EVALUATING PERFORMANCE OF INSTITUTIONAL MUTUAL FUNDS USING KERNEL DENSITY ESTIMATION

by

MEHMET SENCICEK

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Date — Chair of Examining Committee

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Date — Executive Officer

Professor Salih N. Neftci

Professor Michael Grossman

Professor Nusret Cakici

Supervision Committee

THE CITY UNIVERSITY OF NEW YORK

Abstract

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Adviser: Professor Salih N. Neftci

The purpose of this dissertation is to evaluate the performance of U.S. Institutional Mutual Funds using Kernel Density Estimation. Although there is substantial amount of literature on mutual fund performance using unconditional and conditional models, nonparametric methods in general and kernel density estimation in particular have not been used widely. Further, Institutional Mutual Funds have not been considered as a separate category even though they are different from other mutual funds in several respects that could affect their respective performance.

Institutional Mutual Funds are evaluated in nine different styles based on Morningstar's style box. The kernel densities of all funds in a style category and the appropriate benchmark were estimated based on 5 years worth of return data

calculated from weekly historical prices of funds and the benchmark provided by Morningstar using a specially written Matlab code. Areas under the curve were calculated corresponding to selected returns in the left and right tails which were then used for regression analysis. For each style category, kernel density estimates identified the funds with abnormal performance. This approach can also be used to compare fund performances across style categories and to compare performances of IMFs to those of regular mutual funds.

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INTRODUCTION

1.1 Overview of Institutional Mutual Funds

1.1.1 Recent Growth in Mutual Fund Industry

The mutual fund industry has experienced a tremendous growth in the last decade and has become one of the principal financial intermediaries controlling trillions of dollars in assets (see Figure 1.1). The diversity of funds has increased simultaneously to bring out the concept of 'mutual fund supermarket': investors can choose from funds that hold assets ranging from

Relatively safe short term instruments to risky stocks domestically or internationally. This growing interest in mutual funds has taken place despite numerous academic studies showing that actively managed funds perform as well as a market index at best, and often under-perform.

There has been a parallel growth of interest in mutual funds by institutional investors, most notably by retirement plans, due in great part to the bullish

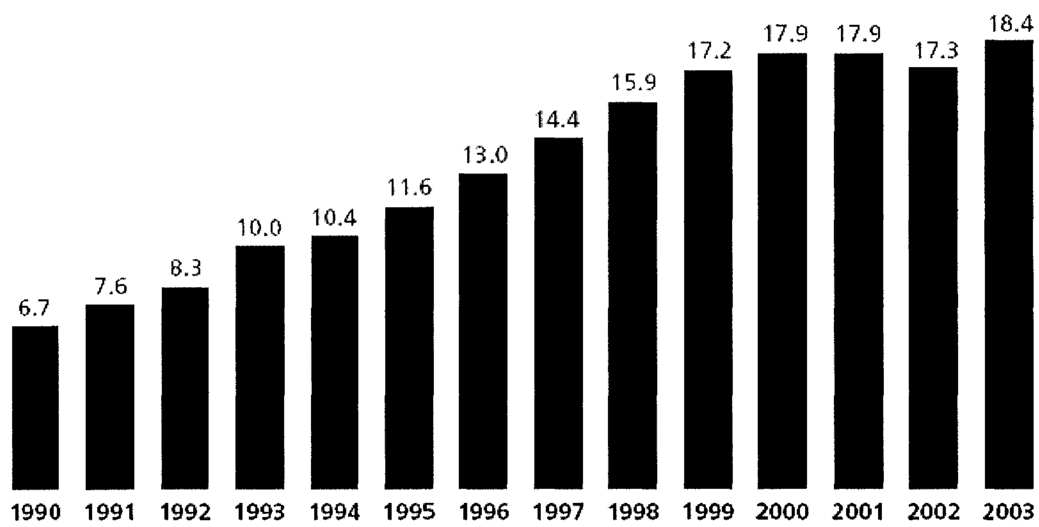


Figure 1.1. Share of Household Financial Assets Held in Mutual Funds, 1990–2003
(percent of total household financial assets)
Sources: Federal Reserve Board and Investment Company Institute

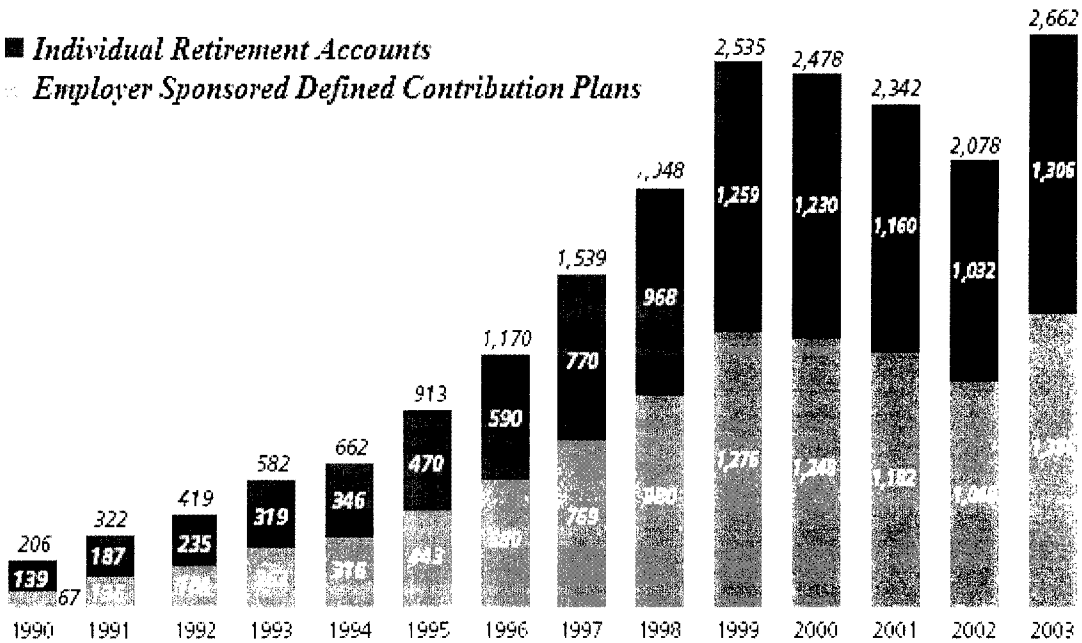
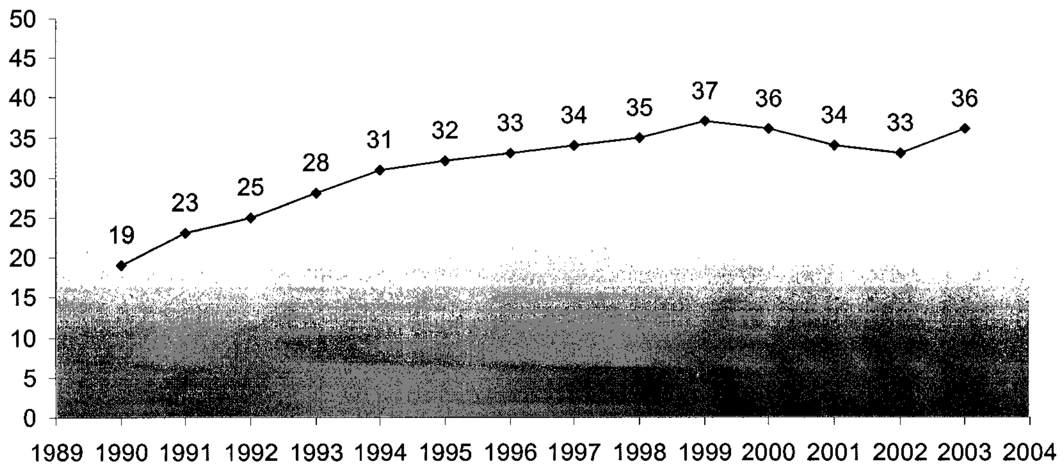


Figure 1.2. Retirement Assets Invested in Mutual Funds, 1990 –2003 *($ billions)*
Source: Investment Company Institute

stock market of the 1990s. While $206 billions of retirement assets were invested in mutual funds in 1990, this rose to $2,662 billions in 2003 representing a 1,190% increase in 13 years. While this growth rate is impressive, it was dwarfed by the rate of growth of mutual funds held by defined contribution plans, from $67 billions in 1990 to $1,356 in 2003, a whopping 2,023%. Not surprisingly, retirement plans including individual accounts and employer sponsored plans control a much larger share of mutual funds; the percentage of mutual funds were held by retirement accounts increased from 19% in 1990 to 36% in 2003 (ICI, 2004). These extraordinary increases are illustrated in Figure 1.2 and Figure 1.3, respectively.

Figure 1.3. Share of Mutual Funds held in Retirement Accounts, 1990-2003 (percent)



Source: Investment Company Institute

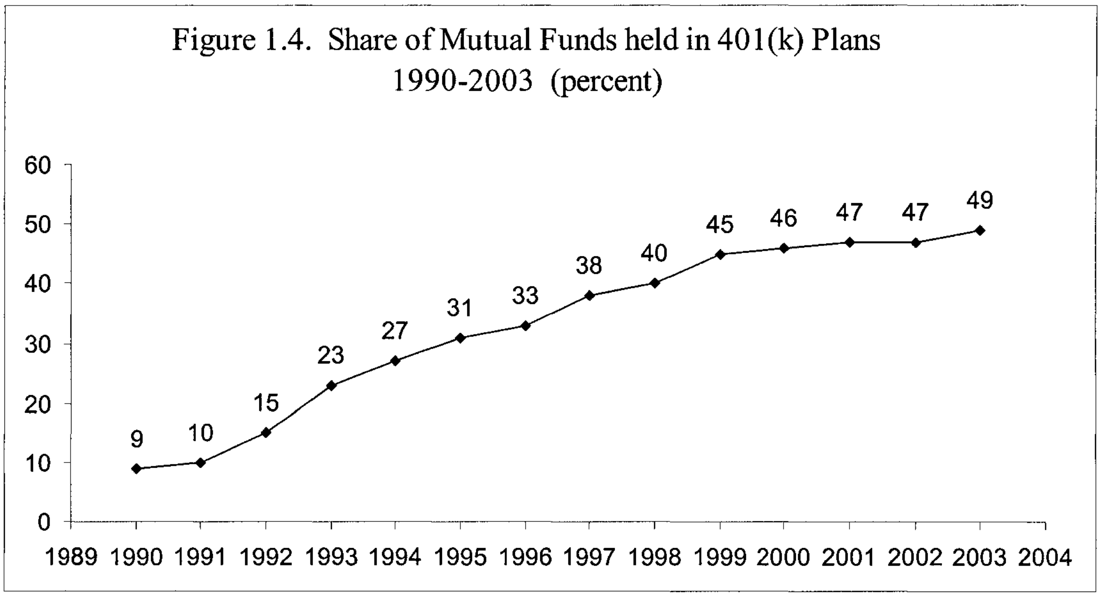
The fund companies have responded to the growing interest by offering more and more funds geared towards such investors. In the case of employee sponsored plans, the relevant type of fund is the institutional (mutual) funds. Institutional mutual funds are different from other "regular" mutual funds, in that, among other respects, the investors have a closer relationship with the fund manager and fund inflows are discrete and large compared to continuous and small inflows of regular mutual funds. Institutional mutual funds require high minimum initial investments often in millions of dollars as well as substantial subsequent investment.

