097075 .2723594 0.770 0.441 -.3241072 .7435222
hsgradum | -.2060974 .2622405 -0.786 0.432 -.7200794 .3078846
lthsdum | .1362321 .3963804 0.344 0.731 -.6406593 .9131234
outerdum | -.8684687 .2530353 -3.432 0.001 -.364409 -.3725286
crimedum | -.1681896 .2321433 -0.725 0.469 -.6231822 .2868029
racedk | 1.003124 .3238656 3.097 0.002 .3683589 1.637889
racegood | .7958099 .2279466 3.491 0.000 .3490428 1.242577
incdkdum | .2742249 .4340366 0.632 0.528 -.5764712 1.124921
hiinc | .0531879 .3099394 0.172 0.864 -.5542821 .660658
loinc | .4821892 .2370478 2.034 0.042 .017584 .9467943
ideodk | -.1677451 .5507396 -0.305 0.761 -1.247175 .9116847
consideo | -.7229377 .2497394 -2.895 0.004 -1.212418 -.2334575
libideo | .8482507 .2308706 3.674 0.000 .3957526 1.300749
dkracedu | -1.478887 .8316037 -1.778 0.075 -3.108801 .1510259
whitedum | -2.87207 .2508974 -11.447 0.000 -3.363819 -2.38032
longdk | .2429099 .5274759 0.461 0.645 -.7909239 1.276744
longgood | .4401762 .2906927 1.514 0.130 -.129571 1.009923
longbad | -.9220934 .2377756 -3.878 0.000 -1.388125 -.4560618
rsex | -.1897133 .1990129 -0.953 0.340 -.5797715 .2003449
age65up | -.2768605 .3483108 -0.795 0.427 -.9595371 .4058161
age4564 | .0148732 .2502431 0.059 0.953 -.4755943 .5053408
age1829 | -.0496928 .2573627 -0.193 0.847 -.5541144 .4547287
_cons | 2.762377 .5074948 5.443 0.000 1.767706 3.757049

```

Neither/No Vote V. Giuliani

```

hispdum | -.9148122 .6409108 -1.427 0.153 -2.170974 .3413499
jewish | .8782657 .4866297 1.805 0.071 -.0755109 1.832042

```

```

somecoll | .5604964 .5426764 1.033 0.302 -.5031298 1.624123
hsgradum | .0693931 .5671604 0.122 0.903 -1.042221 1.181007
lthsdum  | .7244766 .7605451 0.953 0.341 -.7661645 2.215118
outerdum | -.2830959 .5330378 -0.531 0.595 -1.327831 .7616391
crimedum | -1.170405 .6399649 -1.829 0.067 -2.424713 .0839028
racedk   | -.2057223 .7898814 -0.260 0.795 -1.753861 1.342417
racegood | -.7683728 .5889387 -1.305 0.192 -1.922671 .3859258
incdkdum | .9306927 .8508171 1.094 0.274 -.7368782 2.598263
hiinc    | .8985589 .5893061 1.525 0.127 -.2564598 2.053578
loinc    | 1.130668 .4868568 2.322 0.020 .1764466 2.08489
ideodk   | -.0600612 1.157371 -0.052 0.959 -2.328467 2.208345
consideo | -.9592978 .538647 -1.781 0.075 -2.015026 .0964309
libideo  | .3135974 .4551885 0.689 0.491 -.5785556 1.20575
dkracedu | -32.45987 1.32e 0.000 1.000 -2.58e 2.58e
whitedum | -1.269362 .511394 -2.482 0.013 -2.271676 -.267047
longdk   | -.7487289 1.172739 -0.638 0.523 -3.047255 1.549797
longgood | -1.316832 .8181448 -1.610 0.107 -2.920366 .2867028
longbad  | -.9255597 .4393917 -2.106 0.035 -1.786752 -.0643679
rsex     | -.4145513 .393558 -1.053 0.292 -1.185911 .3568082
age65up  | -.6338183 .6900604 -0.918 0.358 -1.986312 .7186753
age4564  | -.1216344 .4796551 -0.254 0.800 -1.061741 .8184724
age1829  | -.8230718 .5735605 -1.435 0.151 -1.94723 .3010861
_cons    | -.049585 1.020591 -0.049 0.961 -2.049907 1.950737
-----

```

(Outcome dinkgiul==Giuliani is the comparison group)

. *Based on the mlogit procedure that is essentially interactive in that each variable's predictive value is based in part on how they interact with the others, it is very interesting that being Jewish (for example) is significant here, and being Hispanic is significant. In the cross tabs, it was the opposite. Perhaps this is because taken on their own, they have unequal relationships with support for the candidates, but when put into the context of race for example, they exhibit opposite tendencies.

*Being Jewish is strongly correlated with being white, but being white is slightly correlated with being Hispanic. Therefore, it makes sense that being white might counteract being Jewish in the mlogit but being Hispanic would perhaps be brought out.

. *Back to the mlogit, additionally the influence of outer boro residence is apparent, as is opinions about race relations. Race Relations did not appear as significant in the 1989 equation. Also being pessimistic is significant, another factor that was insignificant in the mlogit equation for 1989. Income class is significant in both so both will stay. Based on the above mlogit I am dropping Jewish, age, education, sex, and crime

Parsimonious Model in 1993

```
. mlogit dinkgiul hispdum outerdum racedk racegood incdkdum hiinc loinc
ideodk consideo libideo dkracedu whitedum longdk longgood longbad
```

```
Iteration 0: Log Likelihood =-638.69416
Iteration 1: Log Likelihood =-474.35624
Iteration 2: Log Likelihood =-462.98843
Iteration 3: Log Likelihood =-462.50661
Iteration 4: Log Likelihood =-462.49302
Iteration 5: Log Likelihood =-462.48847
Iteration 6: Log Likelihood = -462.4868
Iteration 7: Log Likelihood =-462.48619
Iteration 8: Log Likelihood =-462.48596
Iteration 9: Log Likelihood =-462.48588
Iteration 10: Log Likelihood =-462.48585
Iteration 11: Log Likelihood =-462.48584
Iteration 12: Log Likelihood =-462.48583
Iteration 13: Log Likelihood =-462.48583
Iteration 14: Log Likelihood =-462.48583
Iteration 15: Log Likelihood =-462.48583
Iteration 16: Log Likelihood =-462.48583
Iteration 17: Log Likelihood =-462.48583
Iteration 18: Log Likelihood =-462.48583
Iteration 19: Log Likelihood =-462.48583
Iteration 20: Log Likelihood =-462.48583
Iteration 21: Log Likelihood =-462.48583
Iteration 22: Log Likelihood =-462.48583
Iteration 23: Log Likelihood =-462.48583
Iteration 24: Log Likelihood =-462.48583
Iteration 25: Log Likelihood =-462.48583
Iteration 26: Log Likelihood =-462.48583
Iteration 27: Log Likelihood =-462.48583
Iteration 28: Log Likelihood =-462.48583
Iteration 29: Log Likelihood =-462.48583
Iteration 30: Log Likelihood =-462.48583
```

```
Multinomial regression                    Number of obs =   762
chi2(30)    = 352.42
Prob > chi2  = 0.0000
Log Likelihood = -462.48583                Pseudo R2    = 0.2759
```

```
-----+-----
dinkgiul |Coef.  Std. Err.   z   P>|z|   [95% CI]
-----+-----
Dinkins v. Giuliani
    hispdum | -1.511731   .2880171  -5.249  0.000  -2.076234  -.947228
    outerdum | -.9376753   .247066   -3.795  0.000  -1.421916  -.4534349
      racedk | .9331947   .3176603   2.938  0.003   .3105918  1.555797
    racegood | .8179487   .2215284   3.692  0.000   .383761   1.252136
    incdkdum | .1858169   .4249085   0.437  0.662  -.6469885  1.018622
      hiinc  | .0893865   .3031394   0.295  0.768  -.5047559  .6835289
      loinc  | .4174766   .2176092   1.918  0.055  -.0090296  .8439829
      ideodk | -.1425867   .5300487  -0.269  0.788  -1.181463  .8962896
    consideo | -.735277   .2476564  -2.969  0.003  -1.220675  -.249879
      libideo | .8488222   .2272675   3.735  0.000   .4033861  1.294258
    dkracedu | -1.502661   .8266105  -1.818  0.069  -3.122788  .1174663
    whitedum | -2.818358   .2356613  -11.959  0.000  -3.280246  -2.35647
      longdk | .2476393   .5151822   0.481  0.631  -.7620993  1.257378
    longgood | .4283477   .2863442   1.496  0.135  -.1328765  .989572
```

```

longbad | -.8896967 .2344857 -3.794 0.000 -1.34928 -.4301131
_cons | 2.44613 .3766196 6.495 0.000 1.707969 3.184291
-----+-----
Neither/No Vote v. Giuliani

hispdum | -.8924948 .623672 -1.431 0.152 -2.114869 .32988
outerdum | -.3802445 .5202774 -0.731 0.465 -1.39997 .6394805
racedk | -.4491345 .7787799 -0.577 0.564 -1.975515 1.077246
racegood | -.7273377 .5654407 -1.286 0.198 -1.835581 .3809057
incdkdum | .9266715 .8354226 1.109 0.267 -.7107267 2.56407
hiinc | .8904131 .5666411 1.571 0.116 -.2201831 2.001009
loinc | 1.092817 .4465838 2.447 0.014 .2175286 1.968105
ideodk | .0232693 1.121594 0.021 0.983 -2.175015 2.221553
consideo | -.8840251 .5182775 -1.706 0.088 -1.89983 .1317801
libideo | .4022801 .4388642 0.917 0.359 -.4578778 1.262438
dkracedu | -31.35749 8609185 0.000 1.000 -1.69e 1.69e
whitedum | -.9902412 .4633406 -2.137 0.033 -1.898372-.0821103
longdk | -.4728668 1.120335 -0.422 0.673 -2.668683 1.722949
longgood | -1.247779 .8027304 -1.554 0.120 -2.821102 .3255438
longbad | -.7460473 .4253424 -1.754 0.079 -1.579703 .0876086
_cons | -.9815693 .7679957 -1.278 0.201 -2.486813 .5236745
-----+-----

```

(Outcome dinkgiul==Giuliani is the comparison group)

```

.
.
*Ok, now I can start on my recycled predictions
.
.

```

```

. *First I am going to look at Hispanics
.

```

```

. *What if everyone was Hispanic

```

```

. replace hispdum=1

```

```

(655 real changes made)

```

```

. predict hispdink, outcome(1)

```

```

. predict hispgiul, outcome(2)

```

```

. predict hispnlv, outcome(3)

```

```

. sum hispdink hispgiul hispnlv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
hispdink	762	.2999491	.2777739	.0114957	.9690535
hispgiul	762	.6685962	.2785358	.0274971	.9810113
hispnlv	762	.0314547	.0268057	2.77e-16	.1417934

```

. *So, if you were Hispanic in 1993, you would have had a 67%
probability of supporting Giuliani, a 30% probability of supporting
Dinkins and only a 3% probability of supporting neither candidate

```

```

. replace hispdum=0
(762 real changes made)

```

```

. predict nhispdin, outcome(1)

```

```

. predict nhispgiu, outcome(2)

```

```
. predict nhispnv, outcome(3)
```

```
. sum nhispdin nhispgiu nhispnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
nhispdin	762	.5065948	.3147248	.0495784	.9918925
nhispgiu	762	.4511255	.3048291	.0062068	.9330245
nhispnv	762	.0422797	.0361002	2.97e-16	.1782073

```
.
. *So, if you were not Hispanic, you would be more included to support
Dinkins by 51% probability, and have a 45% probability of supporting G.
```

```
.
. replace hispdum=hispbk
(107 real changes made)
```

```
.
. *Now I am going to look at outer borough residents vs. Manhattanites
. replace outerdum=1
(150 real changes made)
```

```
. predict outerdin, outcome(1)
```

```
. predict outergiu, outcome(2)
```

```
. predict outernv, outcome(3)
```

```
. sum outerdin outergiu outernv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
outerdin	762	.4419044	.299808	.013655	.9796457
outergiu	762	.5156098	.291739	.0175691	.9676745
outernv	762	.0424858	.0355868	2.97e-16	.1782073

```
.
. *Outer borough residence makes you 52% more likely to support Giuliani
as compared to 44% to support Dinkins
```

```
.
. replace outerdum=1
(0 real changes made)
```

```
.
. replace outerdum=0
(762 real changes made)
```

```
. predict mandink, outcome(1)
```

```
. predict mangiul, outcome(2)
```

```
. predict mannv, outcome(3)
```

```
. sum mandink mangiul mannv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
mandink	762	.5854686	.2870147	.0338642	.9914241
mangiul	762	.3737718	.2729137	.0069617	.9396192
mannv	762	.0407595	.0363061	2.06e-16	.1686786

. *But, if you were a Manhattan resident, you were 59% more likely to support Dinkins, and only 37% likely to support G

. replace outerdum=outerbk
(612 real changes made)

. *now onto race relations
. replace racegood=1
(553 real changes made)

. replace racedk=0
(82 real changes made)

. predict rgooddin, outcome(1)

. predict rgoodgiu, outcome(2)

. predict rgoodnv, outcome(3)

. sum rgooddin rgoodgiu rgoodnv

Variable	Obs	Mean	Std. Dev.	Min	Max
rgooddin	762	.5586022	.2934296	.0279708	.9914241
rgoodgiu	762	.4218287	.2896427	.0069617	.9633677
rgoodnv	762	.0195691	.0146627	1.26e-16	.0721716

. *If you think that race relations are good, you are 56% more probable to support Dinkins. This makes sense. Non-whites were more likely to think that race relations were good, and to support Dinkins

. replace racegood=racedbk
(553 real changes made)

. corr dinkdum whitedum racegood
(obs=762)

	dinkdum	whitedum	racegood
dinkdum	1.0000		
whitedum	-0.4412	1.0000	
racegood	0.1960	-0.0643	1.0000

. *Non-whites had a negative strong correlations with supporting Dinkins and had a strongish correlation with feeling that race relations were good.

. replace racegood=0
(209 real changes made)

. predict rbaddink, outcome(1)

. predict rbadgiul, outcome(2)

. predict rbadnv, outcome(3)

```
. sum rbaddink rbadgiul rbadnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
rbaddink	762	.4162155	.2913452	.0124236	.9769962
rbadgiul	762	.5278002	.2885798	.0155445	.9695361
rbadnv	762	.0559843	.0385002	4.74e-16	.1782073

```
. *So, if you thought race relations were generally bad in this city you
would be 53% more probable to support Giuliani.
```

```
.
. replace racedk=1
(762 real changes made)
```

```
. predict rdkdink, outcome(1)
```

```
. predict rdkgiul, outcome(2)
```

```
. predict rdknv, outcome(3)
```

```
. sum rdkdink rdkgiul rdknv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
rdkdink	762	.5740789	.2895098	.0311942	.9918925
rdkgiul	762	.4017572	.2844019	.0062068	.9574365
rdknv	762	.0241639	.0181156	1.50e-16	.0887789

```
. *If you didn't know or had no options on race relations you would be
more inclined to support Dinkins by 57%
```

```
.
. replace racegood= racegdbk
(209 real changes made)
```

```
. replace racedk= racedkbk
(680 real changes made)
```

```
.
. *Now I am going to look at income
```

```
.
. replace loinc=1
(500 real changes made)
```

```
. replace hiinc=0
(97 real changes made)
```

```
. replace incdkdum=0
(43 real changes made)
```

```
. *For all low income people
. predict lowdink, outcome(1)
```

```
. predict lowgiul, outcome(2)
```

```
. predict lownv, outcome(3)
```

```
. sum lowdink lowgiul lownv
```

Variable	Obs	Mean	Std. Dev.	Min	Max

```

-----+-----
lowdink | 762 .5027089 .301736 .0170962 .9914241
lowgiul | 762 .4365312 .2840902 .0069617 .9610106
lownv | 762 .0607599 .0436974 2.97e-16 .1782073

. *So if you were low income you were more likely to support Dinkins,
makes sense given that race is a factor with low income people
*
. replace loinc= loincbk
(500 real changes made)

. corr dinkdum whitedum loinc
(obs=762)

      | dinkdum whitedum loinc
-----+-----
dinkdum | 1.0000
whitedum | -0.4412 1.0000
loinc | 0.1230 -0.2222 1.0000

. *The negative correlations between whitedum and loinc indicates a
tendency for non-whites to be low income in this sample
.
. replace loinc=0
(262 real changes made)

. predict middink, outcome(1)

. predict midgiul, outcome(2)

. predict midnv, outcome(3)

. sum middink midgiul midnv

Variable | Obs      Mean   Std. Dev.      Min      Max
-----+-----
middink | 762 .4548714 .3060348 .0114957 .9886417
midgiul | 762 .5194419 .3002252 .010539 .9810113
midnv | 762 .0256867 .0186912 1.32e-16 .0802671

. *Middle income indicates a tendency towards Giuliani. Hmmm. By 52%

.
. replace hiinc=1
(762 real changes made)

. predict hidink, outcome(1)

. predict highiul, outcome(2)

. predict hinv, outcome(3)

. sum hidink highiul hinv

Variable | Obs      Mean   Std. Dev.      Min      Max
-----+-----
hidink | 762 .4555137 .3026566 .0124236 .9885381
highiul | 762 .4871206 .2891662 .0096368 .9695361
hinv | 762 .0573657 .0404197 3.04e-16 .1702534

```



```
. *Evenly split primarily, but more inclined to support Giuliani.
```

```
.
. replace hiinc=hiincbk
(665 real changes made)
```

```
. corr libdum hiinc giuldum
(obs=762)
```

```
      |  libdum  hiinc  giuldum
-----+-----
libdum|   1.0000
hiinc |   0.0159   1.0000
giuldum| -0.1958   0.0386   1.0000
```

```
. corr condum hiinc giuldum
r(111);
```

```
. corr consdum hiinc giuldum
(obs=762)
```

```
      |  consdum  hiinc  giuldum
-----+-----
consdum|   1.0000
hiinc |   0.0288   1.0000
giuldum|   0.2059   0.0386   1.0000
```

```
. *Very slight correlations between conservative or liberal and high
income
```

```
.
. replace hiinc=0
(97 real changes made)
```

```
. replace incdkdum=1
(762 real changes made)
```

```
. predict incdkdin, outcome(1)
```

```
. predict incdkgiu, outcome(2)
```

```
. predict incdknv, outcome(3)
```

```
. sum incdkdin incdkgiu incdknv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
incdkdin	762	.469871	.3029665	.013655	.9895202
incdkgiu	762	.4729443	.2885797	.0087596	.9676745
incdknv	762	.0571848	.0405641	2.96e-16	.169657

```
. *evenly split.
```

```
.
. replace loinc= loincbk
```

```

(262 real changes made)

. replace hiinc= hiincbk
(97 real changes made)

. replace incdkdum= dkincbk
(719 real changes made)

.
.
. *Now onto ideology

.
. *liberals
. replace libideo=1
(533 real changes made)

. replace consideo=0
(210 real changes made)

. replace ideodk=0
(25 real changes made)

. predict libdink, outcome(1)

. predict libgiul, outcome(2)

. predict libnv, outcome(3)

. sum libdink libgiul libnv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
libdink	762	.5895358	.278165	.0741746	.9918925
libgiul	762	.3608912	.256732	.0062068	.8553014
libnv	762	.049573	.0412265	2.85e-16	.1782073

```

. *Liberals in the trad. NY sense, are 59% more likely to support
Dinkins.

. replace libideo=0
(762 real changes made)

. predict moddink, outcome(1)

. predict modgiul, outcome(2)

. predict modnv, outcome(3)

. sum moddink modgiul modnv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
moddink	762	.4581943	.2950416	.033976	.9826869
modgiul	762	.493309	.2819036	.01437	.9239318
modnv	762	.0484967	.037285	4.05e-16	.1686786

```

. *Moderates were slightly more likely to support Giuliani

```

```

.
. replace consideo=1
(762 real changes made)

. predict condink, outcome(1)

. predict congiul, outcome(2)

. predict connv, outcome(3)

. sum condink congiul connv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
condink	762	.3553749	.2863294	.0170962	.9679738
congiul	762	.6176047	.282487	.0295278	.9633677
connv	762	.0270204	.0206966	2.97e-16	.1025208

```

. *But, conservatives were 62% more likely to support Giuliani, huge
margin

```

```

.
. replace consideo=0
(762 real changes made)

. replace ideodk=1
(762 real changes made)

. predict ideodkdn, outcome(1)

. predict ideodkgl, outcome(2)

. predict ideodknv, outcome(3)

. sum ideodkdn ideodkgl ideodknv

```

Variable	Obs	Mean	Std. Dev.	Min	Max
ideodkdn	762	.4349069	.2941111	.0295594	.9800083
ideodkgl	762	.512952	.2814429	.0165271	.9304103
ideodknv	762	.0521411	.0394937	4.66e-16	.1822188

```

. *Now onto everyone white
. replace whitedum=1
(318 real changes made)

. replace dkracedu=0
(8 real changes made)

. predict wdink, outcome(1)

. predict wgiul, outcome(2)

. predict wnv, outcome(3)

. sum wdink wgiul wnv

```

Variable	Obs	Mean	Std. Dev.	Min	Max

```

-----+-----
wdink | 762 .2763351 .2128948 .0114957 .8867275
wgiul | 762 .6756364 .2132619 .1042895 .9810113
wnv | 762 .0480285 .0380218 .0020288 .1782073

. *Whites were 68% more probable to support Giuliani

. replace whitedum=0
(762 real changes made)

. predict nwdink, outcome(1)

. predict nwgiul, outcome(2)

. predict nwnv, outcome(3)

. sum nwdink nwgiul nwnv

Variable | Obs      Mean   Std. Dev.      Min      Max
-----+-----
nwdink | 762 .7561142 .1838942 .1612979 .9914241
nwgiul | 762 .2117329 .1734777 .0069617 .8218053
nwnv | 762 .0321529 .026054 .0008193 .1107569

. *Non whites were 76% more probable to support Dinkins

.
. replace dkracedu=1
(762 real changes made)

. predict dkracdin, outcome(1)

. predict dkracgiu, outcome(2)

. predict dkracnv, outcome(3)

. sum dkracdin dkracgiu dkracnv

Variable | Obs      Mean   Std. Dev.      Min      Max
-----+-----
dkracdin | 762 .5241355 .2486444 .0418501 .9694115
dkracgiu | 762 .4758645 .2486444 .0305885 .95815
dkracnv | 762 2.04e-15 1.68e-15 8.56e-17 7.28e-15

. replace whitedum=whitebk
(444 real changes made)

. replace dkracedu=dkracebk
(754 real changes made)

.
.
. *Long term outlook
.
. *Positive
.
. replace longgood=1
(610 real changes made)

. replace longbad=0

```

(399 real changes made)

. replace longdk=0

(28 real changes made)

. predict lgddink, outcome(1)

. predict lgdgiul, outcome(2)

. predict lgdnv, outcome(3)

. sum lgddink lgdgiul lgdnv

Variable	Obs	Mean	Std. Dev.	Min	Max
lgddink	762	.6097568	.275098	.0615265	.9914241
lgdgiul	762	.3749372	.2700393	.0069617	.9257045
lgdnv	762	.015306	.0122971	2.58e-16	.0512282

. *Positive long-term outlook means a 61% probability of supporting Dinkins

.

. replace longgood=0

(762 real changes made)

. predict lsamedin, outcome(1)

. predict lsamegiu, outcome(2)

. predict lsamenv, outcome(3)

. sum lsamedin lsamegiu lsamenv

Variable	Obs	Mean	Std. Dev.	Min	Max
lsamedin	762	.5193963	.2860358	.0396824	.9808934
lsamegiu	762	.4193867	.2707857	.0105707	.9235221
lsamenv	762	.0612171	.0440985	9.44e-16	.1782073

. *If you felt that the city would remain the same you were more likely to support Dinkins 52% to 42% with 6% supporting neither/no vote.

*

.

. replace longbad=1

(762 real changes made)

. predict lbaddink, outcome(1)

. predict lbadgiul, outcome(2)

. predict lbadnv, outcome(3)

. sum lbaddink lbadgiul lbadnv

Variable	Obs	Mean	Std. Dev.	Min	Max
lbaddink	762	.3899554	.287113	.0170962	.9649893
lbadgiul	762	.5663997	.2830558	.025316	.9664922
lbadnv	762	.0436449	.0300432	4.74e-16	.1280739

. *If you were negative about the city's future you were 57% more probable to vote for Giuliani

.

. replace longbad=0

(762 real changes made)

. replace longdk=1

(762 real changes made)

. predict ldkdink, outcome(1)

. predict ldkgiul, outcome(2)

. predict ldknv, outcome(3)

. sum ldkdink ldkgiul ldknv

Variable	Obs	Mean	Std. Dev.	Min	Max
ldkdink	762	.5709038	.2813985	.0511109	.9875116
ldkgiul	762	.3938256	.2709114	.0083076	.921307
ldknv	762	.0352706	.0270368	5.73e-16	.1106747

. *If you were unclear about the city's future or didn't know, you were 57% more probable to support Dinkins.

.

. Interesting

Appendix 5.3

. *This will be my mlogit with an interaction term for race and class.

Note: nwhiteuc dropped due to collinearity.