The concept/term of institutional mutual fund may be viewed as an oxymoron since mutual funds were originally intended to provide small individual investors the expertise and purchasing power that large investors, such as institutional investors, can afford. The rising popularity of defined contribution retirement plans, among other developments, has given impetus to the growth of these types of funds (see Figure 1.2 and Table 1.2); these funds now hold a significant portion of their assets as mutual funds. As an example, mutual funds constituted 49% of the assets of 401(k) plans in 2003, compared to 9% in 1990 (see Table 1.1 and Figure 1.4). Mutual funds investing in domestic securities have remained the fund type of choice by all defined contribution plans representing the majority type in each year between 1996 and 2003 (see Table 1.2).

Table 1.1. Assets in 401(k) Plans, 1990–2003 *(billions of dollars)*

	401(k) Plan Assets in Mutual Funds	Other 401(k) Plan Assets	Total
1990	$35	$350	$385
1991	46	394	440
1992	83	471	553
1993	140	476	616
1994	185	491	675
1995	266	598	864
1996	350	711	1,061
1997	479	785	1,264
1998	618	923	1,541
1999	813	977	1,790
2000	819	966	1,785
2001	792	923	1,715
2002	697	823	1,521
2003	898	970	1,867

Sources: Investment Company Institute, Federal Reserve Board, Department of Labor



Source: Investment Company Institute

Table 1.2. Defined Contribution Plan Holdings of Mutual Funds by Type of Fund, 1996-2003 (billions)

	Domestic Equity	Foreign Equity	Hybrid	Bond	Money Market	Total
	Assets	Assets	Assets	Assets	Assets	Assets
1996	$383	$39	$56	$44	$59	$580
1997	530	54	76	50	59	769
1998	686	63	93	63	75	980
1999	916	101	102	65	92	1,276
2000	882	102	103	63	98	1,248
2001	781	86	113	87	115	1,182
2002	622	76	110	117	121	1,046
2003	854	114	147	127	115	1,356

Source: Investment Company Institute

The trend of the relationship between mutual fund market and the retirement market as presented is summarized in Table 1.3. Despite numerous academic studies of performance evaluation of mutual funds, institutional mutual funds have received little or no special attention. As of the starting date of this dissertation, there was no published study specifically on the performance evaluation of institutional mutual funds.

Table 1.3. Summary of the trend in mutual fund and retirement market relationship, 1990-2003.

	1990	2003
Total Retirement Assets Invested in Mutual Funds (billions),	$206	$2,662
Share of Mutual Funds held in Retirement Accounts (percent)	19	36
Assets of Employer Sponsored defined contribution plans in mutual funds (billions)	$67	$1,336
Percentage of 401(k) assets held as mutual funds	9	49

1.1.2. A Brief History of Mutual Funds

The mutual fund industry's roots date back to the mid-1800s in England. After the enactment of two British laws, the Joint Stock Companies Acts of 1862 and 1867, investors began to share in the profits of an investment enterprise, with investor liability limited to the amount of investment capital devoted to the enterprise. In 1868, the Foreign and Colonial Government Trust which resembled a mutual fund in basic structure, formed in London, providing "the investor of moderate means the same advantages as the large capitalists... by spreading the investment over a number of different stocks" (Investment Company Institute, 2004)

The concept was introduced in the United States by British Investment Trusts that invested in American railroad bonds and other financial assets. The "open-end" or mutual fund—in which new shares are issued as new money is invested—was introduced by The Massachusetts Investors Trust in March of 1924 in Boston. Formed as a common law trust, this fund's innovations to the investment company concept included a simplified capital structure, continuous offering of shares, the ability to redeem shares rather than hold them until dissolution of the fund, and a set of clear investment restrictions and policies. By the end of 1929, a handful of funds managed $140 million. The stock market crash and the ensuing Great Depression prevented the progress of the industry. It was not until the passage of landmark security laws, beginning with the Securities Act of 1933 and concluding with the Investment Company Act of 1940, that investors had renewed confidence in funds. This, in turn, led to a relatively steady growth in industry assets since then; fund assets and shareholder accounts grew from $448 million and 296 thousand in 1940 to $7.4 trillion and 261 million by year-end 2003.

1.1.3. The Benefits of Mutual Funds

A mutual fund is an investment company that pools funds from individual or institutional investors by issuing them shares and collectively invests those funds in securities such as domestic or foreign stocks, bonds, or money market instruments. Investors share in the returns from the fund's portfolio while benefiting from professional investment management, diversification, liquidity, and other benefits and services.

Mutual fund shares are subject to financial risks just as equity shares do, as the fund's portfolio may increase or decrease in value. However, mutual funds, at least in principle, provide certain benefits to their shareholders that they cannot get by investing in other financial intermediaries or directly in the financial markets (Pozen, 2002): The most important of these benefits are listed below.

1. *Diversification and Economies of Scale.* Mutual funds allow investors with limited funds to hold a diversified portfolio of financial securities at low transactions costs. Since mutual funds buy and sell large volumes of securities, their transactions cost are much lower per unit than for individual investors.

2. *Professional management.* The investment strategy of a mutual fund is developed by financial professionals, who are presumably better able (than individual investors) to select the right stocks (selectivity) at the right time (timing ability).

3. *Customer services and liquidity.* Shareholders can transfer money between funds within the same family at low cost. Mutual fund shares are easy to buy through an intermediary or directly, by telephone or through the Internet. In

addition, they have the liquidity advantage, as holders can sell their shares at net asset value at any time.

These claimed benefits make mutual funds very attractive especially to small investors who do not have the time, expertise and resources to develop a sound strategy, but understand the importance of diversification as well as selection and timing ability.

In an effort to test the validity of the claims benefits listed above, academic researchers have evaluated performance of mutual fund managers. It has been shown that actively managed funds, on average, do not earn positive performance adjusted for risk and expenses (Gruber, 1996 and others). Some funds do have superior risk-adjusted performance. Using a sample largely free of survivorship bias and applying absolute and relative benchmarks, Brown and Goetzmann (1995) find relative risk-adjusted performance that is mostly due to funds that lag the Standard and Poors 500 index. Their analysis also indicates that poor performance increases the probability that the fund will disappear. Carhart (1997) finds that many funds consistently underperform their benchmarks. Despite the poor performance, most shareholders of mutual funds with consistently poor performance do not sell their shares, indicating that there may be various institutional and psychological factors at work (Gruber, 1996; Sirri and Tufano, 1998).

1.1.4 Institutional and Retail Mutual Funds

There are important differences between institutional mutual funds and "retail" mutual funds. The former are more closely associated with pension funds and have more in common with them than with retail mutual funds. The institutional investors have a closer relationship with the fund manager whom they closely monitor. Institutional mutual funds require high minimum initial investments often in millions of dollars as well as substantial subsequent investment. The fund inflows are discrete and large compared to continuous and small inflows of regular mutual funds.

Del Guercio and Tkac (2002) compared the behavior of retail mutual fund investors to those of the institutional investor. They found that institutional clients used "quantitatively sophisticated measures like Jensen's alpha, tracking error, and outperformance of a market benchmark" and punished "poorly performing managers by withdrawing assets under management". Retail investors were likely to make selections based on recent performance, "flocking" to recent winners, but they did not punish recent losers by withdrawing funds. The retail investors were found to be heavily influenced by Morningstar ratings, some of them "vigilantly monitoring" Morningstar information (Del Guercio and Tkac, 2001).

Retail investors use recent fund performance as the most important selection criterion, and prefer those funds that have high return or risk-adjusted performance relative to other funds in their class (Ippolito, 1992, Chevalier and Ellison, 1997, Lettau, 1997, and Sirri and Tuffano, 1998). Funds are regularly ranked by their performance and these rankings are published in the financial media such as the Wall Street Journal and Money magazine.

Institutional investors of domestic stock funds pay particular attention to the stated objective and Morningstar style classification which is enjoying growing interest by the media as well as the academic and applied researchers (Bogle,1998, and Davis, 2001).

1.2 Overview of Mutual Fund Performance Measures

Performance evaluation of mutual funds started over 50 years ago with Harry Markowitz (1952). His Portfolio Theory which advocated diversification proposed evaluating the risk-reward characteristics of the portfolio as a whole, rather than those of individual assets in it. This theory was the basis for Capital Asset Pricing Model. Although Treynor (1961) and Lintner (1965) have done parallel work, CAPM is generally attributed to William Sharpe (1964) who, for his work on the model, shared the 1990 Nobel Prize in Economics with Markowitz and Merton Miller. A one factor model, CAPM describes a linear relationship between expected returns and systematic risk as measured by 'beta', the idea being that investors demand additional expected return (called 'the risk premium') to accept additional risk. It provides a benchmark against which mutual funds and actively managed portfolios can be evaluated. CAPM continues to be the most widely used portfolio evaluation tool in MBA classes and by finance practitioners despite its highly restrictive and theoretical assumptions, and the wide criticism leveled by academicians and proponents of other methods. There are reincarnations of the model that incorporate new approaches to deal with such criticism although the basic elements are the same.

Three risk adjusted performance measures were based on Capital Asset Pricing Model and Markowitz's Portfolio Theory: the Treynor Index (1965), the Sharpe Ratio (1966) and Jensen's 'alpha' (1968). All three measures have the common aspect of trying to reduce the risk-reward dimensions of portfolio performance to a single measure (as their singular names would suggest), that indicates a risk-adjusted return. Sharpe introduced his measure for the performance of portfolios/mutual funds with the term reward-to-variability ratio, the term is fitting in that it includes standard deviations of returns (rewards), and it shows the reward per unit of variability. Computed using the mean and standard deviation of a differential return, it is a ratio of average expected (historical) differential (or excess) return to predicted (historical) standard deviation.[vi]

Treynor (1965) incorporated risk into a performance measure by considering the portfolio's rate of return with respect to the market rate of return. Like Sharpe Ratio, Treynor index also measures a portfolio's excess return per unit of risk. However, it uses portfolios beta instead of the standard deviation of returns. As such, it is the ratio of the portfolio's rate of return minus the risk-free rate of return to the portfolio's beta. The Jensen measure is a simpler extension of Treynor index and more often used in practice. It evaluates performance using alpha, which is the expected excess return of the portfolio minus the product of portfolio's beta and expected excess return of the market portfolio. The higher the Jensen index, the higher is the level of return for the given level of risk of the investment. A positive alpha indicates that the fund "beat the market".

The above three measures above are known as the "traditional performance Measures" and there are problems associated with all three, although they are still widely used. The Sharpe Ratio, for instance, does not take into account systematic risk which is the real risk in Markowitz's mean-variance world. Jensen's Alpha, on the other hand, is based on an estimate systematic risk that is upwardly biased estimate for an investment strategy characterized by "market timing".

Since they are based on Capital Asset Pricing Model, which assumes a single period investment horizon, Sharpe Ratio, Treynor Index and Jensen's Index are single period models. In reality, investors have multiple investment horizons; this implies that the functional form of the relationship between expected returns and systematic risk will be nonlinear. Tobin (1965) was the first to study multi-period investments based on CAPM. Jensen (1969), Lee (1976), Levhari and Levy (1977), Fabozzi, Francis and Lee (1980), McDonald (1983), Lee, Wu and Wei (1990) among others have examined the implications of the multi-period investment horizon. These studies resulted in three variations of the functional form of CAPM: Constant Elasticity of Substitution (CES) functional form, Generalized Functional Form and Translog Functional Form, introduced by Lee (1976), Fabozzi, Francis and Lee (1980), and Lee, Wu and Wei (1990), respectively.

All of the preceding models assume no time variation in portfolio (or mutual fund) risk. However, time variation in risk and expected returns is recognized and generally interpreted as a reflection of superior information on firm specific risk and/or overall market risk. A manager's ability to outperform the market is reflected in deviation from CAPM (Jensen's alpha). Jensen conceded that managers are able to change the risk structure of their portfolios in expectation of wide market movements. According to Fama (1972), managers can achieve abnormal returns through superiority ability in security election and in market timing. Selection ability is defined as being able to identify undervalued. Market timing ability refers to the ability to correctly time the market cycles; a manager with this ability increases the relative volatility of his portfolio prior to bull market to earn abnormal returns and decreases its volatility anticipation of a bear market in order to minimize potential losses. A portfolio manager's superior market timing ability will allow his portfolio to earn higher than the normal risk premium for his portfolio's level of risk.

In order to examine fund managers' market timing ability, Treynor and Mazuy developed a quadratic model known as Treynor-Mazuy statistic (TM) (1966) or the "squared regression model". The model includes a timing ability measure, gamma, in addition to the selection ability measure, alpha. The model shows that the portfolio returns of a fund manager with forecasting power will be a concave, not linear, function of market returns. This is because he is expected to gain more than the market in upturns, but lose less than the market during downturns.

Jensen's selectivity and timing model (1972) compares the ex post return of a mutual fund with the market returns to detect fund managers' selection and market timing skills. Assuming a joint normal distribution for a market timer's forecasted market return and the actual return on the market, this manager's forecasting ability can be measured by the correlation between the forecasted and actual market returns.

Building on Jensen's model, Bhattacharya and Pfleiderer's model (1983) uses a simple regression technique to accurately estimate the measures of timing and selection ability. Whereas Jensen's model assumes that the manager uses the unadjusted forecast of the market factor in the timing decision, the manager will adjust his forecasts in this model. Assuming that the manager observes a signal $\pi_t + \varepsilon_t$ at the beginning of period t, the manager will adjust his forecasts to minimize the variance of the forecast error (where ε_t is normally distributed and independent of π_t,). Henriksson and Merton (1981) used the Option Pricing Model as a basis to develop their market-timing model. In this model, a manager attempts to anticipate when the market portfolio return will exceed the risk-free rate. In each period, he is assumed to receive a binary signal (high or low) that is correlated with the actual outcome of the market return. In response to the signal, he chooses either 'high' or 'low' for the portfolio beta: he adjusts the portfolio to a higher target beta when a market upturn is anticipated, to a lower target beta when the market forecast is unfavorable. Using this model for a sample of 116 mutual funds, Henriksson (1984) found little evidence of superior market timing ability.

Connor and Korajczyk (1991) extended Henriksson-Merton model to allow for manager's true selectivity and timing ability based on superior information as variation in the market risk of the portfolio caused by dynamic trading and asset beta nonlinearities. This Connor-Korajczyk version has the advantage over the original Henriksson-Merton model due to its consistent measure of performance when the mutual fund buys or sells costly options. However, it is subject to limitations that the Henriksson-Merton is not, namely, one month horizon with European options only, and the inability to decompose market-timing skill and selectivity skill.

Grinblatt and Titman (1989a) introduced the positive period weighting measure (PPWM) which, by design, assigns positive performance to selection ability and/or market timing ability if the portfolio manager is a positive market timer and selectivity and timing information are independent. The PPWM measure is obtained by first selecting a weighting vector and then computing performance as a weighted average of the period-by-period portfolio excess returns.

Jensen's Alpha and the Treynor-Mazuy total performance measures can be expressed as a specific case of a PPWM. The 'perverse' behavior of Jensen's Alpha can then be explained in terms of negative marginal utility, e.g. negative weights, at wealth levels that excess the satiation point of the quadratic utility investor: Successful timers having very high betas when the market returns are very high are penalized rather than rewarded. In the absence of market timing and with the assumption of normality, Jensen's Alpha, the Treynor-Mazuy measure, and the PPWM measure would all be identical.

Another market-timing and selectivity model is the Treynor-Mazuy Total Performance Model put forth by Grinblatt and Titman (1994). This model is specifically designed to detect beta variations that are linearly correlated with the return of the benchmark portfolio.

One of the underlying assumptions of the Capital Asset Pricing Model, time constant beta, has been called into question as betas and expected market returns vary over time and are correlated. To address this problem, Ferson and Schadt (1996) proposed a modification of the CAPM by incorporating lagged information variables such as lagged T-Bill yields. By assuming "semi-strong form" of market efficiency of Fama (1970), the model controls common variation due to public information and reduces related bias as well as estimating time-varying conditional betas. This conditional model is essentially an unconditional “multiple factor model”, with the market index as the first factor and the product of the market and lagged information variables as additional factors.

Among the alternatives to Capital Asset Pricing Model, Arbitrage Pricing Theory differs from CAPM in its assumptions and explanation of risk factors associated with the risk of an asset. This is a relatively new theory that predicts a relationship between the returns of portfolio and the returns of a single asset through a linear combination of variables. Arbitrage Pricing Theory is based on one assumption: arbitrage opportunities do not exist in balanced market conditions. If such an opportunity were to exist, the market would quickly eliminate it.

Although the APT has been developed as an alternative to the Capital Asset Pricing Model, the APT equation is in fact a generalization of the CAPM equation. According to this equation, asset value fluctuation is influenced not only the market portfolio value, but by other factors such as foreign currency exchange rates, energy prices, inflation and unemployment rates, which are non-market risk factors. If only one factor is considered as risk factor (i.e. the market portfolio value), then the APT equation will coincide with the Capital Asset Pricing Model equation. Taking several factors into account creates a stricter model resulting in more precise forecasting of asset price (portfolio value) changes and the reduction of non-systematic risk.

It is worth noting that every measure has its advantages and disadvantages relative to other measures. The insight and simplicity, for example. of the Capital Asset Pricing Model, Sharpe's Ratio and Jensen's Index are their advantages. This may be one factor that explains why the traditional models are still widely used in MBA classrooms and financial analysis alike despite continuous criticism from researchers who propose either alternative models or modifications to the existing models. Performance Evaluation Models are discussed in greater detail and depth in Chapter 2.

1.3 Overview of Kernel Density Estimation

The convention in performance evaluation methods including those discussed above has been to use parametric density estimation when the underlying density function and therefore its parameters are not known. Tapia and Thompson draw attention to the inherent danger by explaining that such an approach, although might be fine in the presence of perfect information, "would be a catastrophe as the front end of an estimation procedure based on data."

The alternative approach, nonparametric density estimation has the advantage of not requiring a priori knowledge or assumptions about the true density. The distribution of the error term or the relationship with the dependent and explanatory variable are not seen as taking a specific functional form involving specific parameters. Therefore, the estimates are robust to erroneous assumptions about that might have been made with the parametric estimation.

A histogram is the simplest and most frequently used non-parametric density estimator. However, histograms suffers from well known difficulties in that they are not smooth although the underlying density function is often assumed to be smooth, they depend on end points of bins and on width of bins. The determination of binwidth and, to some extent, the choice of end points, determine the shape of the histogram.

Rosenblatt (1956) Whittle (1958), and Parzen (1962) developed an approach that avoids these problems except the determination of binwidth. Instead of a box, they used a smooth kernel function as the basic building block which they centered directly over each observation. The result was Kernel Density Estimation which has become increasingly popular especially as a data exploration tool. The debate regarding kernel density estimation centers on "smoothing", i.e. the choice of the bandwidth, also referred to as "the smoothing parameter". Silverman (1986) and Wand and Jones (1995) have written excellent books on Kernel Density estimation in general, and on smoothing parameters, in particular. Silverman is also credited with a smoothing method, used in this study, that bears his name: Silverman's Rule of Thumb.