```
Iteration 0: Log Likelihood =-638.69416
Iteration 1: Log Likelihood =-384.73348
Iteration 2: Log Likelihood =-333.49615
Iteration 3: Log Likelihood =-325.25459
Iteration 4: Log Likelihood =-324.41217
Iteration 5: Log Likelihood =-324.38041
Iteration 6: Log Likelihood =-324.37736
Iteration 7: Log Likelihood =-324.37625
Iteration 8: Log Likelihood =-324.37584
Iteration 9: Log Likelihood = -324.3757
Iteration 10: Log Likelihood =-324.37564
Iteration 11: Log Likelihood =-324.37562
Iteration 12: Log Likelihood =-324.37561
Iteration 13: Log Likelihood =-324.37561
Iteration 14: Log Likelihood =-324.37561
Iteration 15: Log Likelihood =-324.37561
Iteration 16: Log Likelihood =-324.37561
Iteration 17: Log Likelihood =-324.37561
Iteration 18: Log Likelihood =-324.37561
Iteration 19: Log Likelihood =-324.37561
Iteration 20: Log Likelihood =-324.37561
Iteration 21: Log Likelihood =-324.37561
Iteration 22: Log Likelihood =-324.37561
Iteration 23: Log Likelihood =-324.37561
Iteration 24: Log Likelihood =-324.37561
Iteration 25: Log Likelihood =-324.37561
Iteration 26: Log Likelihood =-324.37561
Iteration 27: Log Likelihood =-324.37561
Iteration 28: Log Likelihood =-324.37561
Iteration 29: Log Likelihood =-324.37561
Iteration 30: Log Likelihood =-324.37561
Iteration 31: Log Likelihood =-324.37561
```

```
Multinomial regression          Number of obs = 762
chi2(70) = 628.64
Prob > chi2 = 0.0000
Log Likelihood = -324.37561      Pseudo R2 = 0.4921
```

```
-----+-----
dinkgiul |Coef.  Std. Err.  z    P>|z|    [95% CI]
-----+-----
Dinkins v. Giuliani
|
  rsex |-.1854179 .2506957 -0.740 0.460 -.6767724 .3059367
  longbad |-.8183318 .2957405 -2.767 0.006 -1.39797 -.2386909
  longgood|.7292409 .3819523 1.909 0.056 -.019371 1.477854
  longdk |1.032733 .7459063 1.385 0.166 -.429216 2.494682
  libdum|.3527438 .2869531 1.229 0.219 -.209674 .9151616
  consdum|-.7374136 .3205262 -2.301 0.021 -1.36563 -.1091938
  dkideodu|-.3620811 .68726 -0.527 0.598 -1.70909 .9849238
  whitedum|-1.334555 1.003751 -1.330 0.184 -3.30187 .6327606
  dkracedu|-16.38306 1.441245 -11.37 0.000 -19.2079 -13.55828
  loincdum|.5811991 2.064772 0.281 0.778 -3.46568 4.628077
  hiincdum|.7573113 1.27471 0.594 0.552 -1.74108 3.255706
  dkincdum|-.14.9658 . . . . .
  racegood|.809292 .2823739 2.866 0.004 .2558493 1.362735
```

```

racedk | 1.30034 .4502538 2.888 0.004 .4178665 2.182829
crimedum | .014661 .2938893 0.050 0.960 -.561352 .5906733
outerdum | -1.06969 .327891 -3.262 0.001 -1.71228 -.4269733
lths dum | -.012490 .5002215 -0.025 0.980 -.992906 .9679257
somecoll | .5215109 .3485359 1.496 0.135 -.1616068 1.204629
hsgradum | -.0872159 .331812 -0.263 0.793 -.7375545 .5631226
decong d | .0053553 .3211209 0.017 0.987 -.62403 .6347406
deconhrt | -.038935 .3286913 -0.118 0.906 -.683158 .6052882
decondk | .2443786 .6246307 0.391 0.696 -.979875 1.468632
jewish | -.118460 .3581183 -0.331 0.741 -.820359 .5834386
hispdum | -1.39914 .340662 -4.107 0.000 -2.06683 -.7314558
whitewc | .1373084 2.09965 0.065 0.948 -3.97793 4.252547
nwhitewc | .9274975 2.292487 0.405 0.686 -3.56569 5.420689
nwhitemc | 1.060509 1.053261 1.007 0.314 -1.00384 3.124862
whiteuc | -.449652 1.311604 -0.343 0.732 -3.020348 2.121044
giul89 | -5.238465 .575985 -9.095 0.000 -6.367374 -4.109555
wont89 | -2.681148 .7824896 -3.426 0.001 -4.214799 -1.147496
didnt89 | -1.897065 .286549 -6.620 0.000 -2.45869 -1.33544
age1829 | .1751584 .321340 0.545 0.586 -.454657 .8049739
age4564 | .0314906 .3261205 0.097 0.923 -.607694 .670675
age65up | -.318703 .485066 -0.657 0.511 -1.269415 .6320086
dkclass | 15.68967 .7465082 21.017 0.000 14.22654 17.1528
_cons | 2.893221 1.163017 2.488 0.013 .6137501 5.172692
-----
Neither/No Vote v. Giuliani
rsex | -.3737689 .4261699 -0.877 0.380 -1.20905 .4615087
longbad | -.8469212 .474659 -1.784 0.074 -1.77724 .0833938
longgood | -1.246677 .891375 -1.399 0.162 -2.99374 .5003858
longdk | -1.180003 1.33003 -0.887 0.375 -3.78681 1.4268
libdum | .0491976 .500778 0.098 0.922 -.932309 1.030704
consdum | -.858357 .593794 -1.446 0.148 -2.02217 .3054579
dkideodu | -.129323 1.23639 -0.105 0.917 -2.55261 2.293965
whitedum | -2.21551 1.731181 -1.280 0.201 -5.608559 1.177546
dkracedu | -29.2908 1.36e 0.000 1.000 -2.66e 2.66e
loincdum | .8970241 1.844428 0.486 0.627 -2.717989 4.512037
hiincdum | .4597659 2.008047 0.229 0.819 -3.475934 4.395466
dkincdum | 4.515403 .
racegood | -.6428224 .6148126 -1.046 0.296 -1.847833 .5621882
racedk | .1513339 .8302992 0.182 0.855 -1.476023 1.77869
crimedum | -1.14049 .6680961 -1.707 0.088 -2.449934 .1689546
outerdum | -.411681 .5786728 -0.711 0.477 -1.545859 .7224969
lths dum | .5436647 .8390023 0.648 0.517 -1.10075 2.188079
somecoll | .9324707 .5835311 1.598 0.110 -.2112293 2.076171
hsgradum | -.056049 .6107937 -0.092 0.927 -1.253183 1.141085
decong d | -1.505722 .7235629 -2.081 0.037 -2.92388 -.0875652
deconhrt | -.4928715 .6354319 -0.776 0.438 -1.738295 .7525521
decondk | .2741059 .882953 0.310 0.756 -1.45645 2.004662
jewish | .7285989 .5525503 1.319 0.187 -.3543797 1.811578
hispdum | -1.295545 .648852 -1.997 0.046 -2.56727 -.0238188
whitewc | .5206694 1.81736 0.286 0.774 -3.041291 4.08263
nwhitewc | -1.322638 .
nwhitemc | -1.486107 1.917409 -0.775 0.438 -5.244159 2.271945
whiteuc | -.1675847 2.05748 -0.081 0.935 -4.200171 3.865002
giul89 | -2.850493 .856231 -3.329 0.001 -4.52868 -1.172311
wont89 | .9991149 .7649218 1.306 0.191 -.5001044 2.498334
didnt89 | .1946378 .5154721 0.378 0.706 -.815669 1.204945
age1829 | -1.165703 .6259306 -1.862 0.063 -2.392504 .0610985
age4564 | .0944323 .5205681 0.181 0.856 -.9258624 1.114727
age65up | -.4829272 .7890928 -0.612 0.541 -2.029521 1.063666
dkclass | -4.469123 1.247887 -3.581 0.000 -6.91494 -2.023309
_cons | 1.829069 2.017036 0.907 0.365 -2.124248 5.782387

```

(Outcome dinkgiul==Giuliani is the comparison group)

Appendix 6.1

```
tab dinkgiul vote1989, col chi2
```

vote1989						
DINKGIUL	Dink.	Giul.	No Say	No vote	DK/NA	Total

Dinkins	273	4	1	79	3	360
	80.29	1.92	10.00	41.80	20.00	47.24

Giuliani	57	202	5	95	11	370
	16.76	97.12	50.00	50.26	73.33	48.56

Neither/	10	2	4	15	1	32
	2.94	0.96	40.00	7.94	6.67	4.20

Total	340	208	10	189	15	762
	100.00	100.00	100.00	100.00	100.00	100.00

```
Pearson chi2(8) = 392.8102 Pr = 0.000
```

```
. mlogit dinkgiul giul89 wont89 didnt89, rrr
```

```
Iteration 0: Log Likelihood =-638.69416
Iteration 1: Log Likelihood =-451.19788
Iteration 2: Log Likelihood =-425.69566
Iteration 3: Log Likelihood = -423.0173
Iteration 4: Log Likelihood =-422.76974
Iteration 5: Log Likelihood =-422.76517
Iteration 6: Log Likelihood =-422.76517
```

```
Multinomial regression      Number of obs = 762
                           chi2(6) = 431.86
Prob > chi2 = 0.0000
Log Likelihood = -422.76517      Pseudo R2 = 0.3381
```

dinkgiul	RRR	Std. Err.	z	P> z	[95% CI]	

Dinkins						
giul89	.0041345	.0021727	-10.44	0.000	.0014761	.0115806
wont89	.0521978	.0301533	-5.111	0.000	.0168242	.1619455
didnt89	.1736264	.0365818	-8.310	0.000	.1148878	.2623963

Neither/						
giul89	.0564356	.0445268	-3.643	0.000	.0120218	.2649337
wont89	1.78125	1.0981	0.936	0.349	.5320822	5.963085
didnt89	.9	.397161	-0.239	0.811	.3789796	2.137318

```
(Outcome dinkgiul==Giuliani is the comparison group)
(Dinkins is the comparison group for the 1989 voters.)
```

```
. mlogit dinkgiul giul89 wont89 didnt89
```

```
Iteration 0: Log Likelihood =-638.69416
Iteration 1: Log Likelihood =-451.19788
Iteration 2: Log Likelihood =-425.69566
Iteration 3: Log Likelihood = -423.0173
Iteration 4: Log Likelihood =-422.76974
Iteration 5: Log Likelihood =-422.76517
Iteration 6: Log Likelihood =-422.76517
```

```
Multinomial regression                      Number of obs = 762
Chi2(6)      = 431.86
Prob > chi2   = 0.0000
Log Likelihood = -422.76517                Pseudo R2    = 0.3381
```

```
-----
-----
dinkgiul |Coef.  Std. Err.      z    P>|z|    [95% CI]
```

```
-----+-----
Dinkins v. Giuliani
```

```
giul89 | -5.48839   .525506  -10.444  0.000  -6.518368  -.45842
wont89 | -2.95271   .577673   -5.111  0.000  -4.08493  -.820495
didnt89 | -1.75085   .210692   -8.310  0.000  -2.1638  -1.337899
 _cons | 1.566421   .145625   10.756  0.000   1.28099  1.851842
-----+-----
```

```
Neither/No Vote v. Giuliani
```

```
giul89 | -2.874654   .7889831  -3.643  0.000  -4.42103  -1.328276
wont89 | .5773154   .616477   0.936  0.349  -.630957  1.785588
didnt89 | -.105361   .44129   -0.239  0.811  -.970273  .7595519
 _cons | -1.74046   .3428467  -5.077  0.000  -2.41243  -1.068499
-----+-----
```

```
(Outcome dinkgiul==Giuliani is the comparison group)
(Dinkins is the comparison group for the 1989 voters.)
```

```
. lrtest, saving (0)
```

```
. quietly mlogit dinkgiul vote1989
```

```
. lrtest
```

```
Mlogit: likelihood-ratio test                chi2(4)    = 361.96
Prob > chi2 = 0.0000
```

```
. Recycled predictors.
```

```
. *What if everyone was for Dinkins in 1989
. replace giul89=0
(208 real changes made)
```

```
. replace wont89=0
(25 real changes made)
```

```
. replace didnt89=0
(189 real changes made)
```

```
. predict d89dink, outcome(1)
```

```
. predict d89giul, outcome(2)
. predict d89nv, outcome(3)
. sum d89giul d89dink d89nv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
d89giul	762	.1676471	0	.1676471	.1676471
d89dink	762	.8029412	0	.8029412	.8029412
d89nv	762	.0294118	0	.0294118	.0294118

```
. * Now what if everyone was for Giuliani
```

```
. replace giul89=1
(762 real changes made)
```

```
. predict g89dink, outcome(1)
. predict g89giul, outcome(2)
. predict g89nv, outcome(3)
. sum g89dink g89giul g89nv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
g89dink	762	.0192308	0	.0192308	.0192308
g89giul	762	.9711539	0	.9711539	.9711539
g89nv	762	.0096154	0	.0096154	.0096154

```
. * Now what if everyone won't say how they voted in 1989
. replace giul89=0
(762 real changes made)
```

```
. replace wont89=1
(762 real changes made)
```

```
. predict wnt89din, outcome(1)
. predict wnt89giu, outcome(2)
. predict wnt89nv, outcome(3)
. sum wnt89din wnt89giu wnt89nv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
wnt89din	762	.16	0	.16	.16
wnt89giu	762	.64	0	.64	.64
wnt89nv	762	.2	0	.2	.2

```
.
. *Now what if everyone didn't vote in 1989
. replace wont89=0
(762 real changes made)
```

```
. replace didnt89=1
(762 real changes made)
```

```
. predict dnt89din, outcome(1)
. predict dnt89giu, outcome(2)
. predict dnt89wnv, outcome(3)
. sum dnt89din dnt89giu dnt89wnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
dnt89din	762	.4179894	0	.4179894	.4179894
dnt89giu	762	.5026455	0	.5026455	.5026455
dnt89wnv	762	.0793651	0	.0793651	.0793651

```
. sum d89dink d89giul d89nv g89dink g89giul g89nv wnt89din wnt89giu
wnt89nv dnt89din dnt89giu dnt89wnv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
d89dink	762	.8029412	0	.8029412	.8029412
d89giul	762	.1676471	0	.1676471	.1676471
d89nv	762	.0294118	0	.0294118	.0294118
g89dink	762	.0192308	0	.0192308	.0192308
g89giul	762	.9711539	0	.9711539	.9711539
g89nv	762	.0096154	0	.0096154	.0096154
wnt89din	762	.16	0	.16	.16
wnt89giu	762	.64	0	.64	.64
wnt89nv	762	.2	0	.2	.2
dnt89din	762	.4179894	0	.4179894	.4179894
dnt89giu	762	.5026455	0	.5026455	.5026455
dnt89wnv	762	.0793651	0	.0793651	.0793651

Appendix 6.2

Dummy variable created for those who switched from Dinkins to Giuliani versus those who did not switch or did not vote.

d89g93	Freq.	Percent	Cum.
0	705	92.52	92.52
1	57	7.48	100.00
Total	762	100.00	

Cross tabulations showing the relationship between the dummy variable and other independent variables.

d89g93	RSEX		Total
	Male	Female	
0	320	385	705
	93.84	91.45	92.52
1	21	36	57
	6.16	8.55	7.48
Total	341	421	762
	100.00	100.00	100.00

Pearson $\chi^2(1) = 1.5585$ Pr = 0.212

LONGTERM					
d89g93	Better	Same	Worse	DK/NA	Total
0	145	171	361	28	905
	95.39	93.44	90.48	100.00	92.52
1	7	12	38	0	57
	4.61	6.56	9.52	0.00	7.48
Total	152	183	399	28	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 6.7120 Pr = 0.082

POLVIEWS					
d89g93	Liberal	Moderate	Conser.	DK/NA	Total
0	212	277	192	24	705
	92.58	92.95	91.43	96.00	92.52
1	17	21	18	1	57
	7.42	7.05	8.57	4.00	7.48
Total	229	298	210	25	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 0.8807 Pr = 0.830

EDUC					
d89g93	LT HS	HS Grad	Some College	BA	Total
0	69	199	170	267	705
	95.83	89.24	97.14	91.44	92.52
1	3	24	5	25	57
	4.17	10.76	2.86	8.56	7.48
Total	72	223	175	292	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 10.5111 Pr = 0.015

AGECAT					
d89g93	18-29	30-44	45-64	65 plus	Total
0	177	245	193	90	705
	95.68	91.08	91.04	93.75	92.52
1	8	24	19	6	57
	4.32	8.92	8.96	6.25	7.48
Total	185	269	212	96	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 4.3530 Pr = 0.226

NEWRACE				
d89g93	White	Non-Whit	DK/NA	Total
0	407	291	7	705
	91.67	93.87	87.50	92.52
1	37	19	1	57
	8.33	6.13	12.50	7.48
Total	444	310	8	762
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 1.5760 Pr = 0.455

INCCCLASS					
d89g93	Lower	Middle	Upper	DK/NA	Total
0	248	329	87	41	705
	94.66	91.39	89.69	95.35	92.52
1	14	31	10	2	57
	5.34	8.61	10.31	4.65	7.48
Total	262	360	97	43	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 4.0127 Pr = 0.260

RACE RELATIONS				
d89g93	Good	Bad	DK/NA	Total
0	196	429	80	705
	93.78	91.08	97.56	92.52
1	13	42	2	57
	6.22	8.92	2.44	7.48
Total	209	471	82	762
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 4.8959 Pr = 0.086

HISPANIC				
d89g93	Hispanic	Non-Hisp	DK/NA	Total
0	96	604	5	705
	89.72	92.92	100.00	92.52
1	11	46	0	57
	10.28	7.08	0.00	7.48
Total	107	650	5	762
	100.00	100.00	100.00	100.00

Pearson chi2(2) = 1.7693 Pr = 0.413

DECON4YR					
d89g93	Helped	No Diff.	Hurt	DK/NA	Total
0	134	405	121	45	705
	95.04	91.22	93.08	95.74	92.52
1	7	39	9	2	57
	4.96	8.78	6.92	4.26	7.48
Total	141	444	130	47	762
	100.00	100.00	100.00	100.00	100.00

Pearson chi2(3) = 3.1441 Pr = 0.370

crimedum			
d89g93	Else	Victim	Total
0	553	152	705
	92.79	91.57	92.52
1	43	14	57
	7.21	8.43	7.48
Total	596	166	762
	100.00	100.00	100.00

Pearson chi2(1) = 0.2788 Pr = 0.598

outerdum			
d89g93	Manhattan	Outer boro	Total
0	142	563	705
	94.67	91.99	92.52
1	8	49	57
	5.33	8.01	7.48
Total	150	612	762
	100.00	100.00	100.00

Pearson chi2(1) = 1.2439 Pr = 0.265

Jewish			
d89g93	Non-Jewish	Jewish	Total
0	605	100	705
	92.93	90.09	92.52
1	46	11	57
	7.07	9.91	7.48
Total	651	111	762
	100.00	100.00	100.00

Pearson chi2(1) = 1.1082 Pr = 0.292
 Now here are the logistic regression coefficients.

```
. logistic d89g93 hispdum jewish decondk deconhrt decong d hsgradum
somecoll lthsdum outerdum crimedum racedk racegood dkincdum hiincdum
loincdum dkracedu whitedum dkideodu consdum libdum longdk longgood
longbad rsex
```

Note: longdk=0 predicts failure perfectly
 longdk dropped and 28 obs not used

```
Number of obs = 734
chi2(23) = 36.51
Prob > chi2 = 0.0366
Log Likelihood = -182.13246 Pseudo R2 = 0.0911
```

```
-----
d89g93 | OR Std. Err. z P>|z| [95% CI]
-----+-----
hispdum | 2.449604 1.045399 2.099 0.036 1.061292 5.65401
jewish | 1.552716 .6262386 1.091 0.275 .7043476 3.422923
decondk | .5975887 .4547783 -0.677 0.499 .134468 2.655741
deconhrt | .7811506 .311126 -0.620 0.535 .3578558 1.705146
decong d | .5658537 .2505716 -1.286 0.198 .2375607 1.347826
hsgradum | 1.652933 .5747658 1.445 0.148 .8361255 3.267677
somecoll | .3118527 .1643508 -2.211 0.027 .111008 .8760822
lthsdum | .6818817 .4636111 -0.563 0.573 .1798777 2.584881
outerdum | 1.396149 .6012395 0.775 0.438 .6003014 3.24709
crimedum | 1.156883 .3885523 0.434 0.664 .5989683 2.234473
racedk | .2978838 .2253239 -1.601 0.109 .0676371 1.311924
racegood | .9537246 .3393488 -0.133 0.894 .4748466 1.915546
dkincdum | .4368015 .3453927 -1.047 0.295 .0927283 2.057576
hiincdum | 1.375404 .572725 0.765 0.444 .6081147 3.110819
loincdum | .5715672 .214076 -1.493 0.135 .2743194 1.190908
dkracedu | 2.672807 3.169033 0.829 0.407 .2616583 27.30239
whitedum | 1.502067 .5506325 1.110 0.267 .7322392 3.08124
dkideodu | 1.054969 1.161482 0.049 0.961 .1219268 9.128107
consdum | 1.190246 .4236688 0.489 0.625 .5924488 2.391236
libdum | 1.091488 .3879451 0.246 0.805 .5438491 2.190582
longgood | .7383155 .3754121 -0.597 0.551 .2725402 2.000108
longbad | 1.492053 .5455727 1.094 0.274 .7286859 3.055119
rsex | 1.645689 .5050269 1.623 0.105 .9018458 3.003056
```

** So, being Hispanic and having attended some college are the only significant predictors

```
Iteration 0: Log Likelihood = -200.38825
Iteration 1: Log Likelihood = -184.58032
Iteration 2: Log Likelihood = -182.22918
Iteration 3: Log Likelihood = -182.1329
Iteration 4: Log Likelihood = -182.13246
Iteration 5: Log Likelihood = -182.13246
```

```
Logit Estimates Number of obs = 734
chi2(23) = 36.51
Prob > chi2 = 0.0366
Log Likelihood = -182.13246 Pseudo R2 = 0.0911
```

d89g93	Coef.	Std. Err.	z	P> z	[95% CI]
hispdum	.8959263	.4267623	2.099	0.036	.0594875 1.732365
jewish	.4400058	.4033181	1.091	0.275	-.3504833 1.230495
decondk	-.514852	.7610223	-0.677	0.499	-2.006429 .9767238
deconhrt	-.246987	.398292	-0.620	0.535	-1.027625 .5336506
decong	-.569419	.4428206	-1.286	0.198	-1.437332 .2984926
hsgradum	.5025514	.3477247	1.445	0.148	-.1789766 1.184079
somecoll	-1.16522	.5270143	-2.211	0.027	-2.198153 -.132295
lthsdum	-.382899	.6798996	-0.563	0.573	-1.715478 .9496797
outerdum	.3337179	.4306412	0.775	0.438	-.5103234 1.177759
crimedum	.1457295	.3358613	0.434	0.664	-.5125466 .8040055
racedk	-1.21105	.7564152	-1.601	0.109	-2.693598 .271495
racegood	-.047380	.3558143	-0.133	0.894	-.7447635 .6500028
dkincdum	-.828276	.7907314	-1.047	0.295	-2.378081 .7215286
hiincdum	.3187472	.4164051	0.765	0.444	-.4973917 1.134886
loincdum	-.559373	.3745421	-1.493	0.135	-1.293462 .1747158
dkracedu	.9831293	1.185657	0.829	0.407	-1.340716 3.306974
whitedum	.406842	.3665833	1.110	0.267	-.311648 1.125332
dkideodu	.0535118	1.100962	0.049	0.961	-2.104335 2.211358
consdum	.1741597	.3559507	0.489	0.625	-.5234909 .8718103
libdum	.0875419	.3554277	0.246	0.805	-.6090836 .7841674
longgood	-.303384	.5084711	-0.597	0.551	-1.299969 .6932011
longbad	.400153	.3656524	1.094	0.274	-.3165125 1.116818
rsex	.4981593	.3068786	1.623	0.105	-.1033117 1.09963
_cons	-3.90798	.8158611	-4.790	0.000	-5.507041 -.308925

```
. ** Now for the parsimonious model

. logit d89g93 hispdum hsgradum somecoll lths dum

Iteration 0: Log Likelihood = -202.6079
Iteration 1: Log Likelihood = -196.13971
Iteration 2: Log Likelihood = -195.62089
Iteration 3: Log Likelihood = -195.6126
Iteration 4: Log Likelihood = -195.61259

Logit Estimates               Number of obs = 762
                        chi2(4) = 13.99
                        Prob > chi2 = 0.0073
Log Likelihood = -195.61259      Pseudo R2 = 0.0345
```

```
-----+-----
d89g93 | Coef.  Std. Err.  z    P>|z|  [95% CI]
-----+-----
hispdum | .5547048 .3642385  1.523  0.128  -.1591895 .268599
hsgradum | .2006259 .3038545  0.660  0.509  -.394918 .7961698
somecoll | -1.22807 .503194  -2.441  0.015  -2.21431 -.2418275
lths dum | -.8911789 .6337846  -1.406  0.160  -2.133374 .3510161
_cons | -2.41992 .2133482 -11.34  0.000  -2.838075 -2.001766
-----+-----
```

```
.
. lrtest, saving (0)

. quietly logit d89g93 hispdum

. lrtest
Logit: likelihood-ratio test      chi2(3)    = 12.69
                        Prob > chi2 = 0.0053

. quietly logit d89g93 educ

. lrtest
Logit: likelihood-ratio test      chi2(3)    = 13.98
                        Prob > chi2 = 0.0029

. quietly logit d89g93 educ hispdum

. lrtest
Logit: likelihood-ratio test      chi2(2)    = 12.62
                        Prob > chi2 = 0.0018
quietly logit d89g93 educ

. lrtest
Logit: likelihood-ratio test      chi2(3)    = 13.98
                        Prob > chi2 = 0.0029

. quietly logit d89g93 educ hispdum

. lrtest
Logit: likelihood-ratio test      chi2(2)    = 12.62
                        Prob > chi2 = 0.0018
. quietly logit d89g93 hispdum

. lrtest
Logit: likelihood-ratio test      chi2(3)    = 12.69
                        Prob > chi2 = 0.0053
```

. **So, education is the biggest contributor.
.
.

```
. logistic d89g93 hisp dum hsgradum somecoll lthsdum
```

```
Logit Estimates               Number of obs = 762
                        chi2(4) = 13.99
                        Prob > chi2 = 0.0073
Log Likelihood = -195.61259      Pseudo R2 = 0.0345
```

```
-----+-----
d89g93 | Odds Ratio   Std. Err.   z    P>|z|   [95% CI]
-----+-----
hisp dum | 1.741427   .6342947  1.523  0.128   .8528347  3.555868
hsgradum | 1.222167   .3713611  0.660  0.509   .6737353  2.217033
somecoll | .2928573   .1473641 -2.441  0.015   .1092286  .7851916
lthsdum  | .4101719   .2599607 -1.406  0.160   .118437   1.42051
-----+-----
```

```
. lstat
```

```
Logistic model for d89g93
```

```
-----+----- True -----
Classified |      D      ~D      Total
-----+-----+-----
+ |      0      0 |      0
- |     57     705 |     762
-----+-----+-----
Total |     57     705 |     762
```

```
Classified + if predicted Pr(D) >= .5
True D defined as d89g93 ~= 0
```

```
-----+-----
Sensitivity           Pr( + | D)  0.00%
Specificity           Pr( - | ~D) 100.00%
Positive predictive value   Pr( D | +)   .%
Negative predictive value   Pr(~D | -)  92.52%
-----+-----
False + rate for true ~D   Pr( + | ~D)  0.00%
False - rate for true D    Pr( - | D) 100.00%
False + rate for classified + Pr(~D | +)   .%
False - rate for classified - Pr( D | -)  7.48%
-----+-----
```

```
Correctly classified      92.52%
```

```
. ** Actually, since Hispanic is no longer significant, I can drop it
out (BA is the reference).
```

```
. logit d89g93 hsgradum somecoll lthsdum
```

```
Iteration 0: Log Likelihood = -202.6079
Iteration 1: Log Likelihood = -197.08938
Iteration 2: Log Likelihood = -196.68472
Iteration 3: Log Likelihood = -196.67858
Iteration 4: Log Likelihood = -196.67857
```

```
Logit Estimates               Number of obs = 762
                        chi2(3) = 11.86
                        Prob > chi2 = 0.0079
Log Likelihood = -196.67857      Pseudo R2 = 0.0293
```

```
-----+-----
d89g93 | Coef.   Std. Err.   z    P>|z|   [95% CI]
-----+-----
```

```

hsgradum | .2531218 .3007276 0.842 0.400 -.3362935 .8425372
somecoll | -1.157988 .4996274 -2.318 0.020 -2.13723 -.1787359
lths dum | -.7671214 .6257567 -1.226 0.220 -1.99358 .4593391
_cons | -2.368373 .2091538 -11.32 0.000 -2.77830 -1.958439
-----

```

```

. ** Now onto recycled predictors
. ** What if everyone was a high school dropout