The other choice involved in Kernel Density Estimation is that of the kernel function. The **kernel density estimator** $f_h(x)$ for the estimation of the density value at point f(x) is defined as

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right), \qquad (1.1)$$

where K(.) denotes a kernel function, and h denotes the bandwidth. The function can be one of several including Uniform, Triangle, Epanechnikov, Quartic, Triweight, Gaussian and Cosinus. It turns out, however, that the choice is mostly academic or of personal preference as it has little, if any, effect on the reliability of the outcome. Each of these functions are discussed in more detail in section 2.4.

Kernel density estimation is a good descriptive tool for seeing modes, location, skewness, tails and asymmetry. It has been and is being widely used in many diverse disciplines including engineering, statistics, archeology, computer science and genetics [xiv]. Financial economists, as of the start of this study, have not shown great interest despite its advantages and high applicability to various estimation needs in the discipline.

1.4 Contributions

Institutional mutual funds differ from other types of mutual funds due to their target market, the institutional investors, resulting in significant differences in fund flow form and frequency, manager-investor relationship and monitoring of the fund manager. Despite the growth in number/diversity and net asset value of institutional mutual funds in the last decade, there has been no academic interest in performance evaluation of these funds specifically. Although there is abundant literature on mutual performance evaluation, the models used are either simplistic and based on unreasonable assumptions and/or assume a parametric structure for the underlying density of returns when the true density cannot be known.

This study aims to add to the sparse literature on performance evaluation in institutional investment via evaluating performance of institutional mutual funds. Nonparametric approach is used so that the model will be robust to erroneous assumptions made with parametric estimation of the density. Although not widely used in financial economics, the popularity of Kernel Density Estimation is growing in other disciplines. It is especially appropriate for performance evaluation because of the nature of the data typically used in such analysis. As of the start of this study, there was no published or publicly available performance evaluation of institutional mutual funds using Kernel Density Estimation. As such, this study will contribute to the performance evaluation of a growing segment of mutual funds geared towards a fast growing market of retirement plans and other institutional investors. It will also contribute to the literature on Kernel Density Estimation in the fields of Finance and Financial Economics by applying it to this specialized type of funds.

1.5 Outline Of the Dissertation

A more detailed and in-depth review of literature on mutual fund performance evaluation is presented in Chapter 2. Background information and literature review on Kernel Density follows in the same chapter. Chapter 3, section 1 describes the data used in the analysis including any shortcomings. The choice of funds and the choice of relevant benchmarks are discussed here. Section 2 describes the methods for processing data for use in kernel density estimation which, in turn, is discussed in section 3 along with the software codes used. Section 4 explains the regression analysis to be used for Kernel Density results.

Chapter 4 is for the reporting and discussion of results including a summary and interpretation of results. Along with figures of estimated densities of performance evaluation of funds, this chapter includes an evaluation of Kernel Density Estimation as a tool for performance measure.

Chapter 5 presents the conclusions and suggestions for future research including application of Kernel Density estimation to other approaches such as comparing performance of institutional mutual funds to other mutual funds offered by the same investment companies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Traditional Measures of Performance

2.1.1 Measuring Risk

The most well-known definition of risk randomness with knowable probabilities) is due to Frank Knight. In his book based on his dissertation

“Risk, Uncertainty and Profit” (1921), Knight made his famous distinction between "risk” and "uncertainty" (randomness with unknowable probabilities). In an effort to provide a theoretical underpinning for profit, he argued that profit existed because actual competition in a modern industrial economy differed from competition in the world of pure competition in one essential regard: competitors in modern economies operated in a world of uncertainty; competitors in pure competition faced risk, but not uncertainty. Facing uncertainty was what made competitors become entrepreneurs: they had to use their critical judgment to make decisions.

There are several variables used to assess risk in performance evaluation, the two most commonly used are beta and standard deviation. The beta for (the manager of) a fund (βp) is the covariance of the fund's risk premium with the benchmark’s risk premium divided by the variance of the benchmark's risk premium:

$$\beta p = \frac{Cov(RP_{pt}, RP_{bt})}{Var(RP_{bt})} \qquad (2.1.1)$$

or

$$\beta p = \frac{\rho_{pb}}{\sigma_m^2} \quad (2.1.2)$$

where ρ_{pb}=, $\dfrac{Cov(RP_{pt}, RP_{bt})}{(\sigma(RP_{pt}))(\sigma(RP_{bt}))}$ and

σ_m^2 is the market volatility.

In economic terms, beta reflects a fund's volatility relative to the market or the only market-related portion of a fund's risk (systematic or undiversifiable risk) rather than the total risk which includes both unsystematic and systematic risk) and is measured by standard deviation.

The following example illustrates the interpretation of beta : If beta equals 1.0 for a particular fund, then it matched the market. If beta equals 1.25 then it did 25% better in a bull market and 25% worse in a bear market.

Beta can also be calculated as follows:

- Periodic (daily, weekly, monthly) returns for both the fund and the relative benchmark are calculated.
- These returns are expressed as risk premiums (or excess returns over the risk free rate of return on a T-Bill).
- A scatter chart of the risk premiums is produced and the line which best fits the observations is estimated using least squares linear regression using the regression equation below:

$$(R_{pt}-r_t)=\alpha_p+\beta_p(R_{bt}-r_t)+\varepsilon_{t,} \qquad (2.1.3)$$

where $R_{pt,}$ R_{bt} and r_t are the fund's return, the benchmark's return and the risk free rate, respectively.

Another commonly used measure of risk, standard deviation measures the volatility of returns around their average. Not being dependent on an index, standard deviation can be used to compare funds across asset classes. Since it is a measure of total risk, both systematic and unsystematic, it captures risk more comprehensively than beta. Standard deviation can be calculated readily through a software package or a program such as Microsoft Excel, or by the following formula:

$$\sigma = \sqrt{\frac{n\sum x^2 - (\sum x)^2}{n(n-1)}} \tag{2.1.4}$$

where fund return observations are substituted for x and n is the sample size.

A third measure, "alpha", is a measure of the differential earned in an average period, given the fund's systematic risk (Beta). It is estimated by regressing fund returns against benchmark returns. "Alpha' is discussed in greater detail in the following pages.

Some of the less often used measures of risk used are Information Ratio, Shortfall Probability and R-square. Information ratio is the ratio of a fund's expected return to the standard deviation of its returns. The higher the information ratio, the lower is the risk taken to achieve a certain level of return. Shortfall Probability refers to the probability that the return will fall short of target. It is an ambiguous and difficult to forecast as the target level depends on individual investor preferences. Calculated by regressing the fund against an appropriate benchmark index, .R-Squared Measure is a measure of correlation between the fund and the benchmark, where a value of 1 indicates perfect correlation.

2.1.2 Portfolio Theory

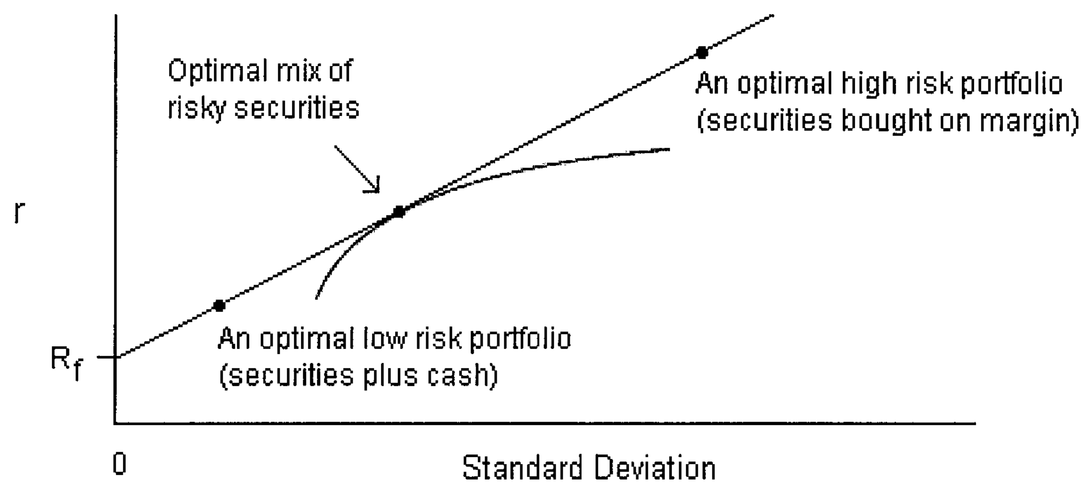
The first rigorous method applicable to mutual fund evaluation was due to Markowitz's Mean-Variance Portfolio Theory (1952, 1959) Prior to Markowitz's paper "Portfolio Selection" (1952), standard investment advice was to construct a portfolio from securities that offered the best opportunities for gain with the least risk. This, of course, could lead to a portfolio of assets all from a single sector, such as utilities. Markowitz formalized the intuition that such a portfolio would be 'foolish' and provided the case for diversification. Instead of merely compiling portfolios from securities that each individually have attractive risk-reward characteristics, he proposed selecting a portfolio based on the overall risk-reward characteristics of the portfolio itself!

Markowitz further explained the portfolio selection process as follows: Treating single-period returns for various securities as random variables, one can assign them expected values, standard deviations and correlations, based on which, one can calculate the expected return and volatility of any portfolio constructed with those securities. Volatility and expected return can be treated as proxies for risk and reward. Out of the entire universe of possible portfolios, the ones that optimally balance risk and reward will comprise an "efficient frontier "of portfolios.

James Tobin (1958) extended the concept to "**super-efficient portfolio**" by combining a risk-free asset with a portfolio on the efficient frontier. This allows the construction of a portfolio with superior risk-return profiles as compared to portfolios on the efficient frontier. Consider Figure 2.1:

In Figure 2.1, a tangent line drawn to the efficient frontier passing through the risk-free rate is called the **capital market line**. The portfolio on the point of tangency is the **super-efficient portfolio**. From a risk-reward standpoint, portfolios which combine the risk free asset with the super-efficient portfolio, that is, those on the Capital Market Line are superior to the portfolios on the efficient frontier.