```

```

. replace lths dum=1
(690 real changes made)

```

```

. replace hsgradum=0
(223 real changes made)

```

```

. replace somecoll=0
(175 real changes made)

```

```

. predict ylths

```

```

. **Now what if everyone was a high school grad
. replace lths dum=0
(762 real changes made)

```

```

. replace hsgraddum=1
hsgraddu not found
r(111);

```

```

. replace hsgradum=1
(762 real changes made)

```

```

. predict yhsgrad

```

```

. ** Now what if everyone had some college
. replace hsgradum=0
(762 real changes made)

```

```

. replace somecoll=1
(762 real changes made)

```

```

. predict ysomcol

```

```

. ** Now what if everyone had a ba
. replace somecol=0
(762 real changes made)

```

```

. predict yba

```

```

. sum ylths yhsgrad ysomcol yba

```

Variable	Obs	Mean	Std. Dev.	Min	Max
ylths	762	.0416667	0	.0416667	.0416667
yhsgrad	762	.1076233	0	.1076233	.1076233
ysomcol	762	.0285714	0	.0285714	.0285714
yba	762	.0856164	0	.0856164	.0856164

Data from the Exit Polls
Frequencies

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Everyone Else	1526516	85.4	88.5	88.5
	Dinkins in 1989 and Giuliani in 1993	197691	11.1	11.5	100.0
	Total	1724207	96.4	100.0	
Missing	System Missing	63772	3.6		
	Total	63772	3.6		
Total		1787979	100.0		

Crosstabs**Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * AGECAT****Crosstab**

			AGECAT				
			18-29	30-44	45-59	60+	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	328764	500033	382856	293817	1505470
		Row %	21.8%	33.2%	25.4%	19.5%	100.0%
		% of Total	19.3%	29.4%	22.5%	17.3%	88.4%
	Dinkins in 1989 and Giuliani in 1993	Count	15764	64541	48964	68422	197691
		Row %	8.0%	32.6%	24.8%	34.6%	100.0%
		% of Total	.9%	3.8%	2.9%	4.0%	11.6%
	Total	Count	344528	564574	431820	362239	1703161
		Row %	20.2%	33.1%	25.4%	21.3%	100.0%
		% of Total	20.2%	33.1%	25.4%	21.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	35369.411 ^a	3	.000
Likelihood Ratio	37144.867	3	.000
Linear-by-Linear Association	30477.166	1	.000
N of Valid Cases	1703161		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 39990.40.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * EDUC

Crosstab

		EDUC					
			HSDrop	HSGrad	SomeColl	Coll	Collplus
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	105077	379303	397047	344939	232186
		row %	7.2%	26.0%	27.2%	23.6%	15.9%
		% of Total	6.4%	23.0%	24.0%	20.9%	14.1%
	Dinkins in 1989 and Giuliani in 1993	Count	7820	52058	41276	52128	39952
		row %	4.0%	26.9%	21.4%	27.0%	20.7%
		% of Total	.5%	3.2%	2.5%	3.2%	2.4%
	Total		Count	112897	431361	438323	397067
			row %	6.8%	26.1%	26.5%	24.0%
			% of Total	6.8%	26.1%	26.5%	24.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	7883.662 ^a	4	.000
Likelihood Ratio	8217.739	4	.000
Linear-by-Linear Association	4033.377	1	.000
N of Valid Cases	1651786		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13207.24.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * Jewish or Non-Jewish

Crosstab

			Jewish or Non-Jewish		
			Non-Jewish	Jewish	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	1323593	202923	1526516
		row %	86.7%	13.3%	100.0%
		% of Total	76.8%	11.8%	88.5%
	Dinkins in 1989 and Giuliani in 1993	Count	122295	75396	197691
		row %	61.9%	38.1%	100.0%
		% of Total	7.1%	4.4%	11.5%
	Total	Count	1445888	278319	1724207
		row %	83.9%	16.1%	100.0%
		% of Total	83.9%	16.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	79814.443 ^b	1	.000		
Continuity Correction ^a	79812.608	1	.000		
Likelihood Ratio	64871.812	1	.000		
Fisher's Exact Test					
Linear-by-Linear Association	79814.397	1	.000		
N of Valid Cases	1724207				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 31911.00.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * Income Class

Crosstab

			Income Class				
			Low Income	Middle Income	High Income	Income DK	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	477747	669892	207455	171422	1526516
		row %	31.3%	43.9%	13.6%	11.2%	100.0%
		% of Total	27.7%	38.9%	12.0%	9.9%	88.5%
	Dinkins in 1989 and Giuliani in 1993	Count	56363	91944	32359	17025	197691
		row %	28.5%	46.5%	16.4%	8.6%	100.0%
		% of Total	3.3%	5.3%	1.9%	1.0%	11.5%
	Total	Count	534110	761836	239814	188447	1724207
		row %	31.0%	44.2%	13.9%	10.9%	100.0%
		% of Total	31.0%	44.2%	13.9%	10.9%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2780.248 ^a	3	.000
Likelihood Ratio	2816.865	3	.000
Linear-by-Linear Association	522.752	1	.000
N of Valid Cases	1724207		

^a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 21606.61.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * IDEOLOGY

Crosstab

			IDEOLOGY				
			Liberal	Moderate	Conserv	DNS	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	425393	587884	400204	113035	1526516
		row %	27.9%	38.5%	26.2%	7.4%	100.0%
		% of Total	24.7%	34.1%	23.2%	6.6%	88.5%
	Dinkins in 1989 and Giuliani in 1993	Count	56300	100781	31683	8927	197691
		row %	28.5%	51.0%	16.0%	4.5%	100.0%
		% of Total	3.3%	5.8%	1.8%	.5%	11.5%
	Total	Count	481693	688665	431887	121962	1724207
		row %	27.9%	39.9%	25.0%	7.1%	100.0%
		% of Total	27.9%	39.9%	25.0%	7.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	16156.258 ^a	3	.000
Likelihood Ratio	16881.494	3	.000
Linear-by-Linear Association	4458.992	1	.000
N of Valid Cases	1724207		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13983.70.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * White v. Nonwhite

Crosstab

			White v. Nonwhite			
			Non-white	White	9.00	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	727590	770691	28235	1526516
		row %	47.7%	50.5%	1.8%	100.0%
		% of Total	42.2%	44.7%	1.6%	88.5%
	Dinkins in 1989 and Giuliani in 1993	Count	35992	159698	2001	197691
		row %	18.2%	80.8%	1.0%	100.0%
		% of Total	2.1%	9.3%	.1%	11.5%
	Total	Count	763582	930389	30236	1724207
		row %	44.3%	54.0%	1.8%	100.0%
		% of Total	44.3%	54.0%	1.8%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	64762.376 ^a	2	.000
Likelihood Ratio	70092.921	2	.000
Linear-by-Linear Association	6151.282	1	.000
N of Valid Cases	1724207		

^a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 3466.74.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * RACEREL

Crosstab

			RACEREL			
			Better	Worse	Same	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	194502	811366	472234	1478102
		row %	13.2%	54.9%	31.9%	100.0%
		% of Total	11.6%	48.5%	28.2%	88.3%
	Dinkins in 1989 and Giuliani in 1993	Count	4940	144433	46453	195826
		row %	2.5%	73.8%	23.7%	100.0%
		% of Total	.3%	8.6%	2.8%	11.7%
	Total	Count	199442	955799	518687	1673928
		row %	11.9%	57.1%	31.0%	100.0%
		% of Total	11.9%	57.1%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	30971.444 ^a	2	.000
Likelihood Ratio	37353.845	2	.000
Linear-by-Linear Association	255.609	1	.000
N of Valid Cases	1673928		

^a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 23331.91.

Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * SAFETY

Crosstab

			SAFETY			
				Less		
			Safer	Safe	Same	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	251559	771372	444883	1467814
		row %	17.1 %	52.6%	30.3%	100.0%
		% of Total	15.1 %	46.3%	26.7%	88.2%
	Dinkins in 1989 and Giuliani in 1993	Count	1306	165424	30368	197098
		row %	.7%	83.9%	15.4%	100.0%
		% of Total	.1 %	9.9%	1.8%	11.8%
Total		Count	252865	936796	475251	1664912
		row %	15.2%	56.3%	28.5%	100.0%
		% of Total	15.2%	56.3%	28.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	74978.957 ^a	2	.000
Likelihood Ratio	95442.928	2	.000
Linear-by-Linear Association	102.634	1	.000
N of Valid Cases	1664912		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 29935.03.

**Voted for Dinkins in 1989 and Giuliani in 1993 Dummy * Hispanic Origin
Crosstabulation**

			Hispanic Origin		
			Non-Hispanic	Hispanic	Total
Voted for Dinkins in 1989 and Giuliani in 1993 Dummy	Everyone Else	Count	1338290	188226	1526516
		row %	87.7%	12.3%	100.0%
	Dinkins in 1989 and Giuliani in 1993	Count	171723	25968	197691
		row %	86.9%	13.1%	100.0%
Total		Count	1510013	214194	1724207
		row %	87.6%	12.4%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	104.308 ^b	1	.000		
Continuity Correction ^a	104.234	1	.000		
Likelihood Ratio	102.861	1	.000		
Fisher's Exact Test					
Linear-by-Linear Association	104.308	1	.000		
N of Valid Cases	1724207				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 24558.67.

Appendix 7.1

EZI Created Variables and their means

```
sum tot93 dnd93 rwg93 totvap nhwvap nhbvap hvap nhasvap pmc plc puc
pdink93 pgiul93 turn93 pwhite pblack pasian phisp wturn93 wvoter
actwvote wdink93 wgiul93 bturn93 bvoter93 bacto93 bgiul93 hturn
phgiul93 aturn93 agiul93
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	5256	335.4519	161.285	1	914
dnd93	5256	162.0987	139.7386	0	808
rwg93	5256	173.3531	157.4022	0	881
totvap	5256	1062.338	577.1671	4	15814
nhwvap	5256	505.2641	466.6194	0	6548
nhbvap	5256	248.5993	391.5798	0	6367
hvap	5256	231.9195	311.4979	0	3502
nhasvap	5256	71.58505	152.2879	0	2287
pmc	5256	.3832199	.1024273	0	1
plc	5256	.4086448	.1992255	0	1
puc	5256	.2081354	.1617381	0	1
pdink93	5256	.4997131	.3255836	0	1
pgiul93	5256	.5002869	.3255836	0	1
turn93	5256	.3362961	.1313621	.0024752	1
pwhite	5256	.4853181	.3628086	0	.9934711
pblack	5256	.233338	.3067966	0	.9819563
pasian	5256	.060824	.0887199	0	.9798629
phisp	5256	.2158272	.2182426	0	.9583333
wturn93	5256	.4037856	.1123277	0	1
wvoter	5256	196.7166	181.4711	0	887.2888
actwvote	5256	.5512597	.3703126	0	.9952826
wdink93	5234	.2499658	.2102881	0	1
wgiul93	5256	.7449261	.2148911	0	1
bturn93	5256	.2998038	.1235878	0	1
bvoter93	5256	75.35932	133.3721	0	2366.614
bacto93	5256	.2258976	.3132886	0	1
bgiul93	5256	.0645254	.0769006	0	1
hturn	5256	.1326171	.0817006	0	1
phgiul93	5256	.1492271	.0671958	0	1
aturn93	5256	.3856416	.1380428	0	1
agiul93	5256	.5607591	.2409317	0	1

. *Now for the sum of 1989 votes

```
. dnd89 rwg89 tot89 pdink89 pgiul89 turn89 wturn89 wgiul89 bturn89
bvoter89 bacto89 bgiul89 hturn89 hvot89 hvoter89 hgiul89 aturn89
asvote89 avoter89 agiul89
```

```
. sum dnd89 rwg89 tot89 pdink89 pgiul89 turn89 wturn89 wgiul89 bturn89
bvoter89 bacto89 bgiul89 hturn89 hvot89 hvoter89 hgiul89 aturn89
asvote89 avoter89 agiul89
```

Variable	Obs	Mean	Std. Dev.	Min	Max
dnd89	5256	168.8411	141.994	0	1270
rwg89	5256	161.1499	141.931	0	665
tot89	5256	330.652	157.1391	1	1282
pdink89	5256	.5171573	.3132966	0	1
pgiul89	5256	.4809962	.3135332	0	1
turn89	5256	.3297548	.1212821	.0086207	.9132321
wturn89	5256	.3873213	.0948982	0	.9272

```

wgiul89 | 5256 .731011 .2219423 0 1
bturn89 | 5256 .3516857 .1387121 0 .9602
bvoter89 | 5256 88.39961 154.1361 0 2607.923
bactvo89 | 5256 .2513652 .3388054 0 1
bgiul89 | 5256 .0525399 .0552629 0 1
hturn89 | 5256 .1451453 .0848833 0 .8717
hvot89 | 5256 35.81726 64.34955 0 1398.92
hvoter89 | 5256 .1316796 .201406 0 1
hgiul89 | 5256 .110813 .0586907 0 1
aturn89 | 5256 .3210935 .1077174 0 .5966
asvote89 | 5256 22.31195 53.28897 0 996.4459
avoter89 | 5256 .0796164 .1550216 0 1
agiul89 | 5256 .4765646 .2103677 0 1

```

. *Now for the regressions

. regress wgiul89 pwhite pmc puc bronxdum manhdum queendum sidum

```

Source |      SS      df      MS      Number of obs = 5256
-----+-----
Model | 70.7606279      7 10.1086611      F( 7, 5248) = 282.04
Residual | 188.09228 5248 .035840755      Prob > F = 0.0000
-----+-----
Total | 258.852908 5255 .049258403      R-squared = 0.2734
                                           Adj R-squared = 0.2724
                                           Root MSE = .18932

```

```

-----
wgiul89 |      Coef.      Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
pwhite | .2693583   .0093933    28.676  0.000   .2509436   .2877731
pmc | -.0868396   .0280985    -3.091  0.002  -.1419244  -.0317548
puc | -.2467422   .0216123   -11.417  0.000  -.2891113  -.2043731
bronxdum | .0904389   .0081207    11.137  0.000   .0745189   .1063589
manhdum | -.1497524   .0076753   -19.511  0.000  -.1647991  -.1347057
queendum | .0922571   .0073576    12.539  0.000   .0778331   .1066811
sidum | .1138441   .0129619     8.783  0.000   .0884333   .1392548
_cons | .6700504   .0112468    59.577  0.000   .648002   .6920987

```

. regress wgiul93 pwhite pmc puc bronxdum manhdum queendum sidum

```

Source |      SS      df      MS      Number of obs = 5256
-----+-----
Model | 76.1018334      7 10.8716905      F( 7, 5248) = 342.54
Residual | 166.564484 5248 .031738659      Prob > F = 0.0000
-----+-----
Total | 242.666318 5255 .046178177      R-squared = 0.3136
                                           Adj R-squared = 0.3127
                                           Root MSE = .17815

```

```

-----
wgiul93 |      Coef.      Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
pwhite | .2862916   .0088394    32.388  0.000   .2689627   .3036205
pmc | -.1689698   .0264417    -6.390  0.000  -.2208066  -.1171331
puc | -.2702534   .0203379   -13.288  0.000  -.3101243  -.2303826
bronxdum | .0743391   .0076419     9.728  0.000   .0593578   .0893204
manhdum | -.1520457   .0072227   -21.051  0.000  -.1662052  -.1378863

```

```

queendum | .1038722 .0069238 15.002 0.000 .0902987 .1174457
sidum | .1342704 .0121976 11.008 0.000 .110358 .1581828
_cons | .7109467 .0105836 67.174 0.000 .6901984 .731695

```

```
. regress wgiuldif pwhite pmc puc bronxdum manhdum queendum sidum
```

```

Source |      SS      df      MS      Number of obs = 5256
-----+-----
Model | .723439659      7 .103348523      F( 7, 5248) = 5.82
Residual | 93.2305476 5248 .017764967      Prob > F = 0.0000
-----+-----
Total | 93.9539873 5255 .01787897      R-squared = 0.0077
                                           Adj R-squared = 0.0064
                                           Root MSE = .13329

```

```

wgiuldif |      Coef.      Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
pwhite | .0169333 .0066132 2.561 0.010 .0039687 .0298979
pmc | -.0821303 .0197823 -4.152 0.000 -.1209118 -.0433487
puc | -.0235113 .0152158 -1.545 0.122 -.0533406 .006318
bronxdum | -.0160998 .0057173 -2.816 0.005 -.027308 -.0048915
manhdum | -.0022933 .0054036 -0.424 0.671 -.0128867 .0083001
queendum | .011615 .00518 2.242 0.025 .00146 .02177
sidum | .0204264 .0091256 2.238 0.025 .0025363 .0383164
_cons | .0408964 .0079181 5.165 0.000 .0253736 .0564191

```

```
. regress bgiul89 pwhite pmc puc bronxdum manhdum queendum sidum
```

```

Source |      SS      df      MS      Number of obs = 5256
-----+-----
Model | .207730794      7 .029675828      F( 7, 5248) = 9.83
Residual | 15.8409533 5248 .003018474      Prob > F = 0.0000
-----+-----
Total | 16.0486841 5255 .003053984      R-squared = 0.0129
                                           Adj R-squared = 0.0116
                                           Root MSE = .05494

```

```

bgiul8 |      Coef.      Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
pwhite | -.0029277 .002726 -1.074 0.283 -.0082718 .0024163
pmc | .0554837 .0081543 6.804 0.000 .0394978 .0714696
puc | .0030288 .006272 0.483 0.629 -.0092669 .0153246
bronxdum | .0003543 .0023567 0.150 0.880 -.0042657 .0049744
manhdum | .0017375 .0022274 0.780 0.435 -.0026291 .0061042
queendum | .0029734 .0021352 1.393 0.164 -.0012125 .0071593
sidum | -.0076133 .0037616 -2.024 0.043 -.0149876 -.000239
_cons | .0313249 .0032639 9.597 0.000 .0249264 .0377235

```

```
. regress bgiul93 pwhite pmc puc bronxdum manhdum queendum sidum
```

```

Source |      SS      df      MS      Number of obs = 5256
-----+-----
Model | .460047778      7 .065721111      F( 7, 5248) = 11.27
Residual | 35.4442222 5248 .006747777      Prob > F = 0.0000
-----+-----
Total | 35.9089999 5255 .006788889

```

Residual		30.616461	5248	.005833929		R-squared	=	0.0148
	+					Adj R-squared	=	0.0135
Total		31.0765088	5255	.005913703		Root MSE	=	.07638

bgiul93		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite		.0200555	.0037897	5.292	0.000	.012626 .0274849
pmc		.0039461	.0113364	0.348	0.728	-.018278 .0261701
puc		-.052452	.0087195	-6.015	0.000	-.0695459 -.0353581
bronxdum		.005255	.0032763	1.604	0.109	-.001168 .0116779
manhdum		.0103601	.0030966	3.346	0.001	.0042895 .0164307
queendum		.0181007	.0029685	6.098	0.000	.0122813 .0239201
sidum		.0021069	.0052295	0.403	0.687	-.0081452 .0123589
_cons		.0565907	.0045375	12.472	0.000	.0476953 .0654862

. regress bgiuldif pwhite pmc puc bronxdum manhdum queendum sidum

Source		SS	df	MS	Number of obs = 5256	
	+					F(7, 5248) = 11.97
Model		.40184667	7	.057406667	Prob > F = 0.0000	
Residual		25.1745554	5248	.004796981	R-squared = 0.0157	
	+					Adj R-squared = 0.0144
Total		25.5764021	5255	.00486706	Root MSE = .06926	

bgiuldif		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite		.0229832	.0034365	6.688	0.000	.0162463 .0297201
pmc		-.0515376	.0102797	-5.014	0.000	-.0716901 -.0313852
puc		-.0554808	.0079067	-7.017	0.000	-.0709813 -.0399803
bronxdum		.0049006	.0029709	1.650	0.099	-.0009236 .0107249
manhdum		.0086226	.0028079	3.071	0.002	.0031178 .0141273
queendum		.0151274	.0026917	5.620	0.000	.0098504 .0204043
sidum		.0097202	.004742	2.050	0.040	.0004238 .0190165
_cons		.0252658	.0041146	6.141	0.000	.0171996 .033332

. regress agiul89 pwhite pmc puc bronxdum manhdum queendum sidum

Source		SS	df	MS	Number of obs = 5256	
	+					F(7, 5248) = 56.02
Model		16.1698832	7	2.30998331	Prob > F = 0.0000	
Residual		216.387876	5248	.041232446	R-squared = 0.0695	
	+					Adj R-squared = 0.0683
Total		232.557759	5255	.044254569	Root MSE = .20306	

agiul89		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite		.1068032	.0100751	10.601	0.000	.0870518 .1265545
pmc		.3330494	.030138	11.051	0.000	.2739664 .3921325

puc	-.060189	.023181	-2.596	0.009	-.1056334	-.0147445
bronzdum	.039849	.0087102	4.575	0.000	.0227735	.0569245
manhdum	.031526	.0082324	3.830	0.000	.0153871	.0476648
queendum	.0069624	.0078917	0.882	0.378	-.0085085	.0224334
sidum	.0489917	.0139027	3.524	0.000	.0217365	.0762468
_cons	.2928572	.0120631	24.277	0.000	.2692085	.3165059

. regress agiul93 pwhite pmc puc bronzdum manhdum queendum sidum

Source	SS	df	MS	Number of obs = 5256	F(7, 5248) = 54.55
Model	20.68849	7	2.95549857	Prob > F = 0.0000	R-squared = 0.0678
Residual	284.35431	5248	.054183367	Adj R-squared = 0.0666	Root MSE = .23277
Total	305.0428	5255	.058048106		

agiul93	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite	.1190449	.0115495	10.307	0.000	.0964031 .1416866
pmc	.3470056	.0345484	10.044	0.000	.2792764 .4147348
puc	-.0243261	.0265733	-0.915	0.360	-.0764209 .0277686
bronzdum	.0445942	.0099848	4.466	0.000	.0250198 .0641685
manhdum	.025713	.0094371	2.725	0.006	.0072124 .0442136
queendum	.0136574	.0090465	1.510	0.131	-.0040776 .0313924
sidum	.053595	.0159373	3.363	0.001	.0223514 .0848387
_cons	.3567173	.0138284	25.796	0.000	.3296078 .3838267

. regress agiuldif pwhite pmc puc bronzdum manhdum queendum sidum

Source	SS	df	MS	Number of obs = 5256	F(7, 5248) = 9.66
Model	.597256229	7	.085322318	Prob > F = 0.0000	R-squared = 0.0127
Residual	46.3483356	5248	.008831619	Adj R-squared = 0.0114	Root MSE = .09398
Total	46.9455918	5255	.008933509		

agiuldif	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite	.0122417	.0046628	2.625	0.009	.0031006 .0213828
pmc	.0139562	.0139481	1.001	0.317	-.0133879 .0413002
puc	.0358628	.0107283	3.343	0.001	.0148308 .0568949
bronzdum	.0047452	.0040311	1.177	0.239	-.0031575 .0126479
manhdum	-.0058129	.00381	-1.526	0.127	-.0132821 .0016563
queendum	.006695	.0036523	1.833	0.067	-.0004651 .013855
sidum	.0046033	.0064343	0.715	0.474	-.0080105 .0172172
_cons	.0638601	.0055829	11.439	0.000	.0529153 .0748049

```
. regress hgiul89 pwhite pmc puc bronxdum manhdum queendum sidum
```

Source	SS	df	MS	Number of obs =	5256
Model	.098226623	7	.014032375	f=(7, 5248) =	4.09
Residual	18.0031228	5248	.003430473	Prob > F =	0.0002
				R-squared =	0.0054
				Adj R-squared =	0.0041
Total	18.1013494	5255	.003444596	Root MSE =	.05857

hgiul89	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite	.0106094	.0029061	3.651	0.000	.0049123 .0163065
pmc	-.0053362	.008693	-0.614	0.539	-.0223782 .0117058
puc	-.0059593	.0066864	-0.891	0.373	-.0190673 .0071488
bronxdum	-.001114	.0025124	-0.443	0.657	-.0060393 .0038113
manhdum	-.0040776	.0023746	-1.717	0.086	-.0087327 .0005775
queendum	.0043256	.0022763	1.900	0.057	-.0001368 .0087881
sidum	.001243	.0040101	0.310	0.757	-.0066185 .0091046
_cons	.1087325	.0034795	31.250	0.000	.1019113 .1155538

```
. regress phgiul93 pwhite pmc puc bronxdum manhdum queendum sidum
```

Source	SS	df	MS	Number of obs =	5256
Model	.684753851	7	.097821979	F(7, 5248) =	22.28
Residual	23.0430281	5248	.004390821	Prob > F =	0.0000
				R-squared =	0.0289
				Adj R-squared =	0.0276
Total	23.727782	5255	.004515277	Root MSE =	.06626

phgiul93	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite	.0195801	.0032878	5.955	0.000	.0131347 .0260255
pmc	-.012217	.0098349	-1.242	0.214	-.0314974 .0070634
puc	.01584	.0075646	2.094	0.036	.0010102 .0306697
bronxdum	-.0031548	.0028424	-1.110	0.267	-.008727 .0024174
manhdum	-.0092419	.0026864	-3.440	0.001	-.0145084 -.0039753
queendum	.0124855	.0025753	4.848	0.000	.0074369 .0175341
sidum	-.0091434	.0045368	-2.015	0.044	-.0180375 -.0002493
_cons	.140678	.0039365	35.737	0.000	.1329607 .1483952

```
. regress hgiuldif pwhite pmc puc bronxdum manhdum queendum sidum
```

Source	SS	df	MS	Number of obs =	5256
Model	.305464814	7	.043637831	F(7, 5248) =	5.66
Residual	40.452326	5248	.007708141	Prob > F =	0.0000
				R-squared =	0.0075
				Adj R-squared =	0.0062
Total	40.7577908	5255	.007756002	Root MSE =	.0878

hgiuldif	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]

-----+-----						

pwhite		.008896	.0043562	2.042	0.041	.0003561 .0174358
pmc		-.0068543	.0130308	-0.526	0.599	-.0324 .0186914
puc		.0228475	.0100228	2.280	0.023	.0031987 .0424963
bronzdum		-.0017152	.003766	-0.455	0.649	-.0090982 .0056677
manhdum		-.0050874	.0035594	-1.429	0.153	-.0120653 .0018906
queendum		.0078281	.0034121	2.294	0.022	.0011389 .0145173
sidum		-.0103277	.0060111	-1.718	0.086	-.022112 .0014566
_cons		.0315048	.0052157	6.040	0.000	.0212798 .0417297

. regress wturn89 pwhite pmc puc bronzdum manhdum queendum sidum

Source		SS	df	MS	Number of obs =	5256
-----+-----						
Model		3.65687646	7	.522410923	F(7, 5248) =	62.78
Residual		43.6679211	5248	.008320869	Prob > F	= 0.0000
-----+-----						
Total		47.3247976	5255	.00900567	R-squared	= 0.0773
					Adj R-squared =	0.0760
					Root MSE	= .09122

-----+-----						

wturn89		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----						
pwhite		-.0312648	.004526	-6.908	0.000	-.0401376 -.022392
pmc		-.0386982	.0135388	-2.858	0.004	-.0652398 -.0121566
puc		.17371	.0104135	16.681	0.000	.1532952 .1941249
bronzdum		.263089	.0039128	6.724	0.000	.0186381 .0339797
manhdum		.0055361	.0036982	1.497	0.134	-.0017139 .012786
queendum		-.0047381	.0035451	-1.337	0.181	-.0116881 .0022118
sidum		.0246842	.0062455	3.952	0.000	.0124405 .0369279
_cons		.3758911	.0054191	69.365	0.000	.3652675 .3865148

. regress wturn93 pwhite pmc puc bronzdum manhdum queendum sidum

Source		SS	df	MS	Number of obs =	5256
-----+-----						
Model		9.04131938	7	1.29161705	F(7, 5248) =	118.37
Residual		57.263681	5248	.010911525	Prob > F	= 0.0000
-----+-----						
Total		66.3050004	5255	.012617507	R-squared	= 0.1364
					Adj R-squared =	0.1352
					Root MSE	= .10446

-----+-----						

wturn93		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----						
pwhite		-.0440611	.0051829	-8.501	0.000	-.0542217 -.0339005
pmc		-.0741983	.0155038	-4.786	0.000	-.1045921 -.0438044
puc		.2279341	.0119249	19.114	0.000	.2045563 .2513119
bronzdum		.0176749	.0044807	3.945	0.000	.0088908 .026459
manhdum		-.0042843	.0042349	-1.012	0.312	-.0125866 .0040179
queendum		-.0195042	.0040597	-4.804	0.000	-.0274629 -.0115456
sidum		.0853356	.0071519	11.932	0.000	.0713148 .0993563
_cons		.4046228	.0062056	65.203	0.000	.3924573 .4167884