Figure 2.1. Capital Market Line



Based on this theory, Sharpe (1964), Lintner (1965), and Mossin (1966) independently developed the Capital Asset Pricing Model (CAPM). Three risk-adjusted portfolio performance measures - the Treynor Index (1965), the Sharpe Index (1966), and the Jensen Index (1968, 1969) - were developed based on CAPM and portfolio theory.

2.1.3 The Capital Asset Pricing Model

William Sharpe intoduced the Capital Asset Pricing Model (CAPM) in (1964); Lintner (1965), and Mossin (1966) performed parallel work. CAPM extended Markowitz's portfolio theory by introducing systematic and specific risk. Sharpe later received the 1990 Nobel Prize in Economics for his work on CAPM, which he shared with Harry Markowitz and Merton Miller. In this model, if investors have homogeneous expectations and optimally hold mean-variance efficient portfolios, then, in the absence of market friction, the market portfolio itself will be a mean-variance efficient portfolio. In equilibrium, all investors will hold combinations of the market portfolio of risky assets and the risk-free asset. The expected return on an asset is a linear function of the asset's systematic risk, beta: the expected return of an asset equals the risk-free rate plus the portfolio's beta multiplied by the expected excess return of the market portfolio.

$$E(R_i)=R_f+ [E(R_m)-R_f]\beta_i \qquad (2.1.4)$$

where,

$E(R_i)$ ***is*** the expected return on the i^{th} asset,

R_f is the risk-free rate,

$E(R_m)$ **is** the expected return on the market portfolio.

$\beta_i = Cov(R_i; R_m)/Var(R_m)$ is the systematic risk of asset i. It measures the volatility of the security, relative to the marketasset class

Let R_p be a portfolio's simple return, and let β now denote the portfolio's beta. We obtain

$$E(R_p)=R_f+ [E(R_m)-R_f]\beta \qquad (2.1.4b)$$

The essential conclusion of CAPM is that a stock's (or portfolio's) excess expected return depends on its beta and not its volatility. In other words, excess return depends on systematic risk and not on total risk.

The marketplace compensates investors for taking systematic risk but not for taking specific risk which can be diversified away. In the market portfolio, each individual asset in that portfolio has specific risk, diversification reduces the investor's net exposure to just the systematic risk of the market portfolio.

Given a beta and an expected return for an asset, investors will bid its current price up or down, adjusting that expected return so that it satisfies the CAPM equation . Accordingly, the CAPM predicts the equilibrium price of an asset. This works because the model *assumes* that all investors agree on the beta and expected return of any asset. In practice, this assumption is unreasonable, so the CAPM is largely of theoretical value. It is the most famous example of an equilibrium pricing model.

Although the simplicity of the beta coefficient has been considered its strength, it has later come under heavy criticism by several economists who have pointed out that the returns may not be related to the respective betas. Roll and Ross (1992), for example, argued that the true market portfolio is unobservable and this presents problems with testing the relationship between betas and returns.

Eugene Fama, the originator of the beta concept in the 1960s and Kenneth French (1991) argued that there is no relationship between beta and returns, as such, the very foundation on which CAPM stands is weak. Portfolios of high-beta stocks did not have higher returns than portfolios of low-beta stocks. Their paper concluded that the month-to-month performance of a diversified portfolio of U.S. stocks can be explained by only three factors: the portfolio's exposure to the market itself, to small-cap stocks, and to value orientation (or price-to-book ratio).

The Capital Asset Pricing Model is not without supporters, who contend that evidence against beta and CAPM may be overstated or due to selection or survivorship biases (Lo and MacKinlay, 1997;). One explanation offered for the results of the study by Fama and French, is that investors may irrationally favor big firms due to visibility and advertising. Another reason may be the cash to buy enough shares for complete diversification.

A one factor model, CAPM describes a linear relationship between expected returns and systematic risk as measured by 'beta', the idea being that investors demand additional expected return (called 'the risk premium') to accept additional risk. It provides a benchmark against which mutual funds and actively managed portfolios can be evaluated. CAPM continues to be the most widely used portfolio evaluation tool in MBA classes and by finance practitioners despite its highly restrictive and theoretical assumptions, and the wide criticism leveled by academicians and proponents of other methods. There are reincarnations of the model that incorporate new approaches to deal with such criticism although the basic elements are the same.

2.1.4 Treynor Index

Three risk adjusted performance measures were based on Capital Asset Pricing Model and Markowitz's Portfolio Theory: the Treynor Index (1965), the Sharpe Ratio (1966) and Jensen's 'alpha' (1968). All three measures have the common aspect of trying to reduce the risk-reward dimensions of portfolio performance to a single measure (as their singular names would suggest), that indicates a risk-adjusted return.

Treynor (1965) incorporated risk into a performance measure by considering the portfolio's rate of return with respect to the market rate of return. Like Sharpe Ratio, Treynor index also measures a portfolio's excess return per unit of risk. However, it uses portfolios beta instead of the standard deviation of returns. As such, it is the ratio of the portfolio's rate of return minus the risk-free rate of return to the portfolio's beta.

According to this model, there are two components of risk: 1). Risk produced by general market fluctuations, and 2). Risk resulting from unique fluctuations in the securities within the portfolio. To identify risk due to market fluctuations, Treynor introduced the characteristic line, which defines the relationship between the rates of return for a portfolio and the rates of return for an appropriate market portfolio. The slope of the characteristic line, the portfolio's beta coefficient, measures the relative volatility of the portfolio's returns in relation to returns for the aggregate market. A higher slope (beta) indicates a portfolio that is more sensitive to market returns.

Treynor attempted to circumvent risk preferences of investors in developing a measure of performance Using the Capital Asset Pricing Theory as a basis, he developed a straight portfolio possibility line that by combining a risk-free asset with different portfolios. He argued that rational, risk-averse investors would always prefer portfolio possibility lines with higher slopes as they would put investors on higher indifference curves. The Treynor index, reward-to-volatility ratio, is given as:

$$TI = \frac{ER_p - r_f}{\beta_p} \tag{2.1.5}$$

where,

ER_p = the average rate of return for the portfolio during a specified time period;

r_f = the average rate of return for risk-free asset;

β_p = the slope of the portfolio's characteristic line during the same time period.

Accordingly, a large Treynor Index indicates a larger slope and a better portfolio (higher indifference curves) for all investors, regardless of their risk preferences. The numerator of risk ratio $(ER_p - r_f)$ is the risk premium and the denominator is a measure of risk; as such, the total expression indicates the portfolio's risk premium return per unit of risk. In this model, beta measures systematic risk, which is the relevant risk measure for a completely diversified portfolio, as is implicitly assumed.

2.1.5. Sharpe Ratio

The Sharpe Ratio or (the Sharpe Index), which uses the capital market line as a benchmark, is defined as the ratio of a portfolio's return in excess of the risk-free rate to the portfolio's standard deviation of returns over a period (Sharpe 1966, 1975). This reward-to-variability ratio is given by:

$$S = \frac{R_p - r_f}{\sigma_p} \tag{2.1.6}$$

where

R_p=the average rate of return on the portfolio during a specified time period;

σ_p = the standard deviation on the portfolio;

r_f =the average rate of return on risk-free assets during the same time period; and

$(R_p\text{-}r_f)$ =the "risk premium"

The risk-free rate of return, available to all investors, is simply the current rate of return on risk-free assets, like Treasury Bills. For a mutual fund, the risk premium is the difference between the fund's average return and the average return on a risk-free asset (i.e. Treasury Bill) over the same time period. This risk premium represents the amount of compensation that risk-averse investors expect to earn for the additional risk undertaken through the purchase of risky assets. To buy into a fund, the risk-averse investor will require the "risk premium"\which captures the uncertainty of buying individual funds.

The Sharpe Ratio evaluates the ability of a portfolio manager on the basis of both rates of return performance and diversification by calculating the total risk of the portfolio using the standard deviation of returns. It is similar to the Treynor Index in the sense that it measures the premium per unit of risk. Unlike the Treynor index, it seeks to measure the total risk of the portfolio by including the standard deviation of returns rather than considering only the systematic risk by using beta. Because the numerator is the portfolio's risk premium, this measure indicates the risk premium return eared per unit of total risk.

The Sharpe Ratio, as the slope of the line connecting the expected return of the portfolio with the risk-free rate, provides a convenient measure of the performance of mutual funds: Steeper slopes, i.e. higher Sharpe Ratios indicate better investment performance, since investors can reach higher levels of expected utility as the slope of the transformation line connecting the risk-free rate and the point representing the risk-return characteristics of the mutual fund becomes steeper. Any portfolio that is positioned on the capital market line has a Sharpe Index equal to that of the market and, therefore, is characterized by neutral performance. This makes sense under the CAPM, because on the basis of public information alone, any investor can construct a portfolio that is positioned on the capital market line.

The Sharpe Ratio's application to mutual funds can be illustrated with the following example: Suppose, fund X had an average return of 8% over a 3-year period when the T-bill rate averaged 2%. If its standard deviation is 5%, the fund's Sharpe Ratio is:

$$S_P X = [(8\%-2\%) / 5\%] = 1.2$$

Suppose that fund Y had the same average return, but a standard deviation of only 3%. Its Sharpe Ratio is

$$S_P Y= [(8\%-2\%) / 3\%] = 2$$

The lower standard deviation indicates that Fund Y carries a lower risk, while Fund X has larger risk. Fund Y's higher Sharpe ratio is more favorable because it indicates a higher return per unit of risk taken.

2.1.6 Jensen's 'Alpha' Measure

The *Alpha* measure developed by Jensen (1968, 1969) is a measure of risk-adjusted performance that is commonly used by academicians and practitioners much like the Sharpe Ratio and Treynor Index above. The model has rsik premiums as the basic random variables and uses the security market line as a benchmark.