```
. regress woutdif pwhite pmc puc bronxdum manhdum queendum sidum
```

Source	SS	df	MS	Number of obs =	5256
Model	1.98001825	7	.28285975	F(7, 5248) =	81.13
Residual	18.2967763	5248	.003486428	Prob > F =	0.0000
				R-squared =	0.0976
				Adj R-squared =	0.0964
Total	20.2767945	5255	.003858572	Root MSE =	.05905

woutdif	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite	-.0127963	.0029297	-4.368	0.000	-.0185396 -.0070529
pmc	-.0355001	.0087637	-4.051	0.000	-.0526805 -.0183197
puc	.0542241	.0067407	8.044	0.000	.0410096 .0674386
bronxdum	-.008634	.0025328	-3.409	0.001	-.0135993 -.0036687
manhdum	-.0098204	.0023938	-4.102	0.000	-.0145133 -.0051275
queendum	-.0147661	.0022948	-6.435	0.000	-.0192648 -.0102674
sidum	.0606514	.0040427	15.003	0.000	.052726 .0685767
_cons	.0287317	.0035078	8.191	0.000	.021855 .0356084

```
. regress bturn89 pwhite pmc puc bronxdum manhdum queendum sidum
```

Source	SS	df	MS	Number of obs =	5256
Model	2.69200823	7	.384572605	F(7, 5248) =	20.51
Residual	98.4197523	5248	.018753764	Prob > F =	0.0000
				R-squared =	0.0266
				Adj R-squared =	0.0253
Total	101.111761	5255	.019241058	Root MSE =	.13694

bturn89	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
pwhite	-.0310035	.0067947	-4.563	0.000	-.044324 -.0176829
pmc	-.0436421	.0203254	-2.147	0.032	-.0834883 -.0037958
puc	.0141827	.0156335	0.907	0.364	-.0164655 .044831
bronxdum	-.03302	.0058742	-5.621	0.000	-.0445359 -.0215041
manhdum	.006393	.005552	1.016	0.310	-.0052449 .0165235
queendum	.0184592	.0053222	3.468	0.001	.0080254 .028893
sidum	.0720477	.0093762	7.684	0.000	.0536665 .0904289
_cons	.3758327	.0081355	46.197	0.000	.3598837 .3917816

```
. regress bturn93 pwhite pmc puc bronxdum manhdum queendum sidum
```

Source	SS	df	MS	Number of obs =	5256
Model	1.28444979	7	.183492828	F(7, 5248) =	12.19
Residual	78.9800897	5248	.01504956	Prob > F =	0.0000
				R-squared =	0.0160
				Adj R-squared =	0.0147

Total | 80.2645395 5255 .015273937 Root MSE = .12268

bturn93	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pwhite	-.016349	.0060868	-2.686	0.007	-.0282817	-.0044163
pmc	-.0159243	.0182078	-0.875	0.382	-.0516191	.0197705
puc	.001119	.0140047	0.080	0.936	-.0263361	.0285741
bronzdum	-.0255675	.0052622	-4.859	0.000	-.0358836	-.0152514
manhdum	-.0086565	.0049736	-1.741	0.082	-.0184068	.0010937
queendum	.0065728	.0047677	1.379	0.168	-.0027739	.0159196
sidum	.0507255	.0083993	6.039	0.000	.0342594	.0671916
_cons	.3147877	.0072879	43.193	0.000	.3005004	.329075

. regress boutdif pwhite pmc puc bronxdum manhdum queendum sidum

Source	SS	df	MS	Number of obs =	5256
Model	.475961257	7	.067994465	F(7, 5248) =	12.85
Residual	27.768153	5248	.005291188	Prob > F =	0.0000
Total	28.2441142	5255	.005374713	R-squared =	0.0169
				Adj R-squared =	0.0155
				Root MSE =	.07274

boutdif	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pwhite	.0146545	.0036092	4.060	0.000	.007579	.0217299
pmc	.0277178	.0107962	2.567	0.010	.0065527	.0488828
puc	-.0130638	.008304	-1.573	0.116	-.0293431	.0032156
bronzdum	.0074525	.0031202	2.388	0.017	.0013356	.0135694
manhdum	-.0142958	.002949	-4.848	0.000	-.0200772	-.0085145
queendum	-.0118864	.002827	-4.205	0.000	-.0174285	-.0063443
sidum	-.0213222	.0049803	-4.281	0.000	-.0310857	-.0115587
_cons	-.061045	.0043213	-14.126	0.000	-.0695165	-.0525734

. regress aturn89 pwhite pmc puc bronxdum manhdum queendum sidum

Source	SS	df	MS	Number of obs =	5256
Model	1.42837315	7	.204053307	F(7, 5248) =	17.98
Residual	59.5455863	5248	.011346339	Prob > F =	0.0000
Total	60.9739594	5255	.011603037	R-squared =	0.0234
				Adj R-squared =	0.0221
				Root MSE =	.10652

aturn89	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pwhite	-.0179986	.0052851	-3.406	0.001	-.0283597	-.0076375
pmc	.0050781	.0158097	0.321	0.748	-.0259154	.0360717
puc	-.0054109	.0121602	-0.445	0.656	-.02925	.0184281
bronzdum	.0200897	.0045691	4.397	0.000	.0111323	.0290471
manhdum	.0155085	.0043185	3.591	0.000	.0070424	.0239745

```

queendum | -.0061319 .0041398 -1.481 0.139 -.0142475 0019838
sidum | .0597818 .007293 8.197 0.000 .0454844 .0740792
_cons | .3211972 .006328 50.758 0.000 .3087916 .3336027

```

```

. regress aturn93 pwhite pmc puc bronxdum manhdum queendum sidum

```

Source	SS	df	MS	Number of obs =	5256
Model	3.09011328	7	.441444755	F(7, 5248) =	23.87
Residual	97.0481825	5248	.018492413	Prob > F =	0.0000
				R-squared =	0.0309
				Adj R-squared =	0.0296
Total	100.138296	5255	.019055813	Root MSE =	.13599

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pwhite	-.0345941	.0067472	-5.127	0.000	-.0478215	-.0213668
pmc	-.0002535	.0201833	-0.013	0.990	-.0398212	.0393141
puc	-.0083531	.0155242	-0.538	0.591	-.038787	.0220808
bronxdum	.0234791	.0058331	4.025	0.000	.0120437	.0349145
manhdum	.0314783	.0055132	5.710	0.000	.0206702	.0422865
queendum	-.0068478	.005285	-1.296	0.195	-.0172086	.003513
sidum	.0816609	.0093106	8.771	0.000	.0634082	.0999135
_cons	.3918145	.0080786	48.500	0.000	.3759771	.407652

```

. regress aoutdif pwhite pmc puc bronxdum manhdum queendum sidum

```

Source	SS	df	MS	Number of obs =	5256
Model	.423056455	7	.060436636	F(7, 5248) =	22.22
Residual	14.2711117	5248	.002719343	Prob > F =	0.0000
				R-squared =	0.0288
				Adj R-squared =	0.0275
Total	14.6941681	5255	.002796226	Root MSE =	.05215

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pwhite	-.0165955	.0025874	-6.414	0.000	-.0216679	-.0115232
pmc	-.0053317	.0077397	-0.689	0.491	-.0205048	.0098414
puc	-.0029422	.0059531	-0.494	0.621	-.0146128	.0087284
bronxdum	.0033894	.0022369	1.515	0.130	-.0009958	.0077746
manhdum	.0159699	.0021142	7.554	0.000	.0118252	.0201145
queendum	-.0007159	.0020267	-0.353	0.724	-.0046891	.0032572
sidum	.0218791	.0035704	6.128	0.000	.0148797	.0288785
_cons	.0706174	.0030979	22.795	0.000	.0645442	.0766906

```

. regress hturn89 pwhite pmc puc bronxdum manhdum queendum sidum

```

Source	SS	df	MS	Number of obs =	5256
Model	2.22833526	7	.318333608	F(7, 5248) =	46.88
Residual	35.634849	5248	.006790177	Prob > F =	0.0000
				R-squared =	0.0589

```
-----+-----
Total | 37.8631842 5255 .007205173
Adj R-squared = 0.0576
Root MSE = .0824
```

```
-----+-----
hturn89 | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
pwhite | -.0149512 .0040885 -3.657 0.000 -.0229664 -.0069359
pmc | -.0300954 .0122303 -2.461 0.014 -.0540718 -.006119
puc | .041778 .009407 4.441 0.000 .0233363 .0602197
bronzdum | .0433012 .0035347 12.250 0.000 .0363718 .0502305
manhdum | .0303939 .0033408 9.098 0.000 .0238446 .0369432
queendum | -.0057076 .0032025 -1.782 0.075 -.0119858 .0005707
sidum | .0115157 .0056418 2.041 0.041 .0004553 .022576
_cons | .1434646 .0048953 29.307 0.000 .1338678 .1530614
-----+-----
```

```
. regress hturn pwhite pmc puc bronzdum manhdum queendum sidum
```

```
-----+-----
Source | SS df MS
-----+-----
Model | 3.64366346 7 .520523352
Residual | 31.4334003 5248 .005989596
Total | 35.0770638 5255 .006674988
Number of obs = 5256
F( 7, 5248) = 86.90
Prob > F = 0.0000
R-squared = 0.1039
Adj R-squared = 0.1027
Root MSE = .07739
```

```
-----+-----
hturn | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
pwhite | .0077839 .00384 2.027 0.043 .000256 .0153118
pmc | -.1468351 .0114867 -12.783 0.000 -.1693537 -.1243165
puc | .0510785 .0088351 5.781 0.000 .033758 .068399
bronzdum | .0312524 .0033197 9.414 0.000 .0247443 .0377605
manhdum | .014096 .0031376 4.493 0.000 .0079449 .0202471
queendum | -.0036718 .0030078 -1.221 0.222 -.0095683 .0022247
sidum | .0600318 .0052988 11.329 0.000 .0496439 .0704197
_cons | .1645652 .0045977 35.793 0.000 .1555519 .1735786
-----+-----
```

```
. regress hturndif pwhite pmc puc bronzdum manhdum queendum sidum
```

```
-----+-----
Source | SS df MS
-----+-----
Model | 2.07471392 7 .296387703
Residual | 61.4264314 5248 .011704732
Total | 63.5011453 5255 .012083948
Number of obs = 5256
F( 7, 5248) = 25.32
Prob > F = 0.0000
R-squared = 0.0327
Adj R-squared = 0.0314
Root MSE = .10819
```

```
-----+-----
hturndif | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
pwhite | .0225891 .005368 4.208 0.000 .0120657 .0331125
pmc | -.1169947 .0160574 -7.286 0.000 -.1484739 -.0855155
puc | .0104006 .0123508 0.842 0.400 -.013812 .0346132
bronzdum | -.011737 .0046407 -2.529 0.011 -.0208348 -.0026392
manhdum | -.0161702 .0043862 -3.687 0.000 -.024769 -.0075715
queendum | .0020502 .0042047 0.488 0.626 -.0061927 .010293
sidum | .048594 .0074073 6.560 0.000 .0340726 .0631154
_cons | .0207869 .0064272 3.234 0.001 .0081869 .0333868
-----+-----
```

```

-----
. sort neigh

```

```

. by neigh: sum      tot93      pdink93      pgiul93      turn93      wturn93      wgiul93
phgiul93 hturn
>      aturn93 agiul93 bturn93 bgiul93

```

```

-> neigh=      Astoria
Variable |      Obs      Mean      Std. Dev.      Min      Max
-----|-----
      tot93 |      170      298.8706      166.5996           2      696
      pdink93 |      170       .300361      .1934053           0      .9797753
      pgiul93 |      170       .699639      .1934053      .0202247           1
      turn93 |      170       .2650822      .1203002      .0058651      .8866995
      wturn93 |      170       .3242312      .1101247       .0091       .7932
      wgiul93 |      170       .8775541      .0985776       .0357           1
      phgiul93 |      170       .1609959      .0954014       .0262           1
      hturn |      170       .0984129      .0836122       .0069      .7708
      aturn93 |      170       .3510153      .1662285           0       .574
      agiul93 |      170       .5716129      .2802273           0           1
      bturn93 |      170       .2894406      .1125035           0      .6612
      bgiul93 |      170       .0813376      .1113625           0           1

```

```

-> neigh=      Baychester
Variable |      Obs      Mean      Std. Dev.      Min      Max
-----|-----
      tot93 |      96      317.0938      137.2814          15      810
      pdink93 |      96       .7757143      .1669261      .2912621      .9747292
      pgiul93 |      96       .2242857      .1669261      .0252708      .7087379
      turn93 |      96       .3036527      .0755177      .147918      .4577465
      wturn93 |      96       .4127667      .0673347       .2536       .5494
      wgiul93 |      96       .6838583      .1599968       .1403       .9196
      phgiul93 |      96       .1466208      .0163078       .1032       .1822
      hturn |      96       .1074958      .0540975       .0461       .3224
      aturn93 |      96       .332375      .1367828           0       .5373
      agiul93 |      96       .5470708      .2375392           0       .6891
      bturn93 |      96       .2668531      .1865053           0       .517
      bgiul93 |      96       .0798583      .1105943           0       .5452

```

```

-> neigh=      Bay Ridge
Variable |      Obs      Mean      Std. Dev.      Min      Max
-----|-----
      tot93 |      59      377.7458      130.449           30      628
      pdink93 |      59       .153759      .039902           .056      .2666667
      pgiul93 |      59       .846241      .039902      .7333333           .944
      turn93 |      59       .3763792      .0858689      .2068966      .5862069
      wturn93 |      59       .3958373      .0784627       .2153       .5942
      wgiul93 |      59       .9061763      .0400421       .7646       .9721
      phgiul93 |      59       .1523712      .0157235       .1138       .1877
      hturn |      59       .1234525      .0406642       .0696       .2544
      aturn93 |      59       .3562322      .1611065           0       .5546
      agiul93 |      59       .5717898      .2306696           0       .8097
      bturn93 |      59       .2862661       .10222           0       .4687
      bgiul93 |      59       .0555898      .0392243           0       .094

```

```

-> neigh=      Bedford Styvesant
Variable |      Obs      Mean      Std. Dev.      Min      Max
-----|-----
      tot93 |      100      282.66      147.1957          12      588

```

pdink93	100	.9624387	.0423877	.7890625	1
pgiul93	100	.0375613	.0423877	0	.2109375
turn93	100	.3480185	.082879	.1176471	.6230366
wturn93	100	.432193	.1221233	0	.6366
wgiul93	100	.644954	.2284683	0	.7866
phgiul93	100	.120017	.036419	0	.1704
hturn	100	.12603	.0512084	.043	.3908
aturn93	100	.431556	.1038762	0	.6466
agiul93	100	.391677	.3124104	0	.6993
bturn93	100	.341065	.0819816	.0687	.6308
bgiul93	100	.022928	.0218616	0	.116

-> neigh= Bensonhurst					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	182	308.956	161.7179	18	776
pdink93	182	.1060653	.0608567	0	.6774194
pgiul93	182	.8939347	.0608567	.3225806	1
turn93	182	.3109204	.0855281	.0266552	.6153846
wturn93	182	.331017	.0794774	.0512	.6181
wgiul93	182	.9529995	.0513163	.4248	1
phgiul93	182	.1553566	.0651313	.1136	1
hturn	182	.0986775	.0325796	.0302	.2602
aturn93	182	.3055066	.1504415	0	.8146
agiul93	182	.6472544	.2026028	0	1
bturn93	182	.2824681	.1185009	0	.5388
bgiul93	182	.0483159	.0846869	0	1

-> neigh= Boro Park					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	50	293.54	135.3172	42	527
pdink93	50	.4500071	.1758456	.1677632	.8970297
pgiul93	50	.5499929	.1758456	.1029703	.8322368
turn93	50	.340955	.1205501	.1185693	.6618705
wturn93	50	.401422	.0969182	.1295	.6946
wgiul93	50	.715472	.1174693	.369	.9398
phgiul93	50	.152628	.0157563	.1197	.1851
hturn	50	.121104	.0571256	.0437	.3456
aturn93	50	.395122	.131764	0	.6474
agiul93	50	.630766	.1013942	0	.689
bturn93	50	.293552	.09394	0	.4566
bgiul93	50	.084568	.0380156	0	.235

-> neigh= Canarsie					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	99	349.3636	127.6143	31	677
pdink93	99	.1555885	.1631964	.0432277	.8942308
pgiul93	99	.8444115	.1631964	.1057692	.9567723
turn93	99	.4191736	.0945988	.1050157	.5881356
wturn93	99	.4364535	.091688	.1054	.6212
wgiul93	99	.9026566	.0999386	.5111	.9865
phgiul93	99	.1531222	.0126887	.1189	.181
hturn	99	.1453616	.0481776	.0587	.3209
aturn93	99	.3772293	.11426	0	.5925
agiul93	99	.6088606	.183029	0	.7351
bturn93	99	.2950616	.1269756	0	.5789
bgiul93	99	.0490293	.0478196	0	.2775

-> neigh= Chinatown

Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	47	326.6383	140.3993	36	645
pdink93	47	.4341209	.1829901	.1471572	.805851
pgiul93	47	.5658791	.1829901	.1941489	.8528428
turn93	47	.2782756	.1886698	.0843012	.790146
wturn93	47	.3874277	.1466896	.182	.8355
wgiul93	47	.8016128	.1025476	.4423	.9376
phgiul93	47	.1514915	.0159217	.1238	.2034
hturn	47	.143117	.1554675	.0377	.6774
aturn93	47	.391366	.1512832	0	.5671
agiul93	47	.5629383	.2229697	0	.853
bturn93	47	.327366	.1107808	0	.5657
bgiul93	47	.0848532	.0596049	0	.3961
-> neigh= Coney Island					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	24	337.6667	142.4126	31	600
pdink93	24	.6942389	.3065587	0	.9534314
pgiul93	24	.3057611	.3065587	.0465686	1
turn93	24	.3076517	.1095741	.1016949	.5466053
wturn93	24	.4004333	.1062657	.1143	.6155
wgiul93	24	.6273333	.2667345	.0737	1
phgiul93	24	.1823792	.1749955	.1201	1
hturn	24	.1269917	.073981	.0441	.3244
aturn93	24	.4132	.1377254	0	.5595
agiul93	24	.6101042	.2111774	0	1
bturn93	24	.2499375	.1588423	0	.5022
bgiul93	24	.1091708	.2137088	0	1
-> neigh= Coop City					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	17	314.1765	76.13823	69	404
pdink93	17	.6631948	.0780374	.5507246	.8106312
pgiul93	17	.3368052	.0780374	.1893688	.4492754
turn93	17	.4041124	.1497274	.025547	.5423477
wturn93	17	.4667471	.1614413	.0394	.6048
wgiul93	17	.6272118	.1317107	.3846	.8448
phgiul93	17	.1532059	.0149084	.1281	.1862
hturn	17	.1824294	.0868077	.0356	.2992
aturn93	17	.3497235	.1481734	0	.5023
agiul93	17	.5738059	.2168007	0	.6925
bturn93	17	.1777176	.1950918	0	.4161
bgiul93	17	.0553588	.1006045	0	.418
-> neigh= Corona					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	28	274	164.6716	15	607
pdink93	28	.8405949	.1628465	.4528302	.9915966
pgiul93	28	.1594051	.1628465	.0084034	.5471698
turn93	28	.2445976	.1281975	.0887931	.4793621
wturn93	28	.3859536	.0862023	.2667	.5389
wgiul93	28	.5944929	.2330311	.0344	.8298
phgiul93	28	.1340464	.0339062	.018	.1824
hturn	28	.0875821	.0503856	.0259	.1931
aturn93	28	.3900179	.1479364	0	.557
agiul93	28	.5012786	.2289937	0	.6775
bturn93	28	.2678821	.1350671	0	.5885

bgiul93	28	.049425	.0306237	0	.1
-> neigh=	Crown Heights				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	109	305.2018	161.3088	17	686
pdink93	109	.9640752	.0464746	.7435898	1
pgiul93	109	.0359248	.0464746	0	.2564103
turn93	109	.3027914	.0903766	.1233831	.575
wturn93	109	.4099046	.0968147	0	.609
wgiul93	109	.4621991	.278266	0	.7994
phgiul93	109	.1244927	.0434156	0	.1784
hturn	109	.0998349	.0392281	.0534	.2488
aturn93	109	.3985028	.1260993	0	.5731
agiul93	109	.4184046	.2899402	0	.7081
bturn93	109	.3276679	.084007	0	.6208
bgiul93	109	.0252486	.0320746	0	.256
-> neigh=	East Harlem				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	63	324.9365	116.952	15	615
pdink93	63	.8310114	.0831778	.5938697	.9633027
pgiul93	63	.1689886	.0831778	.0366972	.4061303
turn93	63	.3519331	.1319531	.1013514	.7820895
wturn93	63	.4551079	.0912179	.2491	.768
wgiul93	63	.7235905	.1277401	.0838	.8309
phgiul93	63	.1146286	.0210676	.0589	.1635
hturn	63	.2516905	.1371731	.0343	.7551
aturn93	63	.5179254	.0834007	0	.6394
agiul93	63	.5144333	.2567076	0	.7239
bturn93	63	.2870302	.1264264	0	.5291
bgiul93	63	.0673444	.0350503	0	.25
-> neigh=	East Midtown				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	66	432.9394	139.6932	13	873
pdink93	66	.3729882	.0991695	.2307692	.6870968
pgiul93	66	.6270118	.0991695	.3129032	.7692308
turn93	66	.326644	.1088306	.0598846	.7454031
wturn93	66	.3483439	.1107641	.077	.7873
wgiul93	66	.6852288	.0905275	.3648	.9061
phgiul93	66	.1503621	.0140162	.1196	.1892
hturn	66	.1100955	.0571514	.0317	.4695
aturn93	66	.3730076	.1373249	0	.6156
agiul93	66	.5988197	.193236	0	.7826
bturn93	66	.3256667	.1236102	0	.5457
bgiul93	66	.0876773	.0818801	0	.6711
-> neigh=	East NY				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	206	248.6117	152.9193	6	653
pdink93	206	.8215635	.2111571	0	1
pgiul93	206	.1784365	.2111571	0	1
turn93	206	.2958754	.1143688	.0289474	.8139535
wturn93	206	.3931233	.1106029	0	.6051
wgiul93	206	.6565471	.2274906	0	1
phgiul93	206	.1360311	.0691707	0	1
hturn	206	.1179961	.0747676	.0293	.7023

aturn93	206	.4084597	.1034469	0	.616
agiul93	206	.4811466	.2848698	0	1
bturn93	206	.3153636	.1272248	0	1
bgiul93	206	.0602383	.093391	0	1
-> neigh= East Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	60	344.0833	112.5221	81	523
pdink93	60	.7212988	.1069596	.2246696	.85
pgiul93	60	.2787012	.1069596	.15	.7753304
turn93	60	.2927521	.1181449	.1109655	1
wturn93	60	.3680883	.1062557	.1882	1
wgiul93	60	.4518533	.2188955	.1701	.843
phgiul93	60	.1402617	.0226644	.0867	.178
hturn	60	.1339733	.1361075	.0406	1
aturn93	60	.3463567	.1827543	0	.5438
agiul93	60	.4870733	.2582392	0	.6861
bturn93	60	.3291683	.1058189	0	.5303
bgiul93	60	.0775	.0166806	0	.0978
-> neigh= Flatbush					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	156	303.3526	156.1103	1	701
pdink93	156	.8382941	.2060424	.102719	1
pgiul93	156	.1617059	.2060424	0	.897281
turn93	156	.2709396	.0945561	.05	.8268251
wturn93	156	.3965282	.0699362	.0814	.8749
wgiul93	156	.5811564	.22718	0	.9761
phgiul93	156	.1446481	.0276067	0	.1865
hturn	156	.0896904	.052645	.0468	.5791
aturn93	156	.4084865	.1218836	0	.6536
agiul93	156	.5469109	.2105634	0	.7248
bturn93	156	.2944564	.1270005	0	.7152
bgiul93	156	.0586083	.0718457	0	.688
-> neigh= Flushing					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	185	373.9784	172.3855	1	783
pdink93	185	.2070199	.1463661	0	1
pgiul93	185	.7929801	.1463661	0	1
turn93	185	.3632309	.1595639	.0038023	.984375
wturn93	185	.4094995	.1377201	.011	.9948
wgiul93	185	.9070038	.1061161	0	1
phgiul93	185	.1638184	.109633	0	1
hturn	185	.1347778	.0969721	.0083	.8901
aturn93	185	.3678038	.1526723	0	.5352
agiul93	185	.5911438	.2482478	0	1
bturn93	185	.3139676	.0850477	0	.6982
bgiul93	185	.0703832	.0965526	0	1
-> neigh= Forest Hills					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	125	348.784	175.992	7	703
pdink93	125	.2816996	.1747676	.0261194	.9545454
pgiul93	125	.7183004	.1747676	.0454545	.9738806
turn93	125	.3293621	.1197342	.0963245	.6499069
wturn93	125	.380708	.0960477	.1778	.6701

wgiul93	125	.8500072	.1100408	.1325	.9882
phgiul93	125	.1545696	.0455959	.1165	.6294
hturn	125	.1117088	.0539099	.031	.3423
aturn93	125	.3818456	.1098191	0	.5065
agiul93	125	.6390832	.1602774	0	.9112
bturn93	125	.3133464	.1023382	0	.6092
bgiul93	125	.07184	.0262369	0	.1094

-> neigh= Fort Greene					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	80	286.275	179.4044	7	619
pdink93	80	.9102897	.0978044	.4285714	1
pgiul93	80	.0897103	.0978044	0	.5714286
turn93	80	.3335483	.1176946	.0356745	.6444445
wturn93	80	.4385638	.0937235	.0806	.6396
wgiul93	80	.4718613	.2746818	0	.8109
phgiul93	80	.1344463	.0324101	0	.1814
hturn	80	.1295537	.0722278	.0284	.4412
aturn93	80	.388895	.1310478	0	.5406
agiul93	80	.4421775	.2913362	0	.7092
bturn93	80	.32335	.1068581	0	.6475
bgiul93	80	.048375	.0430308	0	.228

-> neigh= Greenpoint					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	45	244.1556	146.5148	1	530
pdink93	45	.3140772	.1844055	0	.8636364
pgiul93	45	.6859228	.1844055	.1363636	1
turn93	45	.2410796	.0796658	.0666667	.4795082
wturn93	45	.2886822	.0823819	.1395	.5416
wgiul93	45	.8072267	.1614509	.1356	1
phgiul93	45	.1749	.1316879	.1199	1
hturn	45	.0955733	.0691084	.0449	.4074
aturn93	45	.3639711	.1309703	0	.5528
agiul93	45	.6315778	.1397204	0	.7013
bturn93	45	.2761711	.1235039	0	.5512
bgiul93	45	.06554	.0337536	0	.1037

-> neigh= Harlem					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	118	390.5508	139.0212	1	819
pdink93	118	.9733172	.0434531	.625	1
pgiul93	118	.0266828	.0434531	0	.375
turn93	118	.3829249	.1196212	.0090909	.7777778
wturn93	118	.4742381	.088892	0	.7172
wgiul93	118	.5532424	.2414641	0	.7986
phgiul93	118	.1134297	.036285	0	.206
hturn	118	.1462441	.0740295	.0041	.4614
aturn93	118	.4663186	.1293998	0	.6136
agiul93	118	.4678059	.2794031	0	.7154
bturn93	118	.2830025	.1306822	0	.6665
bgiul93	118	.0180119	.0363882	0	.375

-> neigh= Howard Beach					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	113	340.3894	148.5699	8	765
pdink93	113	.2201879	.1437101	.031746	.6880734

pgiul93	113	.7798121	.1437101	.3119266	.968254
turn93	113	.2910203	.1116931	.0427807	.6272727
wturn93	113	.347615	.0861797	.0622	.6325
wgiul93	113	.9262708	.0505307	.7554	.9913
phgiul93	113	.1500177	.0141017	.1124	.1921
hturn	113	.0956044	.0453261	.0347	.2654
aturn93	113	.3793699	.118277	0	1
agiul93	113	.6352044	.1418336	0	.8078
bturn93	113	.3136088	.0811281	0	.5517
bgiul93	113	.0921531	.0855334	0	.625

-> neigh=					
Inwood					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	36	310.8056	141.1746	30	602
pdink93	36	.4693437	.0935052	.2185185	.6923077
pgiul93	36	.5306563	.0935052	.3076923	.7814815
turn93	36	.3185985	.1122567	.1517932	.6243655
wturn93	36	.3915083	.090634	.2245	.6624
wgiul93	36	.7361556	.11907	.4154	.9125
phgiul93	36	.1599306	.0707039	.1086	.5613
hturn	36	.1441111	.0828977	.0583	.446
aturn93	36	.3267861	.1062721	0	.4181
agiul93	36	.5987306	.1844125	0	.6948
bturn93	36	.2686667	.1177701	0	.4356
bgiul93	36	.0721111	.0266637	0	.0946

-> neigh=					
Jackson Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	125	211.096	159.9959	1	608
pdink93	125	.2700811	.1343998	0	1
pgiul93	125	.7299189	.1343998	0	1
turn93	125	.1997621	.1188131	.0024752	.7615894
wturn93	125	.3042344	.1029836	.0058	.7986
wgiul93	125	.8931144	.095094	0	1
phgiul93	125	.1980408	.1897261	0	1
hturn	125	.071836	.0694501	.0027	.6425
aturn93	125	.3823984	.1427273	0	.6024
agiul93	125	.6527768	.250214	0	1
bturn93	125	.2878496	.1152004	0	.5376
bgiul93	125	.104592	.17069	0	1

-> neigh=					
Middle Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	243	263.3909	175.0009	1	731
pdink93	243	.4453881	.3192936	0	1
pgiul93	243	.5546119	.3192936	0	1
turn93	243	.2742332	.1141714	.011236	.5542169
wturn93	243	.3536342	.1012884	0	.5962
wgiul93	243	.8279391	.1530659	0	1
phgiul93	243	.1660156	.1208283	0	1
hturn	243	.1300165	.0736951	.0152	.4909
aturn93	243	.3545996	.1582774	0	.5618
agiul93	243	.5142424	.2854464	0	1
bturn93	243	.3221481	.1075166	0	.7167
bgiul93	243	.0642543	.0935082	0	1

-> neigh=					
Mott Haven					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	90	278.7444	120.8966	30	674
pdink93	90	.797764	.080002	.5548781	.9336283
pgiul93	90	.202236	.080002	.0663717	.4451219
turn93	90	.3110976	.1004775	.1679721	.8723404
wturn93	90	.43331	.0656053	.3313	.7882
wgiul93	90	.7521578	.0219498	.6964	.8074
phgiul93	90	.1314522	.0571653	.069	.4283
hturn	90	.2379667	.1089731	.0522	.8793
aturn93	90	.3671011	.1422911	0	.6249
agiul93	90	.37655	.3242493	0	.7095
bturn93	90	.2945611	.1188508	0	.5043
bgiul93	90	.0696433	.0270603	0	.181

-> neigh= North Shore					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	36	408.7222	121.5957	189	663
pdink93	36	.5580245	.2169196	.15625	.9503106
pgiul93	36	.4419755	.2169196	.0496894	.84375
turn93	36	.3852043	.0692788	.2374631	.6116236
wturn93	36	.4551222	.0546928	.373	.639
wgiul93	36	.6613083	.1872714	.1427	.9623
phgiul93	36	.1424861	.0134923	.1193	.1747
hturn	36	.1392444	.0420904	.0609	.2999
aturn93	36	.4388917	.1273411	0	.5859
agiul93	36	.612125	.152616	0	.7013
bturn93	36	.3631972	.0611571	.2078	.5088
bgiul93	36	.0776083	.014096	.05	.137

-> neigh= Park Slope					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	128	319.3047	201.5786	5	834
pdink93	128	.6088944	.1459117	.2575758	1
pgiul93	128	.3911056	.1459117	0	.7424242
turn93	128	.3822878	.1009797	.0987654	.6617782
wturn93	128	.4364398	.085569	.1371	.7011
wgiul93	128	.5014477	.1695224	0	.938
phgiul93	128	.1457586	.0196289	0	.1841
hturn	128	.1495656	.0544374	.0314	.3426
aturn93	128	.3314	.1632737	0	.5533
agiul93	128	.5347469	.2522693	0	.7021
bturn93	128	.2816641	.1484126	0	.8166
bgiul93	128	.0684766	.0295804	0	.1031

-> neigh= Battery Park					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	4	277.25	171.2919	50	459
pdink93	4	.4122227	.1018793	.3263473	.56
pgiul93	4	.5877773	.1018793	.44	.6736527
turn93	4	.2139221	.1312236	.0245821	.3170441
wturn93	4	.2338	.1460793	.022	.3414
wgiul93	4	.6797	.074827	.5796	.7567
phgiul93	4	.147075	.0145852	.1296	.1648
hturn	4	.0736	.0146561	.055	.0904
aturn93	4	.497775	.0416442	.4586	.5486
agiul93	4	.610275	.1186054	.4387	.7053
bturn93	4	.30975	.0989857	.1822	.4121
bgiul93	4	.164075	.1644174	.0813	.4107

-> neigh= Pelham Bay					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	258	321.2829	127.6651	44	659
pdink93	258	.4458474	.2995226	.0378788	.9816092
pgiul93	258	.5541526	.2995226	.0183908	.9621212
turn93	258	.3497417	.1061108	.1465875	.8471503
wturn93	258	.4204074	.087974	.1987	.8108
wgiul93	258	.8462256	.0963861	.5047	.9918
phgiul93	258	.1464826	.0286488	.07	.3139
hturn	258	.1683651	.0984166	.0497	.8672
aturn93	258	.4069946	.0984094	0	.6096
agiul93	258	.5944826	.1878266	0	.7329
bturn93	258	.2769291	.150832	0	.521
bgiul93	258	.0590841	.0396501	0	.3014
-> neigh= Queens Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	178	406.0056	155.9804	7	905
pdink93	178	.2414249	.13218	0	.8772321
pgiul93	178	.7585751	.13218	.1227679	1
turn93	178	.4065238	.1193399	.0623886	.8326923
wturn93	178	.4460831	.107611	.0613	.8674
wgiul93	178	.8731073	.105826	.517	1
phgiul93	178	.1568567	.0652033	.1147	1
hturn	178	.1463534	.0691499	.0452	.5496
aturn93	178	.333591	.1598573	0	.6084
agiul93	178	.5694	.2457774	0	1
bturn93	178	.3103551	.0980845	0	.7741
bgiul93	178	.0680433	.0633321	0	.7703
-> neigh= Riverdale					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	98	378.2449	117.8303	119	699
pdink93	98	.3447156	.170541	.0074906	.9481865
pgiul93	98	.6552844	.170541	.0518135	.9925094
turn93	98	.3625497	.1420381	.0662051	.8373102
wturn93	98	.4076612	.1265289	.0666	.864
wgiul93	98	.787852	.1359334	.0661	.9957
phgiul93	98	.1608133	.081256	.1088	.9429
hturn	98	.136249	.0883654	.0424	.5879
aturn93	98	.4072408	.0653602	.1864	.583
agiul93	98	.6321592	.1530156	0	.971
bturn93	98	.2763867	.1792434	0	.4757
bgiul93	98	.0649184	.0990712	0	.9647
-> neigh= Rockaways					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	71	362.0282	173.8349	1	694
pdink93	71	.491189	.3455264	0	1
pgiul93	71	.508811	.3455264	0	1
turn93	71	.3786536	.191639	.0028169	.8843417
wturn93	71	.4400014	.1686377	.0024	.9335
wgiul93	71	.7025493	.2504187	0	1
phgiul93	71	.1659183	.1476879	0	1
hturn	71	.1454437	.1115554	0	.6935
aturn93	71	.3162056	.1428078	.0477	.646

agiul93	71	.608	.1964342	0	1
bturn93	71	.3082127	.0933142	0	.6319
bgiul93	71	.1143099	.1934453	0	1
-> neigh= Satmar					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	18	412.1667	197.5909	16	765
pdink93	18	.1971517	.1373247	.0440367	.4385965
pgiul93	18	.8028483	.1373247	.5614035	.9559633
turn93	18	.4320821	.1064768	.2348083	.6942801
wturn93	18	.4788278	.1056309	.2704	.7496
wgiul93	18	.9206611	.094179	.6057	.9886
phgiul93	18	.2342667	.1471056	.1305	.556
hturn	18	.2334833	.1179885	.065	.5864
aturn93	18	.3552222	.0963329	.0328	.472
agiul93	18	.4465167	.3253544	0	.6965
bturn93	18	.2600167	.1313875	0	.4011
bgiul93	18	.0631889	.0357142	0	.1005
-> neigh= Sheepshead Bay					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	237	323.2236	133.0037	43	758
pdink93	237	.1557293	.090243	0	.6842105
pgiul93	237	.8442707	.090243	.3157895	1
turn93	237	.3717212	.120191	.1079646	.792976
wturn93	237	.3951979	.1109237	.126	.8006
wgiul93	237	.913846	.0721116	.3981	1
phgiul93	237	.1542616	.0569529	.1134	1
hturn	237	.1280207	.0603384	.0422	.4866
aturn93	237	.3854426	.1480288	0	.7782
agiul93	237	.593173	.2417016	0	1
bturn93	237	.2921823	.119268	0	.5277
bgiul93	237	.0656405	.0709081	0	1
-> neigh= Southeast Queens					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	237	384.2532	158.3708	4	709
pdink93	237	.8491227	.2165585	.0909091	1
pgiul93	237	.1508773	.2165585	0	.9090909
turn93	237	.3595449	.1122647	.0487805	.5931624
wturn93	237	.4516304	.0904597	.1037	.6284
wgiul93	237	.5969253	.2144056	0	.9552
phgiul93	237	.1482219	.0229642	0	.2026
hturn	237	.116797	.0443322	0	.2516
aturn93	237	.3801582	.1269898	0	.6798
agiul93	237	.4763591	.2695894	0	.7879
bturn93	237	.315208	.1096503	0	.7353
bgiul93	237	.0519262	.0954679	0	.909
-> neigh= Staten Island					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	251	482.0956	133.4174	63	841
pdink93	251	.1143443	.0795068	.035313	.6841046
pgiul93	251	.8856557	.0795068	.3158954	.964687
turn93	251	.5096378	.09705	.1703817	.9359431
wturn93	251	.5283108	.0922895	.1828	.9599
wgiul93	251	.9419984	.0562346	.5486	.9927

phgiul93	251	.1507339	.0148845	.1136	.1989
hturn	251	.2039414	.0746453	.0561	.7244
aturn93	251	.441441	.1014668	0	.6239
agiul93	251	.6355574	.1326508	0	.8064
bturn93	251	.3438195	.0760135	.0076	.6909
bgiul93	251	.0519833	.0532691	0	.426

-> neigh= Styvesant Town					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	19	436.8421	66.42813	319	571
pdink93	19	.3688004	.0417361	.2778994	.4639498
pgiul93	19	.6311996	.0417361	.5360501	.7221007
turn93	19	.5072855	.0859523	.3277566	.6984816
wturn93	19	.5316789	.0893489	.3589	.7409
wgiul93	19	.6895105	.0454511	.5757	.7695
phgiul93	19	.1466105	.0125639	.1253	.1765
hturn	19	.1990737	.0616523	.1036	.386
aturn93	19	.4302105	.0967716	.1816	.5638
agiul93	19	.6595474	.0179429	.626	.6969
bturn93	19	.3548684	.0577967	.2534	.5027
bgiul93	19	.0825	.0074878	.0705	.1008

-> neigh= Sunset Park					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	65	214.8308	119.8289	1	457
pdink93	65	.5163714	.204244	.1509434	1
pgiul93	65	.4836286	.204244	0	.8490566
turn93	65	.2486518	.0967698	.0999311	.5851648
wturn93	65	.3545385	.0921756	0	.6228
wgiul93	65	.8036092	.1554712	0	.9582
phgiul93	65	.1442923	.0450319	0	.4254
hturn	65	.1234077	.0813326	.031	.4794
aturn93	65	.3401292	.1527104	0	.5434
agiul93	65	.5070446	.2815693	0	.8358
bturn93	65	.2980523	.1068561	0	.5159
bgiul93	65	.0730231	.0242304	0	.1073

-> neigh= Tremont					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	260	265.2923	125.5111	21	678
pdink93	260	.8156503	.149892	.2076923	.99375
pgiul93	260	.1843497	.149892	.00625	.7923077
turn93	260	.2602069	.0994125	.0969828	.6904277
wturn93	260	.3922412	.0745917	.1369	.692
wgiul93	260	.7434181	.0951033	.0778	.952
phgiul93	260	.1269958	.0288088	.0156	.2072
hturn	260	.127545	.0768797	.0289	.5399
aturn93	260	.4412481	.0908879	0	.7672
agiul93	260	.5445073	.2322741	0	.7224
bturn93	260	.2888977	.1397486	0	.5984
bgiul93	260	.0568138	.0344629	0	.267

-> neigh= Upper East Side					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	165	420.6303	120.8011	52	688
pdink93	165	.370024	.0829521	.2266667	.8076923
pgiul93	165	.629976	.0829521	.1923077	.7733333

turn93	165	.3849266	.1165613	.0503876	.8764045
wturn93	165	.4029527	.1149397	.0942	.8936
wgiul93	165	.673043	.071028	.224	.8211
phgiul93	165	.15052	.0148047	.1064	.1918
hturn	165	.1335376	.0691845	.0338	.6201
aturn93	165	.3786127	.1365786	0	.5563
agiul93	165	.5949745	.190313	0	.7078
bturn93	165	.2573558	.1478385	0	.5445
bgiul93	165	.0660552	.0354048	0	.192

-> neigh= Upper West Side					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	185	421.7459	127.1401	41	901
pdink93	185	.6252408	.1249132	.3747368	.9554794
pgiul93	185	.3747592	.1249132	.0445205	.6252632
turn93	185	.3961886	.1245879	.0927184	.9133334
wturn93	185	.4384032	.1211117	.1098	.9353
wgiul93	185	.4613914	.116572	.0988	.8029
phgiul93	185	.1493292	.0166783	.0821	.1935
hturn	185	.1603054	.0916486	.0495	.6681
aturn93	185	.4256595	.1472853	0	.7121
agiul93	185	.5860741	.1922641	0	.7175
bturn93	185	.261813	.1397478	0	.5725
bgiul93	185	.0657341	.0317375	0	.1006

-> neigh=Washington Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	70	311.2	129.0404	34	679
pdink93	70	.7322173	.1240719	.4311377	.9576108
pgiul93	70	.2677827	.1240719	.0423892	.5688623
turn93	70	.1983219	.1032251	.0397059	.7168508
wturn93	70	.3455671	.0754124	.1451	.7171
wgiul93	70	.7280543	.1329857	.1922	.8892
phgiul93	70	.1306871	.0196703	.0758	.1636
hturn	70	.1099414	.0677943	.0289	.4674
aturn93	70	.3655529	.1295464	0	.6856
agiul93	70	.6065971	.1728775	0	.7048
bturn93	70	.30564	.1594972	0	.8944
bgiul93	70	.0708557	.0409677	0	.296

-> neigh= West Midtown					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	109	366.6789	145.1343	34	752
pdink93	109	.5676638	.0868749	.4022472	.7777778
pgiul93	109	.4323362	.0868749	.2222222	.5977528
turn93	109	.3192535	.1114999	.0928899	.6712598
wturn93	109	.3594991	.1060852	.1223	.6926
wgiul93	109	.5035716	.1067668	.2399	.8801
phgiul93	109	.1499505	.0134965	.1224	.1857
hturn	109	.1134642	.0643646	.0347	.3814
aturn93	109	.4114376	.1161328	0	.5518
agiul93	109	.6193569	.1390879	0	.738
bturn93	109	.3215807	.1242008	0	.5293
bgiul93	109	.0741881	.0222414	0	.101

-> neigh= West Village					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	75	408.5067	125.7394	62	607
pdink93	75	.5996648	.0818505	.3971487	.8064516
pgiul93	75	.4003352	.0818505	.1935484	.6028513
turn93	75	.3826525	.1028829	.1923991	.7864078
wturn93	75	.4037413	.1037081	.2031	.8414
wgiul93	75	.4261627	.0869642	.202	.6524
phgiul93	75	.1498053	.0121813	.1212	.1789
hturn	75	.131948	.0702463	.0617	.6118
aturn93	75	.327748	.1796231	0	.5403
agiul93	75	.5307893	.2573481	0	.73
bturn93	75	.3132653	.1293659	0	.5906
bgiul93	75	.0729533	.024833	0	.101

-> neigh=		Windsor				
Variable	Obs	Mean	Std. Dev.	Min	Max	
tot93	83	265.494	199.1138	7	914	
pdink93	83	.1791811	.1314397	0	.5625	
pgiul93	83	.8208189	.1314397	.4375	1	
turn93	83	.291094	.133228	.0969163	.6129597	
wturn93	83	.3449145	.1081131	.1374	.6161	
wgiul93	83	.9297072	.0761554	.5652	1	
phgiul93	83	.1649639	.0995176	0	1	
hturn	83	.0964723	.0548544	0	.2649	
aturn93	83	.3675711	.1211135	0	.6167	
agiul93	83	.6358133	.2380336	0	1	
bturn93	83	.2937626	.1105744	0	.4899	
bgiul93	83	.0812313	.1071856	0	1	

-> neigh=		Lubavitchers				
Variable	Obs	Mean	Std. Dev.	Min	Max	
tot93	17	363	162.9816	97	603	
pdink93	17	.6619317	.1800074	.3720238	.9803537	
pgiul93	17	.3380683	.1800074	.0196464	.6279762	
turn93	17	.2938344	.0780659	.126257	.4411765	
wturn93	17	.3962	.0781369	.168	.5188	
wgiul93	17	.7050059	.160885	.3158	.8757	
phgiul93	17	.1502412	.0103255	.1281	.1707	
hturn	17	.0921353	.0317412	.0497	.1672	
aturn93	17	.3933882	.1202163	.0902	.6109	
agiul93	17	.4119	.3143112	0	.6746	
bturn93	17	.2686176	.1720342	0	.5622	
bgiul93	17	.1101941	.1086387	0	.3598	

. by neigh: sum tot89 pdink89 pgiul89 wturn89 wgiul89 wdink89 bturn89
bgiul89 bdink89 hturn89 hgiul89 hdink89 aturn89 adink89 agiul89

-> neigh=		Astoria				
Variable	Obs	Mean	Std. Dev.	Min	Max	
tot89	170	306.2353	167.9878	5	857	
pdink89	170	.3160287	.1866911	.0833333	.981268	
pgiul89	170	.680884	.1862492	.0172911	.9166667	
wturn89	170	.3251512	.0830293	.2059	.724	
wgiul89	170	.8683706	.1072007	.2947	.9675	
wdink89	170	.1302259	.1049328	.0317	.6924	
bturn89	170	.3458776	.1390267	0	.7614	
bgiul89	170	.0559259	.0256847	0	.1559	
bdink89	170	.7482118	.379035	0	1	

hturn89	170	.09449	.0673964	.0243	.4271
hgiul89	170	.1208482	.0981589	0	1
hdink89	170	.8480359	.0462132	.584	1
aturn89	170	.2918382	.135533	0	.4516
adink89	170	.3829082	.1860505	0	1
agiul89	170	.5064247	.2516209	0	.8892

-> neigh= Baychester					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	96	334.0208	147.0252	17	875
pdink89	96	.7516321	.1867872	.3018868	1
pgiul89	96	.2476629	.1862879	0	.6981132
wturn89	96	.4028281	.0532456	.2879	.5234
wgiul89	96	.7396667	.1653549	0	.935
wdink89	96	.258875	.1640957	.062	1
bturn89	96	.2759771	.1889732	0	.468
bgiul89	96	.0746563	.0930596	0	.4093
bdink89	96	.6413813	.434763	0	.99
hturn89	96	.1650719	.0735768	.0402	.4268
hgiul89	96	.1094135	.0161747	.047	.1387
hdink89	96	.8263052	.095334	0	.9018
aturn89	96	.2773292	.1051489	0	.4446
adink89	96	.4080677	.1192123	0	.5096
agiul89	96	.4656615	.2026626	0	.606

-> neigh= Bay Ridge					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	59	370.661	131.6945	37	617
pdink89	59	.1804951	.0478714	.072	.3048781
pgiul89	59	.8184017	.0478276	.6951219	.928
wturn89	59	.3861983	.069189	.2452	.538
wgiul89	59	.8853864	.0481725	.714	.9724
wdink89	59	.1144475	.0475715	.0374	.2869
bturn89	59	.3271153	.1315267	0	.5728
bgiul89	59	.042778	.0325603	0	.0802
bdink89	59	.7716339	.3731263	0	1
hturn89	59	.1397729	.0588793	.0429	.3133
hgiul89	59	.1261237	.1173488	0	1
hdink89	59	.8352847	.1264059	0	1
aturn89	59	.3002085	.1266824	0	.4645
adink89	59	.3918831	.1957864	0	1
agiul89	59	.4850034	.194862	0	.6246

-> neigh= Bedford Styvesant					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	100	282.23	153.5448	3	590
pdink89	100	.9600042	.0607603	.5714286	1
pgiul89	100	.0394682	.0608303	0	.4285714
wturn89	100	.39966	.1113495	0	.5508
wgiul89	100	.571583	.2840524	0	.7894
wdink89	100	.360682	.2503693	0	1
bturn89	100	.41378	.0814157	.0771	.7847
bgiul89	100	.028548	.0568848	0	.429
bdink89	100	.850989	.2708564	0	1
hturn89	100	.132058	.0660791	0	.4295
hgiul89	100	.091958	.0411923	0	.317
hdink89	100	.838394	.0507229	.553	1
aturn89	100	.356959	.0839379	0	.5966

adink89	100	.384307	.1639976	0	.814
agiul89	100	.303153	.2749005	0	.6133
-> neigh= Bensonhurst					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	182	298.6099	157.192	18	710