A fund's risk premium (or excess return) is the difference between the fund's return and the risk-free rate, r_t, (e.g. the yield on 3-month Treasury Bill)

$$RP_{pt}=R_{pt}-r_t \tag{2.17a}$$

Similarly, a benchmark's risk premium is its excess return over risk-free rate:

$$RP_{bt}=R_{bt}-r_t \tag{2.1.7b}$$

Using this notation, Jensen's 'alpha model' is expressed as follows:

$$(R_{pt}-r_t)=\alpha_p+\beta_p(R_{bt}-r_t)+\varepsilon_{t,}\text{ or} \tag{2.1.8}$$

$$RP_{pt}=\alpha_p+\beta_p(RPpt)+\varepsilon_{t,} \tag{2.1.9}$$

where

$$\beta p= \frac{Cov(RP_{pt}, RP_{bt})}{Var(RP_{bt})} \tag{2.1.10}$$

The Jensen alpha is a measure of that part of return on a portfolio that is attributable to the manager's ability to time the market.. Superior risk-adjusted returns indicate that the manager is good at predicting market turns and/or selecting undervalued issues for the portfolios. Like the Treynor Index, the Jensen Index does not evaluate the ability of the portfolio manager to diversity, because it calculates risk premium in terms of systematic risk.

The Jensen measure is a simpler extension of Treynor index and more often used in practice. It evaluates performance using alpha (α), which is the expected excess return of the portfolio minus the product of portfolio's beta and expected excess return of the market portfolio. The higher the Jensen index, the higher is the level of return for the given level of risk of the investment. A positive alpha indicates that the fund "beat the market".

2.1.6 Other Forms of CAPM

The above three measures above are known as the "traditional performance Measures" and there are problems associated with all three, although they are still widely used. The Sharpe Ratio, for instance, does not take into account systematic risk which is the real risk in Markowitz's mean-variance world. Jensen's Alpha, on the other hand, is based on an estimate of systematic risk that is upwardly biased estimate for an investment strategy characterized by "market timing".

Since they are based on Capital Asset Pricing Model, which assumes a single period investment horizon, Sharpe Index, Treynor Index and Jensen's Index are single period models. In reality, investors have multiple investment horizons; this implies that the functional form of the relationship between expected returns and systematic risk will be nonlinear.

Tobin (1965)[i] was the first to study multi-period investments based on CAPM. By analyzing the effect of the heterogeneous investment horizon on portfolio choices, he generated a relationship between the risk and return measures of the single-period investment horizon and those of the multi-period investment horizon. Tobin's work was followed by Jensen (1969), Lee (1976), Levhari and Levy (1977), McDonald (1983), and others who considered the empirical implications of heterogeneous investment horizons. These studies resulted in three variations of the functional form of CAPM: Constant Elasticity of Substitution (CES) functional form, Generalized Functional Form and Translog Functional Form, introduced by Lee (1976), Fabozzi, Francis and Lee (1980), and Lee, Wu and Wei (1990), respectively.

Jensen (1969) investigated the effect of investment horizon on the estimate of the systematic risk and concluded that the logarithmic linear form of the CAPM could be used to eliminate systematic risk. However, the investment horizon parameter was not included in his model. Levhari and Levy (1977) have shown that systematic bias of the performance measurement index as well as the beta estimate will arise when the holding period is assumed to be different from the investment horizon as in the CAPM model. Lee (1976) extended Jensen's model (1969) and derived the Constant Elasticity of Substitution (CES) functional form of the CAPM. His model includes the functional form investment horizon parameter in the regression and estimates the systematic risk beta in a homogeneous investment horizon framework. Using the generalized Box-Cox transformation technique, Fabozzi, Francis and Lee (1980) developed a generalized functional form of the Capital Asset Pricing Model. They demonstrated that the risk-return relationship measured empirically will be nonlinear thereby improving the explanatory power of the CAPM. Lee, Wu and Wei (1990) developed a generalized CES functional form of the CAPM in order to control the systematic skewness from the squared-term of a benchmark excess return in the CES functional form of the CAPM under a heterogeneous investment horizon framework. These three alternative functional forms of the CAPM improve the explanatory power of the Capital Asset Pricing Model by reducing the misspecification bias in the estimates of systematic risk.

2.2 Market Timing and Selectivity Models

2.2.1 Market Selection and Timing Ability

All of the preceding models assume no time variation in portfolio (or mutual fund) risk. However, time variation in risk and expected returns is recognized and generally interpreted as a reflection of superior information on firm specific risk and/or overall market risk. A manager's ability to outperform the market is reflected in deviation from CAPM (Jensen's alpha). Jensen conceded that managers are able to change the risk structure of their portfolios in expectation of wide market movements. According to Fama (1972), managers can achieve abnormal returns through superiority ability in security election and in market timing. Selection ability is defined as being able to identify undervalued. Market timing ability refers to the ability to correctly time the market cycles; a manager with this ability increases the relative volatility of his portfolio prior to bull market to earn abnormal returns and decreases its volatility anticipation of a bear market in order to minimize potential losses. A portfolio manager's superior market timing ability will allow his portfolio to earn higher than the normal risk premium for his portfolio's level of risk.

2.2.2. Treynor-Mazuy Statistic

In order to examine fund managers' market timing ability, Treynor and Mazuy developed a quadratic model known as Treynor-Mazuy statistic (TM) (1966)[ii] or the "squared regression model". The model includes a timing ability measure, gamma, in addition to the selection ability measure, alpha. The model shows that the portfolio returns of a fund manager with forecasting power will be a concave, not linear, function of market returns. This is because he is expected to gain more than the market in upturns, but lose less than the market during downturns.

Treynor and Mazuy argued that the portfolio beta should be sticky over time if the fund's manager does not engage in market timing. As such, assuming the fund is well diversified, it should earn a fairly constant fraction of the market return over time. If the manager engages in market timing, the relationship between the portfolio returns and the market returns will be nonlinear.

Treynor and Mazuy (1966) examined the timing ability of mutual fund managers by testing for such nonlinearity by fitting the following quadratic to the data:

$$r_{pt} = \alpha_p + \beta_p(r_{mt}) + \gamma_p (r_{mt})^2 + \varepsilon_{pt} \qquad (2.2.1)$$

where

r_{pt} = the excess return on the portfolio

r_{mt} = the excess return on the market portfolio

β_p = measure of the sensitivity of the fund's return to the market return.

γ_p = coefficient of market timing ability

If there is no market timing ability, γ_p should be statistically insignificant from zero indicating a linear relationship between r_{pt} *and* r_{mt},,. However, if there is superior market timing, γ_p will be positive. The addition of squared term in the equation is to improve the empirical fit between r_{pt} *and* r_{mt}. Hence, the coefficient γ_p is as an indicator of the manager's market timing ability. Treynor and Mazuy reported that, of 37 mutual funds studied during 1953 – 1962, only one produced a significantly positive γ_p coefficient. Grinblatt and Titman (1988) similarly found mostly negative γ_p coefficients using the Treynor-Mazuy model.

An alternative to the Treynor-Mazuy model is the Henriksson and Merton Model (1981) which decomposes performance into market timing and selection ability. This model is discussed in detail in the following pages.

2.2.3. Henriksson and Merton Model

In two separate but related papers, Merton(1981) and Henriksson and Merton (1981) developed their market-timing model, which decomposes performance into selectivity and timing ability by extending Jensen's (1968) model. The following regression gives consistent estimates of timing ability:

$$r_{pt} = \alpha_p + \beta_p(r_{mt}) + \gamma_p(y_t) + \varepsilon_{pt} \qquad (2.2.2)$$

where

rpt =the excess return on portfolio p at time t;

α_p=the abnormal return attributable to security selection ability;

r_{mt} = the excess return on the market portfolio at time;

γ_p =the coefficient estimate of timing ability;

y_t=max[0,r_{mt}]; and

ε_{pt} =the random error term with expected mean of zero.

They use γp to capture the market timing component of investment performance following demonstration of potential bias in the estimates by Jensen (1972), Grant (1977), Dybvig and Ross (1985) and Grinblatt and Titman (1989a) who suggested that funds attempting to market time will bias (β_p) upward and the abnormal return (α_p) will be biased downward if market timing (γ_p) is ignored. The Henriksson-Merton model assumes fund managers target two systematic risk levels; one where the manager forecasts the risk-free asset to outperform the market portfolio and the other where the market return is expected to outperform the risk-free rate. Successful market timing exists only where γ_p is significantly positive. As such, the model looks at the direction of the forecast that a portfolio manager uses to re-weight the portfolio between risky assets and the risk-free asset rather than predicting the size of the return differential between risky assets and the risk-free asset. The managers in this model are less sophisticated than those in Jensen (1972), in which they actually forecast he size of the differential return.

Henriksson (1984) estimated the above equation for a sample of 116 mutual funds and found that He found that more of the funds had negative estimated γ_p than positive ones.

2.2.4. Connor and Korajczyk's Extension

Chang and Lewellen (1984), as well as Henriksson (1984), found more significantly negative timing coefficients than positive. In order to produce a negative timing coefficient, a manager must use his superior information it irrationally such as increasing his market risk when "he receives a signal that the market will fall and lowering market risk when he receives a signal that the market will rise. Both Chang and Lewellen (1984) and Henriksson (1984) provided evidence that γ_p is negatively correlated with the estimate of α across funds which they speculated might be due to error in variables.

Connor and Korajczyk (1991) argued that γ_p coefficient would be better captured by the multiple factors of the APT. They extended the Henriksson-Merton model to a multi-factor model where they would expect the $\gamma_{i>}$ coefficient to be greater than zero if and only if the manager has superior information. The α_p term measures selectivity, accordingly $\alpha_p > 0$ implies superior selectivity. They found little change in coefficient γ_i in its comparison with the original Henriksson-Merton model and their version.

The advantage of the Connor-Korajczyk version over the original Henriksson-Merton model is its consistent measure of performance when the mutual fund buys or sells costly options. However, it is subject to limitations that the Henriksson-Merton is not, namely, one month horizon with European options only, and the inability to decompose market-timing skill and selectivity skill.

2.2.5 Jensen and Bhattacharya-Pfleiderer Models of Market Timing and Selectivity

Jensen's selectivity and timing model (1972) compares the ex post return of a mutual fund with the market returns to detect fund managers' selection and market timing skills. Assuming a joint normal distribution for a market timer's forecasted market return and the actual return on the market, this manager's forecasting ability can be measured by the correlation between the forecasted and actual market returns.