pdink89	182	.1362808	.0785308	.0174564	.725
pgiul89	182	.8629545	.0787123	.275	.9825436
wturn89	182	.3171445	.0739911	.0741	.672
wgiul89	182	.9293231	.0733837	.3385	.9946
wdink89	182	.070606	.0735931	.0049	.6641
bturn89	182	.3254434	.1399002	0	.6141
bgiul89	182	.0356253	.0384132	0	.275
bdink89	182	.8022555	.3283808	0	1
hturn89	182	.1083648	.0613563	0	.3655
hgiul89	182	.1155011	.0520864	0	.7868
hdink89	182	.8379995	.0667933	.4346	1
aturn89	182	.2655462	.1112702	0	.4925
adink89	182	.3779962	.1793544	0	1
agiul89	182	.5486341	.1741798	0	.9271
-> neigh= Boro Park					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	50	296.54	144.6347	41	546
pdink89	50	.4474912	.1628857	.1296928	.8144712
pgiul89	50	.5495722	.1630077	.1855288	.8703071
wturn89	50	.389088	.0778962	.1543	.5852
wgiul89	50	.740014	.0920395	.4673	.9121
wdink89	50	.256452	.0912294	.0891	.5266
bturn89	50	.348854	.1200038	0	.6023
bgiul89	50	.08503	.0584788	0	.2903
bdink89	50	.872412	.2609166	0	1
hturn89	50	.08475	.0262843	.0269	.141
hgiul89	50	.106546	.0208345	0	.1347
hdink89	50	.857308	.041734	.777	1
aturn89	50	.331548	.0930504	0	.4543
adink89	50	.362538	.2389715	0	1
agiul89	50	.547076	.0843238	0	.6204
-> neigh= Canarsie					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	99	351.596	117.2461	29	644
pdink89	99	.1588594	.1359113	.0114504	.8196721
pgiul89	99	.8408638	.1360484	.1803279	.9885496
wturn89	99	.4372465	.0793235	.076	.6034
wgiul89	99	.9066566	.0693847	.578	.9961
wdink89	99	.093804	.0699087	.004	.4161
bturn89	99	.3357172	.1409597	0	.561
bgiul89	99	.0439384	.0655436	0	.5818
bdink89	99	.8246576	.31054	0	1
hturn89	99	.1628818	.0833525	.0458	.5324
hgiul89	99	.1213636	.0925841	0	1
hdink89	99	.8348646	.1136688	0	1
aturn89	99	.3228899	.0884632	0	.4706
adink89	99	.359899	.1656464	0	.5113
agiul89	99	.5119626	.1551597	0	.6328
-> neigh= Chinatown					

Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	47	307.8936	129.2618	62	545
pdink89	47	.5160184	.1965669	.1672241	.8539604
pgiul89	47	.4802333	.1968009	.1435644	.8294314
wturn89	47	.3714255	.1274041	.2255	.8443
wgiul89	47	.771517	.1482833	.2606	.9387
wdink89	47	.2264596	.1487386	.0649	.7517
bturn89	47	.3972915	.1018028	0	.6689
bgiul89	47	.0599106	.0194703	0	.0787
bdink89	47	.8560638	.2643207	0	.9874
hturn89	47	.1887766	.0573098	.0563	.3142
hgiul89	47	.1145085	.0116443	.0897	.1379
hdink89	47	.8228043	.0716983	.4728	.9091
aturn89	47	.3282638	.1093265	0	.4572
adink89	47	.3820532	.1493357	0	.4869
agiul89	47	.4689574	.207738	0	.8852

-> neigh= Coney Island					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	24	314.625	131.034	26	594
pdink89	24	.7230986	.2824089	.0769231	.9591837
pgiul89	24	.2730827	.284793	.0375587	.9230769
wturn89	24	.3707917	.0722597	.2206	.5229
wgiul89	24	.6081708	.2720937	.0692	.9813
wdink89	24	.3819083	.2587946	.0224	.9304
bturn89	24	.2967958	.190187	0	.5678
bgiul89	24	.0444917	.035895	0	.1568
bdink89	24	.652675	.4329442	0	.9911
hturn89	24	.1340375	.035853	.066	.2079
hgiul89	24	.1102167	.0112525	.0922	.1324
hdink89	24	.8502042	.0156234	.8211	.8786
aturn89	24	.32825	.1057968	0	.4075
adink89	24	.3657417	.1697793	0	.4949
agiul89	24	.5167125	.1637277	0	.6882

-> neigh= Coop City					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	17	351.5294	86.85845	54	465
pdink89	17	.6344155	.0914099	.4855769	.7875648
pgiul89	17	.3631017	.0917758	.2020725	.5120192
wturn89	17	.4724706	.1635461	.0455	.5981
wgiul89	17	.7114588	.1292164	.4818	.8646
wdink89	17	.2864176	.127746	.1371	.4941
bturn89	17	.1880529	.2059328	0	.4235
bgiul89	17	.0548412	.1067228	0	.434
bdink89	17	.4388471	.4798076	0	.9407
hturn89	17	.1712941	.0858184	.0403	.302
hgiul89	17	.1092471	.0114592	.0858	.127
hdink89	17	.8387471	.0113346	.8167	.8656
aturn89	17	.2999412	.12639	0	.4159
adink89	17	.4607647	.0214438	.4181	.4957
agiul89	17	.4846706	.1862604	0	.6035

-> neigh= Corona					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	28	285.6071	178.265	20	640
pdink89	28	.858704	.1471697	.5443038	1

pgiul89	28	.1411753	.1471744	0	.4556962
wturn89	28	.3819429	.0702017	.2856	.5191
wgiul89	28	.5517964	.2607224	0	.8501
wdink89	28	.4532714	.2623177	.1636	1
bturn89	28	.3329071	.1619923	0	.6999
bgiul89	28	.0347929	.0262693	0	.0806
bdink89	28	.806475	.3380075	0	.995
hturn89	28	.0759464	.0643571	.0271	.2433
hgiul89	28	.1165179	.0150771	.0947	.1624
hdink89	28	.8506286	.045603	.676	.969
aturn89	28	.3099357	.1149813	0	.4265
adink89	28	.3051179	.2085801	0	.5039
agiul89	28	.4283536	.219161	0	.6035

-> neigh= Crown Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	109	299.1651	166.5899	15	728
pdink89	109	.9638075	.0463197	.7798165	1
pgiul89	109	.0353171	.0461936	0	.2178899
wturn89	109	.3827605	.0864875	0	.5421
wgiul89	109	.472389	.2703325	0	.7969
wdink89	109	.4832798	.2706462	0	1
bturn89	109	.3911927	.0828903	0	.6627
bgiul89	109	.021756	.0184104	0	.081
bdink89	109	.812389	.3269482	0	.995
hturn89	109	.1364275	.0660928	.0142	.3327
hgiul89	109	.1113083	.0938095	0	1
hdink89	109	.8439422	.0492487	.527	.9753
aturn89	109	.3299147	.1027687	0	.4651
adink89	109	.3789349	.1492594	0	.5216
agiul89	109	.3597193	.2530506	0	.6268

-> neigh= East Harlem					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	63	347.619	121.4769	47	604
pdink89	63	.849241	.0712231	.6265823	.9604222
pgiul89	63	.1487946	.0706285	.0369393	.3575949
wturn89	63	.4410508	.0655339	.3211	.6499
wgiul89	63	.7124079	.1231889	.1087	.8175
wdink89	63	.2924921	.1206519	.1902	.8985
bturn89	63	.3637619	.1568561	0	.9602
bgiul89	63	.050627	.0227587	0	.117
bdink89	63	.7602492	.3723947	0	1
hturn89	63	.1591429	.0804864	0	.4042
hgiul89	63	.1099175	.0169055	0	.1365
hdink89	63	.8057905	.1631346	0	1
aturn89	63	.3817397	.0615148	0	.4724
adink89	63	.3713365	.165055	0	1
agiul89	63	.448354	.2202852	0	.6151

-> neigh= East Midtown					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	66	424.3182	120.8202	18	613
pdink89	66	.3660679	.1038259	.159292	.7222222
pgiul89	66	.6300164	.104704	.2722222	.840708
wturn89	66	.3397076	.0956115	.0865	.7506
wgiul89	66	.6940333	.0880471	.3165	.8967
wdink89	66	.3030561	.0872477	.1055	.6827

bturn89	66	.3811727	.1272666	0	.7193
bgiul89	66	.0644197	.032009	0	.272
bdink89	66	.8182682	.298484	0	1
hturn89	66	.1351803	.1068321	.0316	.6644
hgiul89	66	.1114652	.0323523	0	.2399
hdink89	66	.7977333	.1731849	0	1
aturn89	66	.3181788	.1089565	0	.4413
adink89	66	.3925909	.1927738	0	1
agiul89	66	.5106606	.1653516	0	.6341

-> neigh= East NY					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	206	241.7718	152.2772	3	636
pdink89	206	.8172483	.2324505	0	1
pgiul89	206	.1822504	.232427	0	1
wturn89	206	.369632	.0954167	0	.5638
wgiul89	206	.6502073	.2498765	0	1
wdink89	206	.316234	.2241873	0	1
bturn89	206	.3575883	.1323292	0	.8301
bgiul89	206	.0520655	.094667	0	1
bdink89	206	.7802689	.3508385	0	.9979
hturn89	206	.1363252	.0640132	.0142	.3226
hgiul89	206	.1068131	.0313066	0	.3728
hdink89	206	.8434398	.064794	0	.9534
aturn89	206	.3414485	.0806462	0	.4802
adink89	206	.3948194	.1552888	0	.816
agiul89	206	.4120073	.248252	0	1

-> neigh= East Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	60	354.6333	126.6724	65	613
pdink89	60	.7470393	.1103637	.2447257	.8949153
pgiul89	60	.2455999	.1095084	.0983051	.7489452
wturn89	60	.3596867	.054709	.2433	.4965
wgiul89	60	.4115717	.211561	.1296	.8142
wdink89	60	.57828	.2104161	.1768	.8602
bturn89	60	.39055	.0929601	0	.6091
bgiul89	60	.0610467	.012793	0	.0821
bdink89	60	.8641867	.2650277	0	1
hturn89	60	.1482283	.0600954	.055	.3655
hgiul89	60	.1145583	.0084919	.0952	.1356
hdink89	60	.8358967	.132237	0	1
aturn89	60	.2918633	.1532253	0	.4848
adink89	60	.408395	.185908	0	1
agiul89	60	.4277533	.2295675	0	.6065

-> neigh= Flatbush					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	156	289.8718	153.0451	7	679
pdink89	156	.8017162	.2322495	.1412429	1
pgiul89	156	.1974287	.2322279	0	.8587571
wturn89	156	.3761558	.0445021	.1825	.5172
wgiul89	156	.6628596	.2297159	0	.9769
wdink89	156	.3349974	.2272594	.0232	1
bturn89	156	.3412321	.1482836	0	.7728
bgiul89	156	.0814577	.0983116	0	.5636
bdink89	156	.7499244	.3781074	0	1
hturn89	156	.1288564	.0676116	0	.3748

hgiul89	156	.1108872	.0171499	0	.149
hdink89	156	.8432628	.0524017	.5019	1
aturn89	156	.3371494	.0920543	0	.5132
adink89	156	.3569468	.1847709	0	1
agiul89	156	.4833	.1663652	0	.6287

-> neigh= Flushing					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	185	365.8	168.856	2	752
pdink89	185	.2383882	.1377865	0	.7826087
pgiul89	185	.7607423	.1386102	.2148338	1
wturn89	185	.3957714	.1147636	.0662	.8811
wgiul89	185	.8960973	.0830516	.4787	1
wdink89	185	.1050795	.0825646	0	.5357
bturn89	185	.3840411	.1096992	0	.786
bgiul89	185	.0505957	.0500757	0	.6
bdink89	185	.7563243	.3677049	0	.9805
hturn89	185	.1430984	.0866426	.0372	.5905
hgiul89	185	.1189865	.0660821	.0865	1
hdink89	185	.8500503	.0472398	.6188	.9774
aturn89	185	.3065865	.1244312	0	.4487
adink89	185	.3591211	.1796039	0	.6567
agiul89	185	.5072973	.2128278	0	1

-> neigh= Forest Hills					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	125	348.76	179.7052	7	743
pdink89	125	.3127114	.1649005	.1197183	.9590444
pgiul89	125	.6855712	.1649231	.0375427	.8802817
wturn89	125	.3772176	.0868666	.1563	.5845
wgiul89	125	.8309824	.1092231	.3349	.9759
wdink89	125	.1688008	.1083074	.0231	.6417
bturn89	125	.3701272	.1162246	0	.6619
bgiul89	125	.05916	.0215589	0	.0893
bdink89	125	.7527072	.3718983	0	.9882
hturn89	125	.1278432	.0683246	0	.3223
hgiul89	125	.1077672	.025811	0	.1474
hdink89	125	.8464624	.0466472	.6054	.9505
aturn89	125	.320028	.08635	0	.4365
adink89	125	.3817952	.1565906	0	.5216
agiul89	125	.5397288	.1291618	0	.795

-> neigh= Fort Greene					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	80	290	184.1824	12	781
pdink89	80	.9149083	.0764896	.6052632	1
pgiul89	80	.0838956	.0751917	0	.368421
wturn89	80	.4199925	.0774123	.1582	.5642
wgiul89	80	.4731188	.2637853	0	.8302
wdink89	80	.5229925	.2655386	.1775	1
bturn89	80	.3817762	.1260016	0	.7256
bgiul89	80	.0425613	.0422277	0	.243
bdink89	80	.709035	.4124407	0	1
hturn89	80	.1360938	.0809306	.0458	.3826
hgiul89	80	.09514	.031119	0	.129
hdink89	80	.8513737	.0385963	.7037	1
aturn89	80	.32227	.1040615	0	.4454
adink89	80	.3793463	.1916472	0	1

agiul89	80	.3888975	.2451874	0	.6223
-> neigh= Greenpoint					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	45	249.1111	151.1045	3	561
pdink89	45	.3449787	.1709751	.1020408	.71875
pgiul89	45	.6545177	.1708072	.28125	.8979592
wturn89	45	.2864667	.0634375	.1409	.4313
wgiul89	45	.7941489	.1208493	.333	.9479
wdink89	45	.2069556	.1225878	.0498	.6718
bturn89	45	.3389333	.144348	0	.5959
bgiul89	45	.0534156	.0275296	0	.0803
bdink89	45	.7439067	.3794377	0	1
hturn89	45	.1039933	.0443235	.0363	.2666
hgiul89	45	.1139556	.0207144	0	.1398
hdink89	45	.8316111	.1393383	0	1
aturn89	45	.3032111	.1017508	0	.5027
adink89	45	.3781667	.1792292	0	1
agiul89	45	.5361822	.1203945	0	.6372
-> neigh= Harlem					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	118	417.5932	142.3268	17	828
pdink89	118	.9722476	.0549861	.4705882	1
pgiul89	118	.0263611	.0547975	0	.5294118
wturn89	118	.4515331	.071301	0	.6099
wgiul89	118	.5537008	.2360108	0	.7772
wdink89	118	.4156153	.2201982	0	1
bturn89	118	.3455458	.1466674	0	.5446
bgiul89	118	.0133644	.0141073	0	.0682
bdink89	118	.7570051	.3660332	0	1
hturn89	118	.1950686	.1127069	.0364	.7204
hgiul89	118	.1036407	.018741	0	.1373
hdink89	118	.8238983	.0932646	.311	1
aturn89	118	.3614932	.0963038	0	.5602
adink89	118	.3723339	.1761686	0	1
agiul89	118	.4153771	.2381951	0	.6246
-> neigh= Howard Beach					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	113	346.6195	149.4916	20	656
pdink89	113	.2187826	.1490347	.0505837	.8666667
pgiul89	113	.7809328	.1491738	.1333333	.9494163
wturn89	113	.3497221	.0893071	.0797	.7182
wgiul89	113	.9237239	.0606628	.6381	.9847
wdink89	113	.0775398	.061089	.0161	.3609
bturn89	113	.3552938	.0924854	0	.5469
bgiul89	113	.0786566	.0759583	0	.5324
bdink89	113	.7962681	.349165	0	1
hturn89	113	.1108345	.0631813	.0297	.3905
hgiul89	113	.1308283	.1463171	0	1
hdink89	113	.8462965	.0789463	.5051	1
aturn89	113	.3229796	.0752985	0	.445
adink89	113	.3618088	.2022577	0	1
agiul89	113	.540315	.1306244	0	.8413
-> neigh= Inwood					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	36	337.3333	163.625	30	655
pdink89	36	.4796687	.0739001	.3214286	.6477273
pgiul89	36	.5169996	.0744466	.3522727	.6785714
wturn89	36	.4023861	.0889882	.1628	.5704
wgiul89	36	.7476167	.1071435	.4647	.9107
wdink89	36	.2512889	.1028551	.0843	.5266
bturn89	36	.3349944	.1383631	0	.4568
bgiul89	36	.0582333	.0216604	0	.0839
bdink89	36	.7408528	.3718897	0	.9817
hturn89	36	.1845	.0876942	.0576	.4368
hgiul89	36	.09435	.0214968	.047	.1378
hdink89	36	.822625	.0833173	.4254	.9551
aturn89	36	.2839889	.0925988	0	.3681
adink89	36	.3552028	.1808614	0	.8075
agiul89	36	.51165	.1594694	0	.6169

-> neigh= Jackson Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	125	221.864	174.4155	5	811
pdink89	125	.2872687	.084038	.1084991	.6746988
pgiul89	125	.7109454	.0844095	.3253012	.8915009
wturn89	125	.3247304	.0720596	.2028	.6729
wgiul89	125	.9030672	.0456118	.5972	.9606
wdink89	125	.09852	.0456656	.0397	.4062
bturn89	125	.3343152	.1366401	0	.5895
bgiul89	125	.0575872	.0229713	0	.0794
bdink89	125	.7337544	.388909	0	1
hturn89	125	.1058592	.0738998	0	.4254
hgiul89	125	.1101544	.020945	0	.1474
hdink89	125	.8354328	.0884706	0	1
aturn89	125	.325364	.1183567	0	.5185
adink89	125	.379956	.1684255	0	.8796
agiul89	125	.5975584	.2240504	0	.8534

-> neigh= Middle Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	243	259.3539	170.3059	2	715
pdink89	243	.4723035	.3226672	0	.9813084
pgiul89	243	.5269837	.3229963	.0186916	1
wturn89	243	.344484	.0851144	0	.6098
wgiul89	243	.8222934	.1508901	0	1
wdink89	243	.1661226	.1208961	0	.8047
bturn89	243	.3773132	.122629	0	.9379
bgiul89	243	.0491996	.0683826	0	1
bdink89	243	.7863263	.3465768	0	.9974
hturn89	243	.131386	.0694492	.0349	.4437
hgiul89	243	.1141909	.0678064	0	1
hdink89	243	.8424202	.0643111	0	.9701
aturn89	243	.2984856	.1307614	0	.4463
adink89	243	.3931572	.1517095	0	.7864
agiul89	243	.4344436	.2414309	0	1

-> neigh= Mott Haven					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	90	275.1111	119.8863	26	679
pdink89	90	.8095134	.069199	.6284585	.9506173
pgiul89	90	.1866259	.0684391	.0452675	.3636364

wturn89	90	.4066733	.0489425	.3163	.6719
wgiul89	90	.7448689	.0205014	.6909	.7962
wdink89	90	.2556444	.0281803	.187	.334
bturn89	90	.3612533	.133335	0	.5652
bgiul89	90	.0566078	.0257843	0	.199
bdink89	90	.7978067	.3217975	0	.999
hturn89	90	.1739322	.1146003	.0378	.8717
hgiul89	90	.10771	.0248844	.0471	.2731
hdink89	90	.8150978	.0927231	.3052	.9193
aturn89	90	.3060267	.115349	0	.5024
adink89	90	.3857978	.1453543	0	.8885
agiul89	90	.3199733	.2761501	0	.6224

-> neigh= North Shore					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	36	374.3333	99.91253	188	590
pdink89	36	.577919	.197902	.2644068	.9899498
pgiul89	36	.4213121	.1982193	.0075377	.7355932
wturn89	36	.4160417	.0473796	.335	.5615
wgiul89	36	.6332944	.1772564	.0273	.8662
wdink89	36	.3652833	.176053	.1365	.9587
bturn89	36	.3971806	.0379621	.2364	.4896
bgiul89	36	.0601667	.0126483	.008	.084
bdink89	36	.8614167	.2639376	0	.9943
hturn89	36	.1329833	.0626517	.0328	.304
hgiul89	36	.1067111	.0225415	0	.1482
hdink89	36	.8515972	.0217007	.8161	.9271
aturn89	36	.3563611	.1056406	0	.5017
adink89	36	.3790278	.1770397	0	.6735
agiul89	36	.5275361	.1320062	0	.6063

-> neigh= Park Slope					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	128	313.6875	199.0814	13	858
pdink89	128	.6130512	.1397583	.2727273	.9534883
pgiul89	128	.3812902	.1388853	.0465116	.7209302
wturn89	128	.4221766	.0677126	.1874	.6644
wgiul89	128	.5010508	.1589043	.1778	.8717
wdink89	128	.4922805	.1603193	.1154	.8301
bturn89	128	.3094023	.1630675	0	.7048
bgiul89	128	.0547023	.0238036	0	.0817
bdink89	128	.6962734	.4140674	0	1
hturn89	128	.1459812	.0798748	.034	.479
hgiul89	128	.1049836	.0208787	0	.1435
hdink89	128	.8385602	.0885104	0	1
aturn89	128	.2787859	.1317051	0	.4475
adink89	128	.3849664	.1932916	0	1
agiul89	128	.4608586	.2128542	0	.6203

-> neigh= Battery Park					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	4	230.25	127.4843	52	334
pdink89	4	.4057305	.0426961	.3584071	.4615385
pgiul89	4	.5882871	.0362097	.5384616	.6238938
wturn89	4	.197275	.1193377	.0226	.2924
wgiul89	4	.687325	.0312103	.6555	.7303
wdink89	4	.306175	.0293618	.2697	.3402
bturn89	4	.336075	.1141019	.1683	.4162

bgiul89	4	.16125	.1943792	.061	.4528
bdink89	4	.936025	.0092601	.9274	.945
hturn89	4	.144575	.0340315	.1047	.1845
hgiul89	4	.11605	.0199897	.0864	.1287
hdink89	4	.87155	.0470261	.8182	.9164
aturn89	4	.36815	.0276794	.3393	.3987
adink89	4	.4147	.0162364	.3926	.4306
agiul89	4	.582325	.0293298	.5484	.6113

-> neigh=		Pelham Bay			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	258	331.3837	130.7653	26	661
pdink89	258	.4540209	.2960854	.0644491	.9809886
pgiul89	258	.5439728	.29756	.0190114	.9355509
wturn89	258	.4087543	.0762878	.2297	.8281
wgiul89	258	.847805	.0901588	.5371	.9842
wdink89	258	.1513876	.0894989	.0165	.4418
bturn89	258	.3180481	.1643544	0	.5895
bgiul89	258	.0476849	.0348688	0	.3728
bdink89	258	.7070961	.4041253	0	1
hturn89	258	.1913407	.1102068	.0253	.7924
hgiul89	258	.1093403	.0615755	0	1
hdink89	258	.8290182	.0867097	.14	1
aturn89	258	.3425058	.0743057	0	.4996
adink89	258	.3916434	.1694185	0	1
agiul89	258	.5084477	.161822	0	.6305

-> neigh=		Queens Village			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	178	403.1742	151.3222	11	714
pdink89	178	.2658986	.1223277	.0686767	.8918919
pgiul89	178	.7336884	.1226901	.1081081	.9313233
wturn89	178	.4394831	.1041629	.1743	.8495
wgiul89	178	.8615275	.1058196	.5267	.9861
wdink89	178	.1387017	.1053514	.0166	.4716
bturn89	178	.3778713	.120766	0	.9446
bgiul89	178	.059341	.0662827	0	.783
bdink89	178	.7281208	.3935398	0	1
hturn89	178	.1776612	.086496	.0338	.5439
hgiul89	178	.1149876	.0685075	0	1
hdink89	178	.8459213	.0518649	.5181	1
aturn89	178	.2846045	.1286906	0	.4786
adink89	178	.4133185	.1273459	0	1
agiul89	178	.4827786	.2094305	0	.823

-> neigh=		Riverdale			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	98	390.2551	115.6306	67	680
pdink89	98	.3805767	.161038	.1108179	.9453682
pgiul89	98	.6172346	.1613099	.0546318	.889182
wturn89	98	.4094816	.1227338	.1015	.8775
wgiul89	98	.7630388	.150326	.0735	.953
wdink89	98	.2364796	.1490157	.0489	.921
bturn89	98	.2858082	.1835819	0	.5262
bgiul89	98	.0451112	.030043	0	.0767
bdink89	98	.6616867	.4222493	0	1
hturn89	98	.1592786	.106571	.0339	.6539
hgiul89	98	.1106041	.0343215	.0689	.4163

hdink89	98	.8393592	.0211039	.8075	1
aturn89	98	.3445112	.0409831	.2217	.4569
adink89	98	.4329163	.0911888	0	1
agiul89	98	.5269786	.1271137	0	.6348

-> neigh= Rockaways					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	71	365.9859	154.8226	3	685
pdink89	71	.4902381	.2987478	.0705128	.9904611
pgiul89	71	.5093102	.2986971	.0079491	.9294872
wturn89	71	.4389761	.1161199	.2034	.678
wgiul89	71	.7394451	.1909806	.0844	.9459
wdink89	71	.2574803	.1877797	.0536	.9202
bturn89	71	.3591084	.097758	0	.5668
bgiul89	71	.0762282	.0748176	0	.333
bdink89	71	.7367803	.3856177	0	.9792
hturn89	71	.1524775	.0912339	0	.381
hgiul89	71	.105969	.0282597	0	.1502
hdink89	71	.8523507	.0667552	.4579	.9607
aturn89	71	.2664817	.1133837	.0311	.5762
adink89	71	.3704366	.1709596	0	.602
agiul89	71	.4958324	.1675508	0	.6685

-> neigh= Satmar					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	18	239.0556	118.2293	15	499
pdink89	18	.4827456	.1222473	.2932862	.7412587
pgiul89	18	.5150236	.1239829	.2552448	.7067138
wturn89	18	.3107111	.1080438	.1767	.5508
wgiul89	18	.6344278	.1073016	.392	.8067
wdink89	18	.3645167	.1076264	.2003	.6161
bturn89	18	.2814944	.1490176	0	.4209
bgiul89	18	.0507167	.028556	0	.0755
bdink89	18	.6845222	.4371981	0	.987
hturn89	18	.1278833	.0514047	.0575	.2467
hgiul89	18	.1129389	.0092869	.0941	.1302
hdink89	18	.8263944	.0904125	.4896	.9346
aturn89	18	.3011833	.0788634	.0265	.3606
adink89	18	.3531111	.1990195	0	.5768
agiul89	18	.3717444	.2712325	0	.5951

-> neigh= Sheepshead Bay					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	237	322.4726	138.7665	39	658
pdink89	237	.2263	.09412	.0454545	.6195652
pgiul89	237	.7715254	.0944273	.3804348	.9545454
wturn89	237	.3873021	.1043332	.1112	.813
wgiul89	237	.8483363	.0831199	.4404	.9927
wdink89	237	.1508359	.083394	.0087	.561
bturn89	237	.3274063	.1376688	0	.5737
bgiul89	237	.0500945	.0297761	0	.0868
bdink89	237	.7732992	.3612782	0	1
hturn89	237	.1337869	.0562315	0	.2866
hgiul89	237	.1133831	.0604271	0	1
hdink89	237	.8496806	.0424561	.585	1
aturn89	237	.3232937	.1179496	0	.5147
adink89	237	.3861093	.1819252	0	1
agiul89	237	.4917152	.2042196	0	.8906

-> neigh= Southeast Queens					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	237	395.2321	172.5282	8	1282
pdink89	237	.8407622	.2392058	.1041096	1
pgiul89	237	.1588049	.2391678	0	.8958904
wturn89	237	.4297283	.0723837	.2519	.7133
wgiul89	237	.5136633	.3257814	0	.9732
wdink89	237	.4844768	.3245327	.0247	1
bturn89	237	.3705405	.1352896	0	.9352
bgiul89	237	.0637785	.1185395	0	.8456
bdink89	237	.7632207	.3720313	0	1
hturn89	237	.1302823	.080532	0	.6393
hgiul89	237	.1062004	.1089424	0	1
hdink89	237	.8436861	.0850152	0	1
aturn89	237	.3182241	.1019725	0	.5901
adink89	237	.3512751	.1917746	0	1
agiul89	237	.3455354	.2663285	0	.6663

-> neigh= Staten Island					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	251	392.3745	103.772	61	616
pdink89	251	.1542081	.080173	.050505	.6794583
pgiul89	251	.8456264	.0804608	.3205418	.949495
wturn89	251	.4338191	.0857622	.1494	.702
wgiul89	251	.9069749	.0549055	.569	.987
wdink89	251	.0935661	.0545574	.0137	.4286
bturn89	251	.4131876	.0576119	.1618	.8234
bgiul89	251	.0414952	.0404599	0	.3751
bdink89	251	.8347116	.2971546	0	.9974
hturn89	251	.1504606	.0682962	.0456	.4054
hgiul89	251	.1153789	.0579519	0	1
hdink89	251	.8425072	.0463177	.477	.9681
aturn89	251	.3670462	.0775667	0	.5147
adink89	251	.3924884	.1602562	0	.9009
agiul89	251	.5346514	.1126218	0	.6879

-> neigh= Styvesant Town					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	19	451.3158	109.5151	320	789
pdink89	19	.3614565	.0442429	.3	.4942857
pgiul89	19	.6343765	.0437249	.5	.6957447
wturn89	19	.5432105	.1314631	.3708	.9272
wgiul89	19	.7032	.0533958	.5681	.7895
wdink89	19	.2943789	.0548761	.2092	.4331
bturn89	19	.4279316	.0552368	.368	.5802
bgiul89	19	.0631316	.0054617	.0552	.0731
bdink89	19	.6409421	.4475883	0	.9891
hturn89	19	.1444526	.1450455	.0433	.6615
hgiul89	19	.1063263	.009638	.0899	.1235
hdink89	19	.8472842	.0188202	.8101	.8906
aturn89	19	.3430947	.0581955	.1757	.4219
adink89	19	.4235895	.1074817	0	.5395
agiul89	19	.5515368	.0265526	.4828	.5825

-> neigh= Sunset Park					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot89	65	222.0154	119.6037	1	455
pdink89	65	.5760984	.1911483	.1975309	1
pgiul89	65	.4233726	.1911833	0	.7942387
wturn89	65	.3530431	.0779818	0	.5735
wgiul89	65	.8071138	.131123	0	.9628
wdink89	65	.1780785	.0861138	0	.4209
bturn89	65	.3316369	.1329573	0	.532
bgiul89	65	.0577338	.0198865	0	.0807
bdink89	65	.8125662	.3126263	0	.995
hturn89	65	.1343062	.0723506	.0487	.413
hgiul89	65	.1104631	.0259632	.0717	.2952
hdink89	65	.8325754	.108965	0	.9682
aturn89	65	.2834031	.1207873	0	.4046
adink89	65	.3561523	.1794744	0	.6872
agiul89	65	.4364431	.2443286	0	.7619

-> neigh=		Tremont			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	260	276.8038	132.3189	27	705
pdink89	260	.8281777	.1334897	.2962963	.9830508
pgiul89	260	.1706046	.1330097	.005291	.6962963
wturn89	260	.3822942	.0575531	.1031	.6368
wgiul89	260	.7349746	.1001393	.0819	.9209
wdink89	260	.2606804	.0929968	.0714	.9212
bturn89	260	.3482638	.1506466	0	.5838
bgiul89	260	.0453269	.0278144	0	.257
bdink89	260	.7799554	.3530494	0	1
hturn89	260	.1747704	.0818185	.0309	.6088
hgiul89	260	.1047588	.0271736	.0171	.3391
hdink89	260	.8211808	.1181634	0	1
aturn89	260	.3627938	.0675549	0	.5717
adink89	260	.3644985	.1871328	0	1
agiul89	260	.4696273	.1985137	0	.6223

-> neigh=		Upper East Side			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	165	397.2667	122.9546	70	640
pdink89	165	.3776548	.0835577	.1867704	.6666667
pgiul89	165	.6189359	.0839692	.3253968	.8112841
wturn89	165	.3788448	.1122162	.1214	.8913
wgiul89	165	.6643552	.0738316	.4176	.8391
wdink89	165	.332443	.0729933	.159	.5835
bturn89	165	.31912	.1662746	0	.545
bgiul89	165	.0545303	.0349158	0	.343
bdink89	165	.7086406	.3895329	0	1
hturn89	165	.1435291	.081951	.0314	.4076
hgiul89	165	.11206	.0254089	0	.3353
hdink89	165	.810383	.1430752	0	1
aturn89	165	.3178115	.1092936	0	.5011
adink89	165	.38016	.2030621	0	1
agiul89	165	.5060982	.1623818	0	.6251

-> neigh=		Upper West Side			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	185	412.6919	121.0582	40	712
pdink89	185	.6480916	.1201865	.4026316	.9625293
pgiul89	185	.3459868	.1196428	.0374707	.5829307
wturn89	185	.4180562	.1009992	.1436	.6971

wgiul89	185	.4342157	.1136303	.178	.8015
wdink89	185	.5581838	.113368	.1946	.8195
bturn89	185	.3242892	.1596222	0	.6053
bgiul89	185	.0516708	.0249454	0	.08
bdink89	185	.7295227	.3880499	0	1
hturn89	185	.1871373	.1029138	.054	.6209
hgiul89	185	.1053178	.0182829	.0357	.1746
hdink89	185	.8123741	.1103016	0	1
aturn89	185	.3372422	.1128129	0	.5607
adink89	185	.3598908	.1717324	0	1
agiul89	185	.5056616	.1605096	0	.621

-> neigh=Washington Heights

Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	70	340.0857	131.1652	59	694
pdink89	70	.7227343	.1304924	.4190476	.9859895
pgiul89	70	.275531	.1305141	.0122592	.5809524
wturn89	70	.3588986	.0670665	.2695	.6682
wgiul89	70	.74734	.1250571	.0503	.8805
wdink89	70	.2528757	.1227761	.1079	.9365
bturn89	70	.3546814	.1517202	0	.5984
bgiul89	70	.0535	.0224621	0	.086
bdink89	70	.7548343	.3700281	0	1
hturn89	70	.18831	.0819172	.0614	.4145
hgiul89	70	.0908386	.04174	.0205	.3425
hdink89	70	.8274643	.0881237	.3381	1
aturn89	70	.3092329	.1022361	0	.56
adink89	70	.35706	.1811056	0	1
agiul89	70	.5219657	.1473788	0	.6132

-> neigh=

Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	109	355.6697	132.713	32	696
pdink89	109	.5794511	.0916735	.3536585	.7635328
pgiul89	109	.4149748	.0935343	.2298578	.6463414
wturn89	109	.3490229	.0961126	.1663	.6779
wgiul89	109	.4863009	.1102934	.276	.8588
wdink89	109	.5069798	.1091276	.1272	.7136
bturn89	109	.3732119	.1269103	0	.5652
bgiul89	109	.0602596	.0181472	0	.0876
bdink89	109	.7912917	.3454066	0	1
hturn89	109	.1669064	.1248324	.0374	.6935
hgiul89	109	.1074789	.0148714	.0615	.137
hdink89	109	.8449972	.0536497	.5937	1
aturn89	109	.3401083	.0919606	0	.4419
adink89	109	.3943376	.2230054	0	1
agiul89	109	.5310284	.1205433	0	.6201

-> neigh=

Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	75	405.9867	122.406	61	633
pdink89	75	.6327621	.0840941	.3846154	.8032787
pgiul89	75	.3612383	.0828851	.1967213	.6070686
wturn89	75	.3996787	.0972316	.1911	.7809
wgiul89	75	.387508	.0903706	.2061	.6282
wdink89	75	.6067573	.0919742	.3625	.7942
bturn89	75	.3680173	.1317688	0	.5416
bgiul89	75	.0592093	.0202328	0	.0809

bdink89	75	.7853547	.340881	0	1
hturn89	75	.120464	.0686216	.0268	.3758
hgiul89	75	.1108013	.0105374	.0904	.138
hdink89	75	.83638	.0906496	.344	1
aturn89	75	.2790533	.1476083	0	.495
adink89	75	.3939547	.1942691	0	1
agiul89	75	.4531707	.2200932	0	.6221

```
-> neigh= Windsor
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Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	83	228.4699	161.2276	6	740
pdink89	83	.2261431	.0935941	.0517241	.5572917
pgiul89	83	.7730307	.0937319	.4427083	.9482759
wturn89	83	.307247	.0666112	.1389	.4923
wgiul89	83	.9183434	.0415722	.7441	.9875
wdink89	83	.0811783	.0412531	.0113	.2557
bturn89	83	.332806	.1256751	0	.5193
bgiul89	83	.0548892	.0256327	0	.0878
bdink89	83	.7832084	.3563252	0	1
hturn89	83	.1073024	.0536414	.0319	.3762
hgiul89	83	.1124602	.0105903	.0904	.1401
hdink89	83	.8399373	.0961803	.1542	1
aturn89	83	.3117759	.0873313	0	.4408
adink89	83	.341406	.1857539	0	.5014
agiul89	83	.5439157	.2083158	0	.8637

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-> neigh= Lubavitchers
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Variable	Obs	Mean	Std. Dev.	Min	Max
tot89	17	313.4706	123.6856	86	495
pdink89	17	.8000297	.1513061	.3794643	.966581
pgiul89	17	.199422	.1515323	.033419	.6205357
wturn89	17	.3571588	.0363412	.3077	.4296
wgiul89	17	.4503824	.1944968	.0372	.7802
wdink89	17	.5525353	.1918824	.2093	.9613
bturn89	17	.3098412	.1877885	0	.5837
bgiul89	17	.0887	.0869841	0	.315
bdink89	17	.6690235	.4456341	0	.9918
hturn89	17	.1018882	.1090892	.0402	.5174
hgiul89	17	.1680235	.2147314	.0909	1
hdink89	17	.8211471	.0894007	.4796	.8786
aturn89	17	.3198647	.0892722	.0872	.4646
adink89	17	.3858706	.1524214	0	.4793
agiul89	17	.3638235	.277592	0	.5935

```
. by neigh: sum tot93 pdink93 pgiul93 turn93 wturn93 wgiul93 wdink93  
phgiul93 hturn hdink93 aturn93 agiul93 adink93 bturn93 bgiul93 bdink93
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-> neigh= Astoria
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Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	170	298.8706	166.5996	2	696
pdink93	170	.300361	.1934053	0	.9797753
pgiul93	170	.699639	.1934053	.0202247	1
turn93	170	.2650822	.1203002	.0058651	.8866995
wturn93	170	.3242312	.1101247	.0091	.7932
wgiul93	170	.8775541	.0985776	.0357	1
wdink93	170	.1206953	.0978846	0	.9666
phgiul93	170	.1609959	.0954014	.0262	1

hturn	170	.0984129	.0836122	.0069	.7708
hdink93	170	.8638394	.0734444	0	1
aturn93	170	.3510153	.1662285	0	.574
agiul93	170	.5716129	.2802273	0	1
adink93	170	.3046106	.160517	0	.8569
bturn93	170	.2894406	.1125035	0	.6612
bgiul93	170	.0813376	.1113625	0	1
bdink93	170	.7480429	.3707156	0	1

-> neigh= Baychester					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	96	317.0938	137.2814	15	810
pdink93	96	.7757143	.1669261	.2912621	.9747292
pgiul93	96	.2242857	.1669261	.0252708	.7087379
turn93	96	.3036527	.0755177	.147918	.4577465
wturn93	96	.4127667	.0673347	.2536	.5494
wgiul93	96	.6838583	.1599968	.1403	.9196
wdink93	96	.31325	.1632267	.0899	.8578
phgiul93	96	.1466208	.0163078	.1032	.1822
hturn	96	.1074958	.0540975	.0461	.3224
hdink93	96	.8387031	.1264728	0	.9241
aturn93	96	.332375	.1367828	0	.5373
agiul93	96	.5470708	.2375392	0	.6891
adink93	96	.3172635	.0953525	0	.404
bturn93	96	.2668531	.1865053	0	.517
bgiul93	96	.0798583	.1105943	0	.5452
bdink93	96	.6191385	.4303216	0	.9336

-> neigh= Bay Ridge					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	59	377.7458	130.449	30	628
pdink93	59	.153759	.039902	.056	.2666667
pgiul93	59	.846241	.039902	.7333333	.944
turn93	59	.3763792	.0858689	.2068966	.5862069
wturn93	59	.3958373	.0784627	.2153	.5942
wgiul93	59	.9061763	.0400421	.7646	.9721
wdink93	59	.0936068	.0399155	.0302	.2353
phgiul93	59	.1523712	.0157235	.1138	.1877
hturn	59	.1234525	.0406642	.0696	.2544
hdink93	59	.8650017	.0431594	.7021	.9573
aturn93	59	.3562322	.1611065	0	.5546
agiul93	59	.5717898	.2306696	0	.8097
adink93	59	.3154153	.1562192	0	.6784
bturn93	59	.2862661	.10222	0	.4687
bgiul93	59	.0555898	.0392243	0	.094
bdink93	59	.7415441	.3805858	0	.9971

-> neigh= Bedford Styvesant					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	100	282.66	147.1957	12	588
pdink93	100	.9624387	.0423877	.7890625	1
pgiul93	100	.0375613	.0423877	0	.2109375
turn93	100	.3480185	.082879	.1176471	.6230366
wturn93	100	.432193	.1221233	0	.6366
wgiul93	100	.644954	.2284683	0	.7866
wdink93	94	.312	.1640106	.1983	1
phgiul93	100	.120017	.036419	0	.1704
hturn	100	.12603	.0512084	.043	.3908

hdink93	100	.86042	.0277186	.6953	1
aturn93	100	.431556	.1038762	0	.6466
agiul93	100	.391677	.3124104	0	.6993
adink93	100	.303693	.1313127	0	.6141
bturn93	100	.341065	.0819816	.0687	.6308
bgiul93	100	.022928	.0218616	0	.116
bdink93	100	.838831	.2667797	0	.9974

-> neigh=		Bensonhurst			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	182	308.956	161.7179	18	776
pdink93	182	.1060653	.0608567	0	.6774194
pgiul93	182	.8939347	.0608567	.3225806	1
tturn93	182	.3109204	.0855281	.0266552	.6153846
wturn93	182	.331017	.0794774	.0512	.6181
wgiul93	182	.9529995	.0513163	.4248	1
wdink93	182	.0467582	.0509555	0	.5668
phgiul93	182	.1553566	.0651313	.1136	1
hturn	182	.0986775	.0325796	.0302	.2602
hdink93	182	.8495005	.0817886	0	1
aturn93	182	.3055066	.1504415	0	.8146
agiul93	182	.6472544	.2026028	0	1
adink93	182	.3072813	.1643898	0	1
bturn93	182	.2824681	.1185009	0	.5388
bgiul93	182	.0483159	.0846869	0	1
bdink93	182	.8008275	.3234479	0	1

-> neigh=		Boro Park			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	50	293.54	135.3172	42	527
pdink93	50	.4500071	.1758456	.1677632	.8970297
pgiul93	50	.5499929	.1758456	.1029703	.8322368
tturn93	50	.340955	.1205501	.1185693	.6618705
wturn93	50	.401422	.0969182	.1295	.6946
wgiul93	50	.715472	.1174693	.369	.9398
wdink93	50	.285176	.1192241	.0601	.6309
phgiul93	50	.152628	.0157563	.1197	.1851
hturn	50	.121104	.0571256	.0437	.3456
hdink93	50	.84945	.0644283	.4159	.8956
aturn93	50	.395122	.131764	0	.6474
agiul93	50	.630766	.1013942	0	.689
adink93	50	.291758	.206746	0	.8734
bturn93	50	.293552	.09394	0	.4566
bgiul93	50	.084568	.0380156	0	.235
bdink93	50	.86336	.2586818	0	1

-> neigh=		Canarsie			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	99	349.3636	127.6143	31	677
pdink93	99	.1555885	.1631964	.0432277	.8942308
pgiul93	99	.8444115	.1631964	.1057692	.9567723
tturn93	99	.4191736	.0945988	.1050157	.5881356
wturn93	99	.4364535	.091688	.1054	.6212
wgiul93	99	.9026566	.0999386	.5111	.9865
wdink93	99	.0974384	.1007347	.0125	.4992
phgiul93	99	.1531222	.0126887	.1189	.181
hturn	99	.1453616	.0481776	.0587	.3209
hdink93	99	.8614626	.0235606	.7551	1

aturn93	99	.3772293	.11426	0	.5925
agiul93	99	.6088606	.183029	0	.7351
adink93	99	.2881354	.1411485	0	.6599
bturn93	99	.2950616	.1269756	0	.5789
bgiul93	99	.0490293	.0478196	0	.2775
bdink93	99	.8091343	.3108882	0	1

-> neigh= Chinatown					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	47	326.6383	140.3993	36	645
pdink93	47	.4341209	.1829901	.1471572	.805851
pgiul93	47	.5658791	.1829901	.1941489	.8528428
turn93	47	.2782756	.1886698	.0843012	.790146
wturn93	47	.3874277	.1466896	.182	.8355
wgiul93	47	.8016128	.1025476	.4423	.9376
wdink93	47	.1961936	.10148	.0766	.5504
phgiul93	47	.1514915	.0159217	.1238	.2034
hturn	47	.143117	.1554675	.0377	.6774
hdink93	47	.8129383	.1862907	0	1
aturn93	47	.391366	.1512832	0	.5671
agiul93	47	.5629383	.2229697	0	.853
adink93	47	.3132936	.1292489	0	.5474
bturn93	47	.327366	.1107808	0	.5657
bgiul93	47	.0848532	.0596049	0	.3961
bdink93	47	.8485553	.262507	0	1

-> neigh= Coney Island					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	24	337.6667	142.4126	31	600
pdink93	24	.6942389	.3065587	0	.9534314
pgiul93	24	.3057611	.3065587	.0465686	1
turn93	24	.3076517	.1095741	.1016949	.5466053
wturn93	24	.4004333	.1062657	.1143	.6155
wgiul93	24	.6273333	.2667345	.0737	1
wdink93	24	.3680125	.2656421	0	.9251
phgiul93	24	.1823792	.1749955	.1201	1
hturn	24	.1269917	.073981	.0441	.3244
hdink93	24	.8994125	.0396329	.8347	1
aturn93	24	.4132	.1377254	0	.5595
agiul93	24	.6101042	.2111774	0	1
adink93	24	.2775625	.1301652	0	.3801
bturn93	24	.2499375	.1588423	0	.5022
bgiul93	24	.1091708	.2137088	0	1
bdink93	24	.6575125	.4321691	0	.9883

-> neigh= Coop City					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	17	314.1765	76.13823	69	404
pdink93	17	.6631948	.0780374	.5507246	.8106312
pgiul93	17	.3368052	.0780374	.1893688	.4492754
turn93	17	.4041124	.1497274	.025547	.5423477
wturn93	17	.4667471	.1614413	.0394	.6048
wgiul93	17	.6272118	.1317107	.3846	.8448
wdink93	17	.3726765	.1298003	.1551	.6115
phgiul93	17	.1532059	.0149084	.1281	.1862
hturn	17	.1824294	.0868077	.0356	.2992
hdink93	17	.8485471	.0375593	.711	.8713
aturn93	17	.3497235	.1481734	0	.5023

agiul93	17	.5738059	.2168007	0	.6925
adink93	17	.3478294	.0239807	.31	.3915
bturn93	17	.1777176	.1950918	0	.4161
bgiul93	17	.0553588	.1006045	0	.418
bdink93	17	.4321765	.4725099	0	.9246

-> neigh= Corona					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	28	274	164.6716	15	607
pdink93	28	.8405949	.1628465	.4528302	.9915966
pgiul93	28	.1594051	.1628465	.0084034	.5471698
turn93	28	.2445976	.1281975	.0887931	.4793621
wturn93	28	.3859536	.0862023	.2667	.5389
wgiul93	28	.5944929	.2330311	.0344	.8298
wdink93	28	.3926929	.23472	.1498	.9608
phgiul93	28	.1340464	.0339062	.018	.1824
hturn	28	.0875821	.0503856	.0259	.1931
hdink93	28	.8741429	.0328853	.8326	1
aturn93	28	.3900179	.1479364	0	.557
agiul93	28	.5012786	.2289937	0	.6775
adink93	28	.2320929	.1709124	0	.3993
bturn93	28	.2678821	.1350671	0	.5885
bgiul93	28	.049425	.0306237	0	.1
bdink93	28	.7515643	.3710924	0	1

-> neigh= Crown Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	109	305.2018	161.3088	17	686
pdink93	109	.9640752	.0464746	.7435898	1
pgiul93	109	.0359248	.0464746	0	.2564103
turn93	109	.3027914	.0903766	.1233831	.575
wturn93	109	.4099046	.0968147	0	.609
wgiul93	109	.4621991	.278266	0	.7994
wdink93	105	.5188038	.2712636	.1872	1
phgiul93	109	.1244927	.0434156	0	.1784
hturn	109	.0998349	.0392281	.0534	.2488
hdink93	109	.8599532	.0175403	.8014	.9069
aturn93	109	.3985028	.1260993	0	.5731
agiul93	109	.4184046	.2899402	0	.7081
adink93	109	.3115165	.1333175	0	.7173
bturn93	109	.3276679	.084007	0	.6208
bgiul93	109	.0252486	.0320746	0	.256
bdink93	109	.8006349	.3225228	0	.997

-> neigh= East Harlem					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	63	324.9365	116.952	15	615
pdink93	63	.8310114	.0831778	.5938697	.9633027
pgiul93	63	.1689886	.0831778	.0366972	.4061303
turn93	63	.3519331	.1319531	.1013514	.7820895
wturn93	63	.4551079	.0912179	.2491	.768
wgiul93	63	.7235905	.1277401	.0838	.8309
wdink93	63	.2673365	.1277834	.1608	.9192
phgiul93	63	.1146286	.0210676	.0589	.1635
hturn	63	.2516905	.1371731	.0343	.7551
hdink93	63	.854727	.0168313	.805	.8874
aturn93	63	.5179254	.0834007	0	.6394
agiul93	63	.5144333	.2567076	0	.7239

adink93	63	.2869317	.1301712	0	.579
bturn93	63	.2870302	.1264264	0	.5291
bgiul93	63	.0673444	.0350503	0	.25
bdink93	63	.7289952	.377762	0	.9976

-> neigh= East Midtown					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	66	432.9394	139.6932	13	873
pdink93	66	.3729882	.0991695	.2307692	.6870968
pgiul93	66	.6270118	.0991695	.3129032	.7692308
turn93	66	.326644	.1088306	.0598846	.7454031
wturn93	66	.3483439	.1107641	.077	.7873
wgiul93	66	.6852288	.0905275	.3648	.9061
wdink93	66	.3142348	.0901598	.0915	.632
phgiul93	66	.1503621	.0140162	.1196	.1892
hturn	66	.1100955	.0571514	.0317	.4695
hdink93	66	.8649924	.0179351	.8302	.9091
aturn93	66	.3730076	.1373249	0	.6156
agiul93	66	.5988197	.193236	0	.7826
adink93	66	.299047	.1223109	0	.523
bturn93	66	.3256667	.1236102	0	.5457
bgiul93	66	.0876773	.0818801	0	.6711
bdink93	66	.8059879	.3061564	0	.9954

-> neigh= East NY					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	206	248.6117	152.9193	6	653
pdink93	206	.8215635	.2111571	0	1
pgiul93	206	.1784365	.2111571	0	1
turn93	206	.2958754	.1143688	.0289474	.8139535
wturn93	206	.3931233	.1106029	0	.6051
wgiul93	206	.6565471	.2274906	0	1
wdink93	199	.3163558	.1950238	0	1
phgiul93	206	.1360311	.0691707	0	1
hturn	206	.1179961	.0747676	.0293	.7023
hdink93	206	.8596728	.026439	.6831	1
aturn93	206	.4084597	.1034469	0	.616
agiul93	206	.4811466	.2848698	0	1
adink93	206	.3152374	.1355547	0	.812
bturn93	206	.3153636	.1272248	0	1
bgiul93	206	.0602383	.093391	0	1
bdink93	206	.7732015	.3468393	0	1

-> neigh= East Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	60	344.0833	112.5221	81	523
pdink93	60	.7212988	.1069596	.2246696	.85
pgiul93	60	.2787012	.1069596	.15	.7753304
turn93	60	.2927521	.1181449	.1109655	1
wturn93	60	.3680883	.1062557	.1882	1
wgiul93	60	.4518533	.2188955	.1701	.843
wdink93	60	.547615	.2192219	.1582	.823
phgiul93	60	.1402617	.0226644	.0867	.178
hturn	60	.1339733	.1361075	.0406	1
hdink93	60	.8465533	.0620544	.5174	.8947
aturn93	60	.3463567	.1827543	0	.5438
agiul93	60	.4870733	.2582392	0	.6861
adink93	60	.3128283	.1506179	0	.8399

bturn93	60	.3291683	.1058189	0	.5303
bgiul93	60	.0775	.0166806	0	.0978
bdink93	60	.83683	.2836775	0	.9975
-> neigh= Flatbush					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	156	303.3526	156.1103	1	701
pdink93	156	.8382941	.2060424	.102719	1
pgiul93	156	.1617059	.2060424	0	.897281
turn93	156	.2709396	.0945561	.05	.8268251
wturn93	156	.3965282	.0699362	.0814	.8749
wgiul93	156	.5811564	.22718	0	.9761
wdink93	156	.4192776	.2302928	.0229	1
phgiul93	156	.1446481	.0276067	0	.1865
hturn	156	.0896904	.052645	.0468	.5791
hdink93	156	.8531833	.0704836	0	.9113
aturn93	156	.4084865	.1218836	0	.6536
agiul93	156	.5469109	.2105634	0	.7248
adink93	156	.2947609	.180376	0	1
bturn93	156	.2944564	.1270005	0	.7152
bgiul93	156	.0586083	.0718457	0	.688
bdink93	156	.7500436	.3719695	0	1
-> neigh= Flushing					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	185	373.9784	172.3855	1	783
pdink93	185	.2070199	.1463661	0	1
pgiul93	185	.7929801	.1463661	0	1
turn93	185	.3632309	.1595639	.0038023	.984375
wturn93	185	.4094995	.1377201	.011	.9948
wgiul93	185	.9070038	.1061161	0	1
wdink93	185	.0917622	.1047746	0	1
phgiul93	185	.1638184	.109633	0	1
hturn	185	.1347778	.0969721	.0083	.8901
hdink93	185	.8643638	.0245141	.8141	1
aturn93	185	.3678038	.1526723	0	.5352
agiul93	185	.5911438	.2482478	0	1
adink93	185	.2818568	.1417463	0	.5093
bturn93	185	.3139676	.0850477	0	.6982
bgiul93	185	.0703832	.0965526	0	1
bdink93	185	.7497849	.3645072	0	.9838
-> neigh= Forest Hills					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	125	348.784	175.992	7	703
pdink93	125	.2816996	.1747676	.0261194	.9545454
pgiul93	125	.7183004	.1747676	.0454545	.9738806
turn93	125	.3293621	.1197342	.0963245	.6499069
wturn93	125	.380708	.0960477	.1778	.6701
wgiul93	125	.8500072	.1100408	.1325	.9882
wdink93	125	.1485992	.1098146	.0122	.8522
phgiul93	125	.1545696	.0455959	.1165	.6294
hturn	125	.1117088	.0539099	.031	.3423
hdink93	125	.853416	.0798098	0	1
aturn93	125	.3818456	.1098191	0	.5065
agiul93	125	.6390832	.1602774	0	.9112
adink93	125	.3019944	.1340234	0	.6105
bturn93	125	.3133464	.1023382	0	.6092

bgiul93	125	.07184	.0262369	0	.1094
bdink93	125	.7304992	.3783641	0	.996
-> neigh=	Fort Greene				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	80	286.275	179.4044	7	619
pdink93	80	.9102897	.0978044	.4285714	1
pgiul93	80	.0897103	.0978044	0	.5714286
turn93	80	.3335483	.1176946	.0356745	.6444445
wturn93	80	.4385638	.0937235	.0806	.6396
wgiul93	80	.4718613	.2746818	0	.8109
wdink93	80	.519645	.2838271	.1682	1
phgiul93	80	.1344463	.0324101	0	.1814
hturn	80	.1295537	.0722278	.0284	.4412
hdink93	80	.8539425	.0362142	.6739	.916
aturn93	80	.388895	.1310478	0	.5406
agiul93	80	.4421775	.2913362	0	.7092
adink93	80	.2931588	.1508259	0	.9576
bturn93	80	.32335	.1068581	0	.6475
bgiul93	80	.048375	.0430308	0	.228
bdink93	80	.7001912	.4074808	0	.998
-> neigh=	Greenpoint				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	45	244.1556	146.5148	1	530
pdink93	45	.3140772	.1844055	0	.8636364
pgiul93	45	.6859228	.1844055	.1363636	1
turn93	45	.2410796	.0796658	.0666667	.4795082
wturn93	45	.2886822	.0823819	.1395	.5416
wgiul93	45	.8072267	.1614509	.1356	1
wdink93	45	.1913022	.1607527	0	.8647
phgiul93	45	.1749	.1316879	.1199	1
hturn	45	.0955733	.0691084	.0449	.4074
hdink93	45	.8090178	.1844601	0	.8942
aturn93	45	.3639711	.1309703	0	.5528
agiul93	45	.6315778	.1397204	0	.7013
adink93	45	.2798267	.1303076	0	.3932
bturn93	45	.2761711	.1235039	0	.5512
bgiul93	45	.06554	.0337536	0	.1037
bdink93	45	.7249622	.3927616	0	1
-> neigh=	Harlem				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	118	390.5508	139.0212	1	819
pdink93	118	.9733172	.0434531	.625	1
pgiul93	118	.0266828	.0434531	0	.375
turn93	118	.3829249	.1196212	.0090909	.7777778
wturn93	118	.4742381	.088892	0	.7172
wgiul93	118	.5532424	.2414641	0	.7986
wdink93	117	.440253	.2395513	.213	1
phgiul93	118	.1134297	.036285	0	.206
hturn	118	.1462441	.0740295	.0041	.4614
hdink93	118	.8583636	.0135221	.8079	.9
aturn93	118	.4663186	.1293998	0	.6136
agiul93	118	.4678059	.2794031	0	.7154
adink93	118	.2945873	.1395099	0	.7905
bturn93	118	.2830025	.1306822	0	.6665
bgiul93	118	.0180119	.0363882	0	.375

bdink93	118	.7444339	.3693681	0	.9949
-> neigh= Howard Beach					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	113	340.3894	148.5699	8	765
pdink93	113	.2201879	.1437101	.031746	.6880734
pgiul93	113	.7798121	.1437101	.3119266	.968254
turn93	113	.2910203	.1116931	.0427807	.6272727
wturn93	113	.347615	.0861797	.0622	.6325
wgiul93	113	.9262708	.0505307	.7554	.9913
wdink93	113	.0719823	.0484882	.0085	.2414
phgiul93	113	.1500177	.0141017	.1124	.1921
hturn	113	.0956044	.0453261	.0347	.2654
hdink93	113	.8547566	.0841186	0	.9793
aturn93	113	.3793699	.118277	0	1
agiul93	113	.6352044	.1418336	0	.8078
adink93	113	.2905664	.1750913	0	1
bturn93	113	.3136088	.0811281	0	.5517
bgiul93	113	.0921531	.0855334	0	.625
bdink93	113	.7896673	.3463571	0	1
-> neigh= Inwood					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	36	310.8056	141.1746	30	602
pdink93	36	.4693437	.0935052	.2185185	.6923077
pgiul93	36	.5306563	.0935052	.3076923	.7814815
turn93	36	.3185985	.1122567	.1517932	.6243655
wturn93	36	.3915083	.090634	.2245	.6624
wgiul93	36	.7361556	.11907	.4154	.9125