Building on Jensen's model, Bhattacharya and Pfleiderer's model (1983) uses a simple regression technique to accurately estimate the measures of timing and selection ability. Whereas Jensen's model assumes that the manager uses the unadjusted forecast of the market factor in the timing decision, the manager in this model will adjust his forecasts. Assuming that the manager observes a signal $\pi_t + \varepsilon_t$ at the beginning of period t, the manager will adjust his forecasts to minimize the variance of the forecast error (where ε_t is normally distributed and independent of π_t,).

2.2.6. Grinblatt and Titman's PPW Measure

Grinblatt and Titman (1989a) introduced the positive period weighting measure (PPWM) which, by design, assigns positive performance to selection ability and/or market timing ability if the portfolio manager is a positive market timer and selectivity and timing information are independent. The PPWM measure is obtained by first selecting a weighting vector and then computing performance as a weighted average of the period-by-period portfolio excess returns.

Jensen's Alpha and the Treynor-Mazuy total performance measures can be expressed as a specific case of a PPWM. The 'perverse' behavior of Jensen's Alpha can then be explained in terms of negative marginal utility, e.g. negative weights, at wealth levels that excess the satiation point of the quadratic utility investor: Successful timers having very high betas when the market returns are very high are penalized rather than rewarded. In the absence of market timing and with the assumption of normality, Jensen's Alpha, the Treynor-Mazuy measure, and the PPWM measure would all be identical.

2.2.7 Other Market Timing and Selectivity Models

Another market-timing and selectivity model is the Treynor-Mazuy Total Performance Model put forth by Grinblatt and Titman (1994). This model is specifically designed to detect beta variations that are linearly correlated with the return of the benchmark portfolio. The Treynor-Mazuy total performance measure is defined as:

$$TM = \alpha_p + \gamma_p \; Var(R_{mt} - R_{ft}) \tag{2.2.3}$$

The standard t-statistic can be used to test whether it is significantly different from zero, when conditioned on the excess returns of the portfolios in the benchmark. The test statistic is *TM/s(TM)*, which has a t-distribution with T-K-1 degrees of freedom if there are T returns and K benchmark portfolios. Where *s(TM)* is the standard error of the Treynor-Mazuy total performance measure.

The method developed by Grinblatt and Titman is quite different from those employed in other studies. Instead of considering the actual returns realized by funds, they study the performance of individual stocks held by funds. This allows them to derive benchmarks that suit the investment styles of the funds better. Moreover, it enables fund returns to be obtained without deducting fees and transaction costs. The comparison with the benchmark is therefore fairer, as benchmarks do not take these expenses into account. It is then possible to see whether fund managers have any stock selection or timing abilities.

The study conducted by Grinblatt and Titman presented some limitations. Their database contained a relatively small number of funds and the time period considered was relatively short. Moreover they did not take size, book-to-market and momentum effects into account.

2.3 Multi-factor Models of Performance

2.3.1 Conditional CAPM

One of the underlying assumptions of the Capital Asset Pricing Model, time constant beta, has been called into question as betas and expected market returns vary over time and are correlated. To address this problem, Ferson and Schadt

(1996) proposed a modification of the CAPM by incorporating lagged information variables such as lagged T-Bill yields. By assuming "semi-strong form" of market efficiency of Fama (1970), the model controls common variation due to public information and reduces related bias as well as estimating time-varying conditional betas. This conditional model is essentially an unconditional "multiple factor model", with the market index as the first factor and the product of the market and lagged information variables as additional factors.

Ferson and Schadt (1996) found that the Jensen's Alpha with the conditional approach can be materially different from that with traditional models. They documented that conditional alphas and unconditional alphas are significantly different, as such, relying on unconditional alphas is likely to lead to a substandard investment decisions, and that a conditional alpha is a more reliable as a guide for mean-variance improving portfolio adjustments. If investors form expectations of future returns and risks using available public information, the conditional expectations will determine the relevant alphas. They found that the products of the future benchmark return and the predetermined variables capture the covariance between the conditional beta and the conditional expected market return given the information vector, Z_t. They contend that this covariance is a major source of bias in the unconditional alphas of mutual funds used in traditional models.

2.3.2. The APT Model

Among the alternatives to Capital Asset Pricing Model, Arbitrage Pricing Theory differs from CAPM in its assumptions and explanation of risk factors associated with the risk of an asset. This is a relatively new theory that predicts a relationship between the returns of portfolio and the returns of a single asset through a linear combination of variables. Arbitrage Pricing Theory is based on one assumption: arbitrage opportunities do not exist in balanced market conditions. If such an opportunity were to exist, the market would quickly eliminate it.

Deviations from the CAPM could come from missing risk factors since the CAPM assumes that stock prices move together only because of common movement with the stock market. The empirical finding that the intercepts of the

CAPM deviate statistically from zero has naturally led to the empirical examination of multi-factor asset pricing models motivated by the **Arbitrage Pricing Theory (APT)** developed by Ross (1976,1977). The logic behind the APT is not much different from that of the Capital Asset Pricing Model: investors get rewarded for taking on non-diversifiable risk. The difference lies with what captures this risk: in the CAPM, the one factor beta captures it. In the APT model, several factors can be the source of this risk, as determined by the historical returns data.

Although the APT has been developed as an alternative to the Capital Asset Pricing Model, the APT equation is in fact a generalization of the CAPM equation. According to this equation, asset value fluctuation is influenced not only the market portfolio value, but by other factors such as foreign currency exchange rates, energy prices, inflation and unemployment rates, which are non-market risk factors. If only one factor is considered as risk factor (i.e. the market portfolio value), then the APT equation will coincide with the Capital Asset Pricing Model equation. Taking several factors into account creates a stricter model resulting in more precise forecasting of asset price (portfolio value) changes and the reduction of non-systematic risk.

It is worth noting that every measure has its advantages and disadvantages relative to other measures. The insight and simplicity, for example. of the Capital Asset Pricing Model, Sharpe's Ratio and Jensen's Index are their advantages. This may be one factor that explains why the traditional models are still widely used in MBA classrooms and financial analysis alike despite continuous criticism from researchers who propose either alternative models or modifications to the existing models.

2.4 The Kernel Density Method

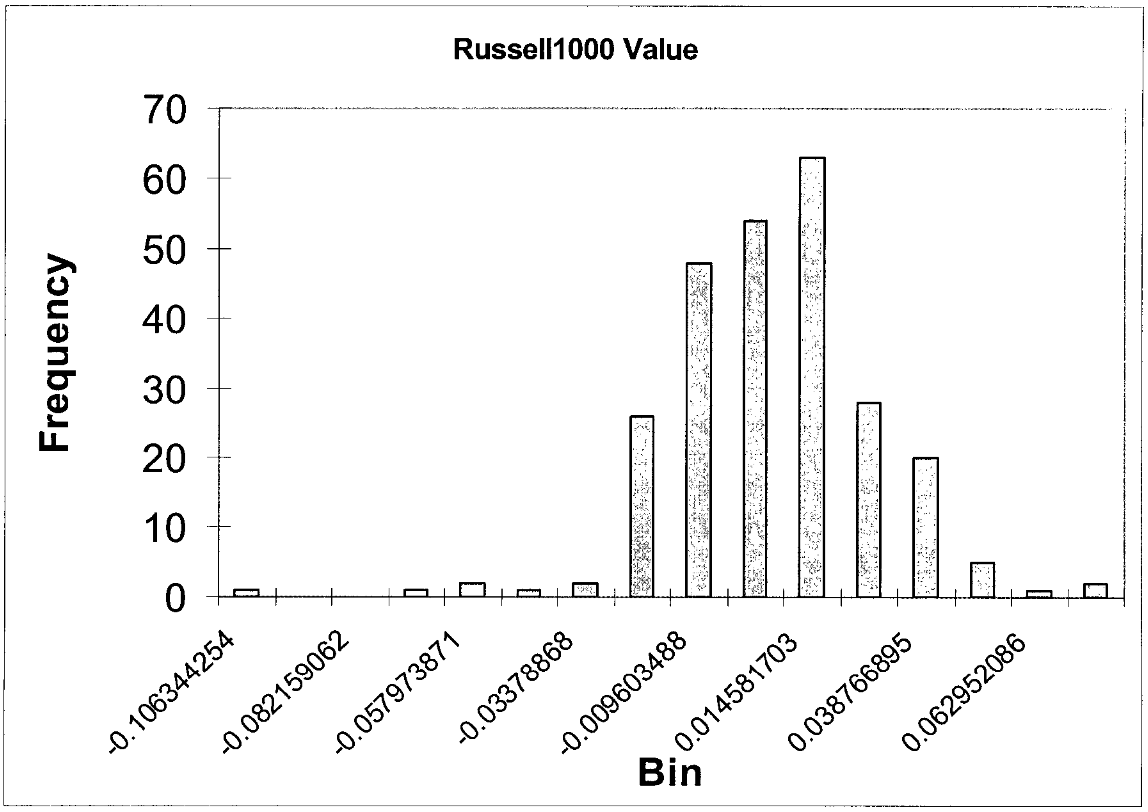
The convention in performance evaluation methods including those discussed above has been to use parametric density estimation when the underlying density function and therefore its parameters are not known. Tapia and Thompson[i] draw attention to the inherent danger by explaining that such an approach, although might be fine in the presence of perfect information, "would be a catastrophe as the front end of an estimation procedure based on data."

Probability density estimation is generally broken down into two basic classes: parametric or nonparametric estimators. Roughly speaking, parametric estimators assume a functional form of the density parameterized by a finite set of parameters, while nonparametric methods consist of all other types of estimators. Typical examples of nonparametric methods are histograms, splines, orthogonal series estimators and kernel estimators.

Nonparametric density estimation has the advantage of not requiring a priori knowledge or assumptions about the true density. The distribution of the error term or the relationship with the dependent and explanatory variable are not seen as taking a specific functional form involving specific parameters. Therefore, the estimates are robust to erroneous assumptions about that might have been made with the parametric estimation.