wdink93	36	.2635889	.1187299	.0879	.5806
phgiul93	36	.1599306	.0707039	.1086	.5613
hturn	36	.1441111	.0828977	.0583	.446
hdink93	36	.8620139	.0637632	.5544	1
aturn93	36	.3267861	.1062721	0	.4181
agiul93	36	.5987306	.1844125	0	.6948
adink93	36	.268575	.1634305	0	.7076
bturn93	36	.2686667	.1177701	0	.4356
bgiul93	36	.0721111	.0266637	0	.0946
bdink93	36	.7135278	.387161	0	.9724
-> neigh= Jackson Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	125	211.096	159.9959	1	608
pdink93	125	.2700811	.1343998	0	1
pgiul93	125	.7299189	.1343998	0	1
turn93	125	.1997621	.1188131	.0024752	.7615894
wturn93	125	.3042344	.1029836	.0058	.7986
wgiul93	125	.8931144	.095094	0	1
wdink93	125	.1049016	.0949014	0	1
phgiul93	125	.1980408	.1897261	0	1
hturn	125	.071836	.0694501	.0027	.6425
hdink93	125	.8694784	.0252922	.8162	1
aturn93	125	.3823984	.1427273	0	.6024
agiul93	125	.6527768	.250214	0	1
adink93	125	.299304	.1410523	0	.8509
bturn93	125	.2878496	.1152004	0	.5376
bgiul93	125	.104592	.17069	0	1
bdink93	125	.7254704	.3836746	0	1

-> neigh= Middle Village					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	243	263.3909	175.0009	1	731
pdink93	243	.4453881	.3192936	0	1
pgiul93	243	.5546119	.3192936	0	1
turn93	243	.2742332	.1141714	.011236	.5542169
wturn93	243	.3536342	.1012884	0	.5962
wgiul93	243	.8279391	.1530659	0	1
wdink93	240	.1606229	.1225243	0	1
phgiul93	243	.1660156	.1208283	0	1
hturn	243	.1300165	.0736951	.0152	.4909
hdink93	243	.8619284	.0631564	0	.946
aturn93	243	.3545996	.1582774	0	.5618
agiul93	243	.5142424	.2854464	0	1
adink93	243	.3149576	.1249458	0	.7507
bturn93	243	.3221481	.1075166	0	.7167
bgiul93	243	.0642543	.0935082	0	1
bdink93	243	.7851568	.3353369	0	.9973
-> neigh= Mott Haven					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	90	278.7444	120.8966	30	674
pdink93	90	.797764	.080002	.5548781	.9336283
pgiul93	90	.202236	.080002	.0663717	.4451219
turn93	90	.3110976	.1004775	.1679721	.8723404
wturn93	90	.43331	.0656053	.3313	.7882
wgiul93	90	.7521578	.0219498	.6964	.8074
wdink93	90	.2386578	.0213339	.1847	.2892
phgiul93	90	.1314522	.0571653	.069	.4283
hturn	90	.2379667	.1089731	.0522	.8793
hdink93	90	.8699389	.0227393	.8212	.9525
aturn93	90	.3671011	.1422911	0	.6249
agiul93	90	.37655	.3242493	0	.7095
adink93	90	.3113156	.1478712	0	.9605
bturn93	90	.2945611	.1188508	0	.5043
bgiul93	90	.0696433	.0270603	0	.181
bdink93	90	.7921444	.3222691	0	.9913
-> neigh= North Shore					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	36	408.7222	121.5957	189	663
pdink93	36	.5580245	.2169196	.15625	.9503106
pgiul93	36	.4419755	.2169196	.0496894	.84375
turn93	36	.3852043	.0692788	.2374631	.6116236
wturn93	36	.4551222	.0546928	.373	.639
wgiul93	36	.6613083	.1872714	.1427	.9623
wdink93	36	.3342278	.1873566	.0426	.8722
phgiul93	36	.1424861	.0134923	.1193	.1747
hturn	36	.1392444	.0420904	.0609	.2999
hdink93	36	.8562333	.0147195	.8309	.8921
aturn93	36	.4388917	.1273411	0	.5859
agiul93	36	.612125	.152616	0	.7013
adink93	36	.2942722	.1431359	0	.5616
bturn93	36	.3631972	.0611571	.2078	.5088
bgiul93	36	.0776083	.014096	.05	.137
bdink93	36	.8490417	.2605897	0	.995

-> neigh=		Park Slope				
Variable	Obs	Mean	Std. Dev.	Min	Max	
tot93	128	319.3047	201.5786	5	834	
pdink93	128	.6088944	.1459117	.2575758	1	
pgiul93	128	.3911056	.1459117	0	.7424242	
turn93	128	.3822878	.1009797	.0987654	.6617782	
wturn93	128	.4364398	.085569	.1371	.7011	
wgiul93	128	.5014477	.1695224	0	.938	
wdink93	128	.4988391	.1697793	.0663	1	
phgiul93	128	.1457586	.0196289	0	.1841	
hturn	128	.1495656	.0544374	.0314	.3426	
hdink93	128	.8398344	.1218218	0	1	
aturn93	128	.3314	.1632737	0	.5533	
agiul93	128	.5347469	.2522693	0	.7021	
adink93	128	.3090461	.1872837	0	1	
bturn93	128	.2816641	.1484126	0	.8166	
bgiul93	128	.0684766	.0295804	0	.1031	
bdink93	128	.6843984	.4143464	0	1	

-> neigh=		Battery Park				
Variable	Obs	Mean	Std. Dev.	Min	Max	
tot93	4	277.25	171.2919	50	459	
pdink93	4	.4122227	.1018793	.3263473	.56	
pgiul93	4	.5877773	.1018793	.44	.6736527	
turn93	4	.2139221	.1312236	.0245821	.3170441	
wturn93	4	.2338	.1460793	.022	.3414	
wgiul93	4	.6797	.074827	.5796	.7567	
wdink93	4	.320075	.0828585	.2391	.4321	
phgiul93	4	.147075	.0145852	.1296	.1648	
hturn	4	.0736	.0146561	.055	.0904	
hdink93	4	.769	.1820485	.4979	.8835	
aturn93	4	.497775	.0416442	.4586	.5486	
agiul93	4	.610275	.1186054	.4387	.7053	
adink93	4	.34335	.0293373	.3104	.3756	
bturn93	4	.30975	.0989857	.1822	.4121	
bgiul93	4	.164075	.1644174	.0813	.4107	
bdink93	4	.931775	.0255727	.9138	.9696	

-> neigh=		Pelham Bay				
Variable	Obs	Mean	Std. Dev.	Min	Max	
tot93	258	321.2829	127.6651	44	659	
pdink93	258	.4458474	.2995226	.0378788	.9816092	
pgiul93	258	.5541526	.2995226	.0183908	.9621212	
turn93	258	.3497417	.1061108	.1465875	.8471503	
wturn93	258	.4204074	.087974	.1987	.8108	
wgiul93	258	.8462256	.0963861	.5047	.9918	
wdink93	258	.1512453	.0944385	.0084	.483	
phgiul93	258	.1464826	.0286488	.07	.3139	
hturn	258	.1683651	.0984166	.0497	.8672	
hdink93	258	.8609663	.0176009	.8271	.9236	
aturn93	258	.4069946	.0984094	0	.6096	
agiul93	258	.5944826	.1878266	0	.7329	
adink93	258	.3038585	.1275659	0	.869	
bturn93	258	.2769291	.150832	0	.521	
bgiul93	258	.0590841	.0396501	0	.3014	
bdink93	258	.691605	.4044737	0	.9961	

-> neigh= Queens Village

Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	178	406.0056	155.9804	7	905
pdink93	178	.2414249	.13218	0	.8772321
pgiul93	178	.7585751	.13218	.1227679	1
turn93	178	.4065238	.1193399	.0623886	.8326923
wturn93	178	.4460831	.107611	.0613	.8674
wgiul93	178	.8731073	.105826	.517	1
wdink93	178	.1258146	.1057722	0	.4825
phgiul93	178	.1568567	.0652033	.1147	1
hturn	178	.1463534	.0691499	.0452	.5496
hdink93	178	.8627315	.0744532	0	1
aturn93	178	.333591	.1598573	0	.6084
agiul93	178	.5694	.2457774	0	1
adink93	178	.3269331	.0969065	0	.5864
bturn93	178	.3103551	.0980845	0	.7741
bgiul93	178	.0680433	.0633321	0	.7703
bdink93	178	.7124607	.3917892	0	.9973

-> neigh=		Riverdale			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	98	378.2449	117.8303	119	699
pdink93	98	.3447156	.170541	.0074906	.9481865
pgiul93	98	.6552844	.170541	.0518135	.9925094
turn93	98	.3625497	.1420381	.0662051	.8373102
wturn93	98	.4076612	.1265289	.0666	.864
wgiul93	98	.787852	.1359334	.0661	.9957
wdink93	98	.2108408	.1367511	.004	.9299
phgiul93	98	.1608133	.081256	.1088	.9429
hturn	98	.136249	.0883654	.0424	.5879
hdink93	98	.855649	.0139658	.8146	.8851
aturn93	98	.4072408	.0653602	.1864	.583
agiul93	98	.6321592	.1530156	0	.971
adink93	98	.3345071	.0605147	0	.4727
bturn93	98	.2763867	.1792434	0	.4757
bgiul93	98	.0649184	.0990712	0	.9647
bdink93	98	.6415684	.4194863	0	.9937

-> neigh=		Rockaways			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	71	362.0282	173.8349	1	694
pdink93	71	.491189	.3455264	0	1
pgiul93	71	.508811	.3455264	0	1
turn93	71	.3786536	.191639	.0028169	.8843417
wturn93	71	.4400014	.1686377	.0024	.9335
wgiul93	71	.7025493	.2504187	0	1
wdink93	71	.2964873	.2500555	0	1
phgiul93	71	.1659183	.1476879	0	1
hturn	71	.1454437	.1115554	0	.6935
hdink93	71	.8583944	.0143599	.8246	.8906
aturn93	71	.3162056	.1428078	.0477	.646
agiul93	71	.608	.1964342	0	1
adink93	71	.2978437	.1424295	0	.6645
bturn93	71	.3082127	.0933142	0	.6319
bgiul93	71	.1143099	.1934453	0	1
bdink93	71	.7280775	.3803346	0	.9797

-> neigh=		Satmar			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	18	412.1667	197.5909	16	765
pdink93	18	.1971517	.1373247	.0440367	.4385965
pgiul93	18	.8028483	.1373247	.5614035	.9559633
turn93	18	.4320821	.1064768	.2348083	.6942801
wturn93	18	.4788278	.1056309	.2704	.7496
wgiul93	18	.9206611	.094179	.6057	.9886
wdink93	18	.0788556	.0947792	.0095	.3941
phgiul93	18	.2342667	.1471056	.1305	.556
hturn	18	.2334833	.1179885	.065	.5864
hdink93	18	.8000944	.2066357	0	.9052
aturn93	18	.3552222	.0963329	.0328	.472
agiul93	18	.4465167	.3253544	0	.6965
adink93	18	.2887667	.1734572	0	.5468
bturn93	18	.2600167	.1313875	0	.4011
bgiul93	18	.0631889	.0357142	0	.1005
bdink93	18	.6788167	.4337269	0	.984
-> neigh= Sheepshead Bay					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	237	323.2236	133.0037	43	758
pdink93	237	.1557293	.090243	0	.6842105
pgiul93	237	.8442707	.090243	.3157895	1
turn93	237	.3717212	.120191	.1079646	.792976
wturn93	237	.3951979	.1109237	.126	.8006
wgiul93	237	.913846	.0721116	.3981	1
wdink93	237	.0857865	.0725446	0	.6078
phgiul93	237	.1542616	.0569529	.1134	1
hturn	237	.1280207	.0603384	.0422	.4866
hdink93	237	.855292	.102295	0	1
aturn93	237	.3854426	.1480288	0	.7782
agiul93	237	.593173	.2417016	0	1
adink93	237	.3077101	.1591197	0	1
bturn93	237	.2921823	.119268	0	.5277
bgiul93	237	.0656405	.0709081	0	1
bdink93	237	.7672717	.3582714	0	1
-> neigh= Southeast Queens					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	237	384.2532	158.3708	4	709
pdink93	237	.8491227	.2165585	.0909091	1
pgiul93	237	.1508773	.2165585	0	.9090909
turn93	237	.3595449	.1122647	.0487805	.5931624
wturn93	237	.4516304	.0904597	.1037	.6284
wgiul93	237	.5969253	.2144056	0	.9552
wdink93	237	.3998118	.2180271	.0361	1
phgiul93	237	.1482219	.0229642	0	.2026
hturn	237	.116797	.0443322	0	.2516
hdink93	237	.8582409	.0620186	0	1
aturn93	237	.3801582	.1269898	0	.6798
agiul93	237	.4763591	.2695894	0	.7879
adink93	237	.2844793	.1705419	0	1
bturn93	237	.315208	.1096503	0	.7353
bgiul93	237	.0519262	.0954679	0	.909
bdink93	237	.7478806	.36821	0	1
-> neigh= Staten Island					
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	251	482.0956	133.4174	63	841
pdink93	251	.1143443	.0795068	.035313	.6841046
pgiul93	251	.8856557	.0795068	.3158954	.964687
turn93	251	.5096378	.09705	.1703817	.9359431
wturn93	251	.5283108	.0922895	.1828	.9599
wgiul93	251	.9419984	.0562346	.5486	.9927
wdink93	251	.0575693	.0553574	.0061	.4265
phgiul93	251	.1507339	.0148845	.1136	.1989
hturn	251	.2039414	.0746453	.0561	.7244
hdink93	251	.842388	.1066499	0	.8941
aturn93	251	.441441	.1014668	0	.6239
agiul93	251	.6355574	.1326508	0	.8064
adink93	251	.3182139	.1412559	0	.944
bturn93	251	.3438195	.0760135	.0076	.6909
bgiul93	251	.0519833	.0532691	0	.426
bdink93	251	.819288	.2928362	0	.9976

-> neigh=	Styvesant Town				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	19	436.8421	66.42813	319	571
pdink93	19	.3688004	.0417361	.2778994	.4639498
pgiul93	19	.6311996	.0417361	.5360501	.7221007
turn93	19	.5072855	.0859523	.3277566	.6984816
wturn93	19	.5316789	.0893489	.3589	.7409
wgiul93	19	.6895105	.0454511	.5757	.7695
wdink93	19	.3105579	.0446895	.2316	.4225
phgiul93	19	.1466105	.0125639	.1253	.1765
hturn	19	.1990737	.0616523	.1036	.386
hdink93	19	.8535105	.0128382	.8364	.8751
aturn93	19	.4302105	.0967716	.1816	.5638
agiul93	19	.6595474	.0179429	.626	.6969
adink93	19	.3265211	.0834989	0	.3876
bturn93	19	.3548684	.0577967	.2534	.5027
bgiul93	19	.0825	.0074878	.0705	.1008
bdink93	19	.6319368	.4413549	0	.983

-> neigh=	Sunset Park				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	65	214.8308	119.8289	1	457
pdink93	65	.5163714	.204244	.1509434	1
pgiul93	65	.4836286	.204244	0	.8490566
turn93	65	.2486518	.0967698	.0999311	.5851648
wturn93	65	.3545385	.0921756	0	.6228
wgiul93	65	.8036092	.1554712	0	.9582
wdink93	64	.18175	.1163696	.0364	.7371
phgiul93	65	.1442923	.0450319	0	.4254
hturn	65	.1234077	.0813326	.031	.4794
hdink93	65	.8541062	.111183	0	1
aturn93	65	.3401292	.1527104	0	.5434
agiul93	65	.5070446	.2815693	0	.8358
adink93	65	.2836169	.1484369	0	.6717
bturn93	65	.2980523	.1068561	0	.5159
bgiul93	65	.0730231	.0242304	0	.1073
bdink93	65	.81642	.3096248	0	.9968

-> neigh=	Tremont				
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	260	265.2923	125.5111	21	678

pdink93	260	.8156503	.149892	.2076923	.99375
pgiul93	260	.1843497	.149892	.00625	.7923077
turn93	260	.2602069	.0994125	.0969828	.6904277
wturn93	260	.3922412	.0745917	.1369	.692
wgiul93	260	.7434181	.0951033	.0778	.952
wdink93	260	.2510273	.0967191	.0451	.9201
phgiul93	260	.1269958	.0288088	.0156	.2072
hturn	260	.127545	.0768797	.0289	.5399
hdink93	260	.8594146	.0155163	.8244	.9278
aturn93	260	.4412481	.0908879	0	.7672
agiul93	260	.5445073	.2322741	0	.7224
adink93	260	.287505	.1402534	0	.6559
bturn93	260	.2888977	.1397486	0	.5984
bgiul93	260	.0568138	.0344629	0	.267
bdink93	260	.7627692	.3559775	0	1

-> neigh= Upper East Side					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	165	420.6303	120.8011	52	688
pdink93	165	.370024	.0829521	.2266667	.8076923
pgiul93	165	.629976	.0829521	.1923077	.7733333
turn93	165	.3849266	.1165613	.0503876	.8764045
wturn93	165	.4029527	.1149397	.0942	.8936
wgiul93	165	.673043	.071028	.224	.8211
wdink93	165	.3269612	.0714242	.1754	.7829
phgiul93	165	.15052	.0148047	.1064	.1918
hturn	165	.1335376	.0691845	.0338	.6201
hdink93	165	.8569655	.099296	0	1
aturn93	165	.3786127	.1365786	0	.5563
agiul93	165	.5949745	.190313	0	.7078
adink93	165	.2883261	.1543584	0	.8529
bturn93	165	.2573558	.1478385	0	.5445
bgiul93	165	.0660552	.0354048	0	.192
bdink93	165	.6864648	.3945929	0	1

-> neigh= Upper West Side					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	185	421.7459	127.1401	41	901
pdink93	185	.6252408	.1249132	.3747368	.9554794
pgiul93	185	.3747592	.1249132	.0445205	.6252632
turn93	185	.3961886	.1245879	.0927184	.9133334
wturn93	185	.4384032	.1211117	.1098	.9353
wgiul93	185	.4613914	.116572	.0988	.8029
wdink93	185	.5377303	.1193195	.1924	.895
phgiul93	185	.1493292	.0166783	.0821	.1935
hturn	185	.1603054	.0916486	.0495	.6681
hdink93	185	.8562103	.0176588	.819	1
aturn93	185	.4256595	.1472853	0	.7121
agiul93	185	.5860741	.1922641	0	.7175
adink93	185	.2835519	.1450273	0	1
bturn93	185	.261813	.1397478	0	.5725
bgiul93	185	.0657341	.0317375	0	.1006
bdink93	185	.7096227	.3893909	0	1

-> neigh=Washington Heights					
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	70	311.2	129.0404	34	679
pdink93	70	.7322173	.1240719	.4311377	.9576108

pgiul93	70	.2677827	.1240719	.0423892	.5688623
turn93	70	.1983219	.1032251	.0397059	.7168508
wturn93	70	.3455671	.0754124	.1451	.7171
wgiul93	70	.7280543	.1329857	.1922	.8892
wdink93	70	.2673714	.1352099	.0973	.808
phgiul93	70	.1306871	.0196703	.0758	.1636
hturn	70	.1099414	.0677943	.0289	.4674
hdink93	70	.8710343	.0251405	.8275	.9841
aturn93	70	.3655529	.1295464	0	.6856
agiul93	70	.6065971	.1728775	0	.7048
adink93	70	.2837057	.1599235	0	1
bturn93	70	.30564	.1594972	0	.8944
bgiul93	70	.0708557	.0409677	0	.296
bdink93	70	.7528914	.3662542	0	1

-> neigh=		West Midtown			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	109	366.6789	145.1343	34	752
pdink93	109	.5676638	.0868749	.4022472	.7777778
pgiul93	109	.4323362	.0868749	.2222222	.5977528
turn93	109	.3192535	.1114999	.0928899	.6712598
wturn93	109	.3594991	.1060852	.1223	.6926
wgiul93	109	.5035716	.1067668	.2399	.8801
wdink93	109	.4961697	.1064987	.1213	.7553
phgiul93	109	.1499505	.0134965	.1224	.1857
hturn	109	.1134642	.0643646	.0347	.3814
hdink93	109	.8548385	.013051	.831	.8926
aturn93	109	.4114376	.1161328	0	.5518
agiul93	109	.6193569	.1390879	0	.738
adink93	109	.3000183	.1619709	0	1
bturn93	109	.3215807	.1242008	0	.5293
bgiul93	109	.0741881	.0222414	0	.101
bdink93	109	.7748633	.3490723	0	1

-> neigh=		West Village			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	75	408.5067	125.7394	62	607
pdink93	75	.5996648	.0818505	.3971487	.8064516
pgiul93	75	.4003352	.0818505	.1935484	.6028513
turn93	75	.3826525	.1028829	.1923991	.7864078
wturn93	75	.4037413	.1037081	.2031	.8414
wgiul93	75	.4261627	.0869642	.202	.6524
wdink93	75	.5738813	.0871979	.3429	.8035
phgiul93	75	.1498053	.0121813	.1212	.1789
hturn	75	.131948	.0702463	.0617	.6118
hdink93	75	.855124	.014042	.8155	.9062
aturn93	75	.327748	.1796231	0	.5403
agiul93	75	.5307893	.2573481	0	.73
adink93	75	.291236	.1208845	0	.5155
bturn93	75	.3132653	.1293659	0	.5906
bgiul93	75	.0729533	.024833	0	.101
bdink93	75	.780812	.3364937	0	.9932

-> neigh=		Windsor			
Variable	Obs	Mean	Std. Dev.	Min	Max

tot93	83	265.494	199.1138	7	914
pdink93	83	.1791811	.1314397	0	.5625
pgiul93	83	.8208189	.1314397	.4375	1

turn93	83	.291094	.133228	.0969163	.6129597
wturn93	83	.3449145	.1081131	.1374	.6161
wgiul93	83	.9297072	.0761554	.5652	1
wdink93	83	.0686614	.075862	0	.4278
phgiul93	83	.1649639	.0995176	0	1
hturn	83	.0964723	.0548544	0	.2649
hdink93	83	.8224145	.1404229	0	.9596
aturn93	83	.3675711	.1211135	0	.6167
agiul93	83	.6358133	.2380336	0	1
adink93	83	.2839542	.1719108	0	1
bturn93	83	.2937626	.1105744	0	.4899
bgiul93	83	.0812313	.1071856	0	1
bdink93	83	.7889265	.3429733	0	1

-> neigh=		Lubavitchers			
Variable	Obs	Mean	Std. Dev.	Min	Max
tot93	17	363	162.9816	97	603
pdink93	17	.6619317	.1800074	.3720238	.9803537
pgiul93	17	.3380683	.1800074	.0196464	.6279762
turn93	17	.2938344	.0780659	.126257	.4411765
wturn93	17	.3962	.0781369	.168	.5188
wgiul93	17	.7050059	.160885	.3158	.8757
wdink93	17	.2814	.1642938	.118	.679
phgiul93	17	.1502412	.0103255	.1281	.1707
hturn	17	.0921353	.0317412	.0497	.1672
hdink93	17	.8613647	.0120118	.8409	.8849
aturn93	17	.3933882	.1202163	.0902	.6109
agiul93	17	.4119	.3143112	0	.6746
adink93	17	.3099471	.1186872	0	.3899
bturn93	17	.2686176	.1720342	0	.5622
bgiul93	17	.1101941	.1086387	0	.3598
bdink93	17	.6620176	.4413072	0	.9927

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¹ A certificate of occupancy is necessary for each residence. It is obtained from the New York City Department of Housing and certifies that the premises are occupied for tax purposes. Failure to obtain a certificate is considered a crime. The J-51 Tax Exemption and Tax Abatement Program maintains a list of two different types of housing. The first is commercial use structures with upper floors rented for residential uses. The second is special places during the 1970 Census that have since been converted to residential use by the time of the Housing and Vacancy Survey.

² An IN-REM housing unit is one there is a failure to pay property tax, so the ownership reverts to New York City.

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