A histogram is the simplest and most frequently used non-parametric density estimator. However, histograms suffers from well known difficulties in that they

Figure 2.2. Histogram of weekly returns of Russell 1000 Value index



are not smooth although the underlying density function is often assumed to be smooth, they depend on end points of bins and on width of bins. The determination of binwidth and, to some extent, the choice of end points, determine the shape of the histogram.

Rosenblatt (1956)[ii] Whittle (1958)[iii], and Parzen (1962) [iv] developed an approach that avoids these problems except the determination of binwidth. Instead of a box, they used a smooth kernel function as the basic building block which they centered directly over each observation. Then, the smooth function is centered directly over each observation. To understand this refinement, suppose that x is the center value of a bin. The histogram can in fact be rewritten as

$$\hat{f}_h(x) = n^{-1}h^{-1}\sum_{i=1}^{n} I(|x - x_i| \leq \frac{h}{2}). \qquad (2.4.1)$$

If we define $K(u)=I(|u| \leq \frac{1}{2})$, then the equation changes to :

$$\hat{f}_h(x) = n^{-1}h^{-1}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right). \qquad (2.4.2)$$

This is the general form of the kernel estimator. Allowing smoother kernel functions like the Gaussian kernel

$$\frac{1}{\sqrt{2\pi}} \exp(-\tfrac{1}{2}u^2)$$

and computing x not only at bin centers gives the kernel density estimator. Kernel estimators can also be derived using weighted averaging of rounded points (WARPing) or by averaging histograms with different origins (Scott, 1985)[v].

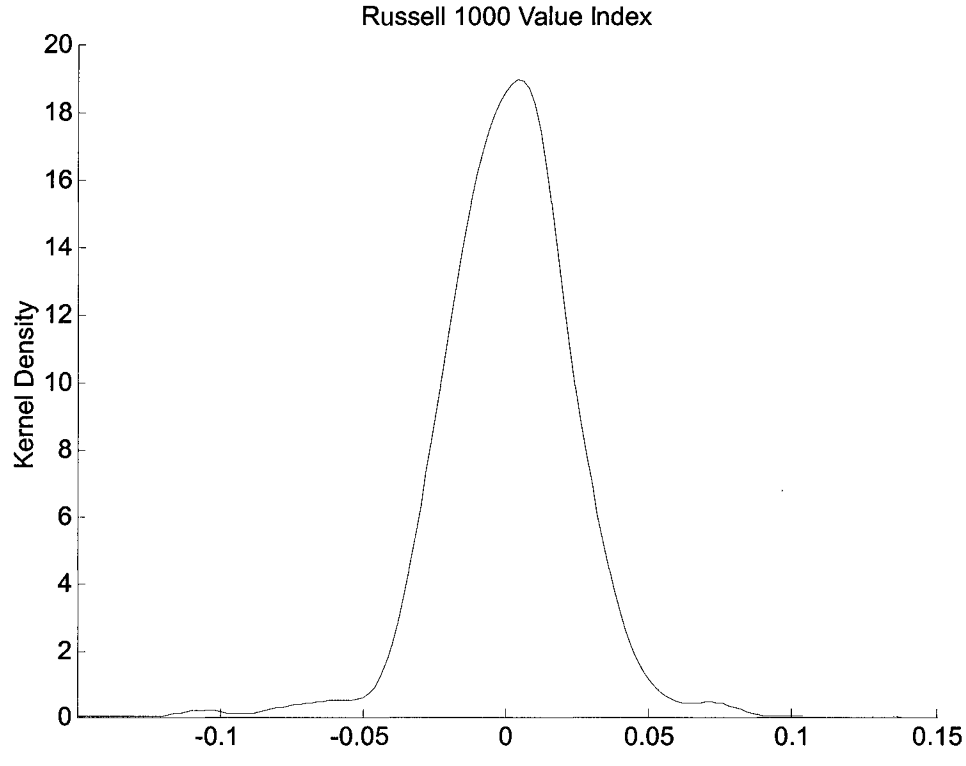
Kernel Density Estimation has become increasingly popular especially as a data exploration tool. Under mild conditions (h must decrease as sample size (n) increases), the kernel estimate converges in probability to the true density (Wand and Jones, 1995)[vi]. Figure 2.3 illustrates the Kernel Density Estimation of the data used to construct the histogram above.

One choice involved in Kernel Density Estimation is that of the kernel function. In the univariate case, the **kernel density estimator** $f_h(x)$ for the estimation of the density value at point f(x) is defined as:

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right), \qquad (2.4.3)$$

where K(.) denotes a kernel function, and h denotes the bandwidth and **∫K(t)*dt*=1** to ensure that the estimates f(x) integrates to 1 and where the kernel function *K* is usually chosen to be smooth and unimodal with a peak at 0.

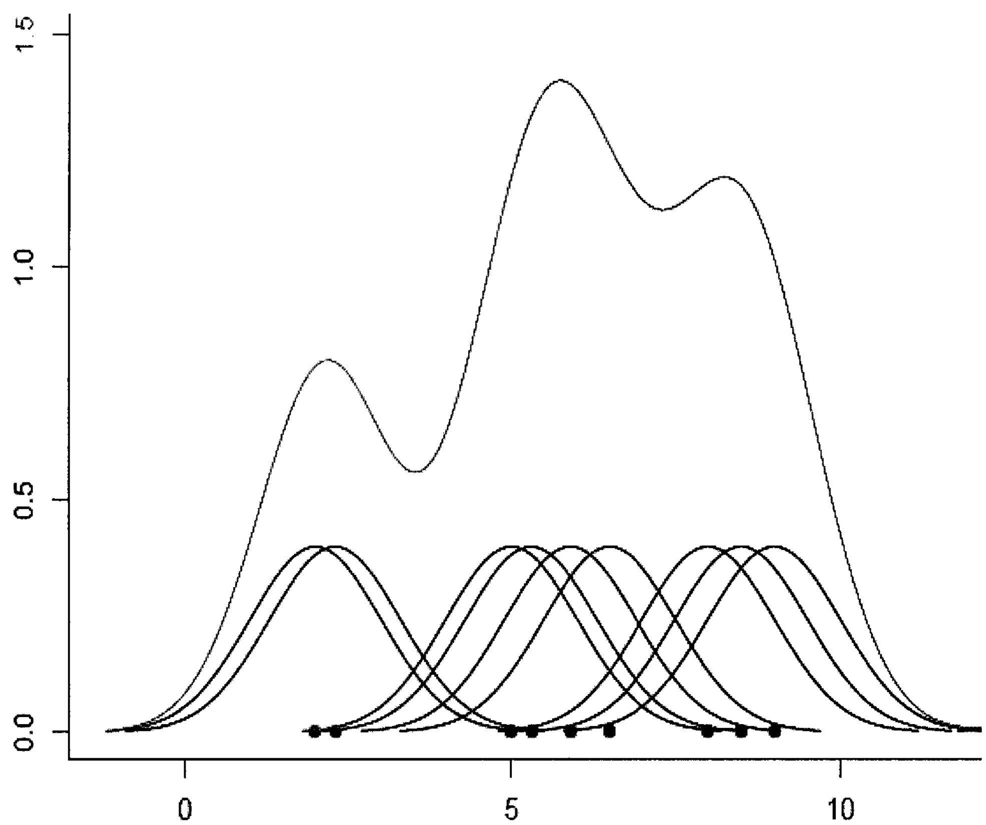
Fig. 2.3 A Kernel Estimate of Russell 1000 Value Index 5 year Returns



The stylized facts about the kernel function K are as follows:

- It can be a proper probability density function. It is usually chosen to be unimodal and symmetric about zero.
- The center of kernel is placed right over each data point. (Figure 2.4)
- Influence of each data point is spread about its neighborhood.
- Contribution from each point is summed to overall estimate.

Fig. 2.4. Construction of a (Gaussian) Kernel Density.



Although the Gaussian kernel is the most often used, the function can be one of several including Uniform, Triangle, Epanechnikov, Quartic, Biweight, Gaussian and Cosinus.

Table 2.1 : Kernel functions.

Kernel	$K(u)$
Uniform	$\frac{1}{2} I(\|u\| \leq 1)$
Triangle	$(1 - \|u\|) I(\|u\| \leq 1)$
Epanechnikov	$\frac{3}{4}(1 - u^2) I(\|u\| \leq 1)$
Quartic	$\frac{15}{16}(1 - u^2)^2 I(\|u\| \leq 1)$
Triweight	$\frac{35}{32}(1 - u^2)^3 I(\|u\| \leq 1)$
Gaussian	$\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}u^2)$
Cosinus	$\frac{\pi}{4} \cos(\frac{\pi}{2}u) I(\|u\| \leq 1)$

The uniform kernel which gives the same weight to all observations x_i around x which may be unjustified. Other kernel functions, including the Gaussian, attribute more weight to observations that are near to x and less weight to the distant observations. Overall, there is very little difference among the kernel functions in terms of efficiency ranging from 0.93 for the Uniform kernel to 1.00 for the Epanechnikov kernel where efficiency is measured by Mean Integrated Square Error (MISE) or Asymptotic MISE (AMISE). As such, the choice is mostly academic or of personal preference.

The debate regarding kernel density estimation centers on “smoothing”, i.e. the choice of the bandwidth, also referred to as “the smoothing parameter”. Silverman (1986)[vii], Scott (1992)[viii] and Wand and Jones (1995)[ix] have written excellent books on Kernel Density estimation in general, and on smoothing parameters, in particular. Silverman is also credited with a smoothing method, used in this study, that bears his name: Silverman’s Rule of Thumb.

The importance of the optimal smoothing parameter cannot be overstated as choosing a too small smoothing parameter will result in under-smoothing while choosing it too large will result in over-smoothing. An under-smoothed kernel will look jagged or rough, and may inaccurately yield more modes that there actually exist. Over-smoothing, on the other hand, will hide or obscure the true structure of the data. Figure 2.5 and figure 2.6 show examples under-smoothing and over-smoothing, respectively, using the same data as the previous kernel estimation. The optimal smoothing parameter as computed by Silverman's Rule of Thumb and used previously was 0.0077. The under-smoothed example uses a bandwidth of 0.003 and the over-smoothed uses one of 0.03.

Fig. 2.5 Optimal and Under-smoothed Kernels

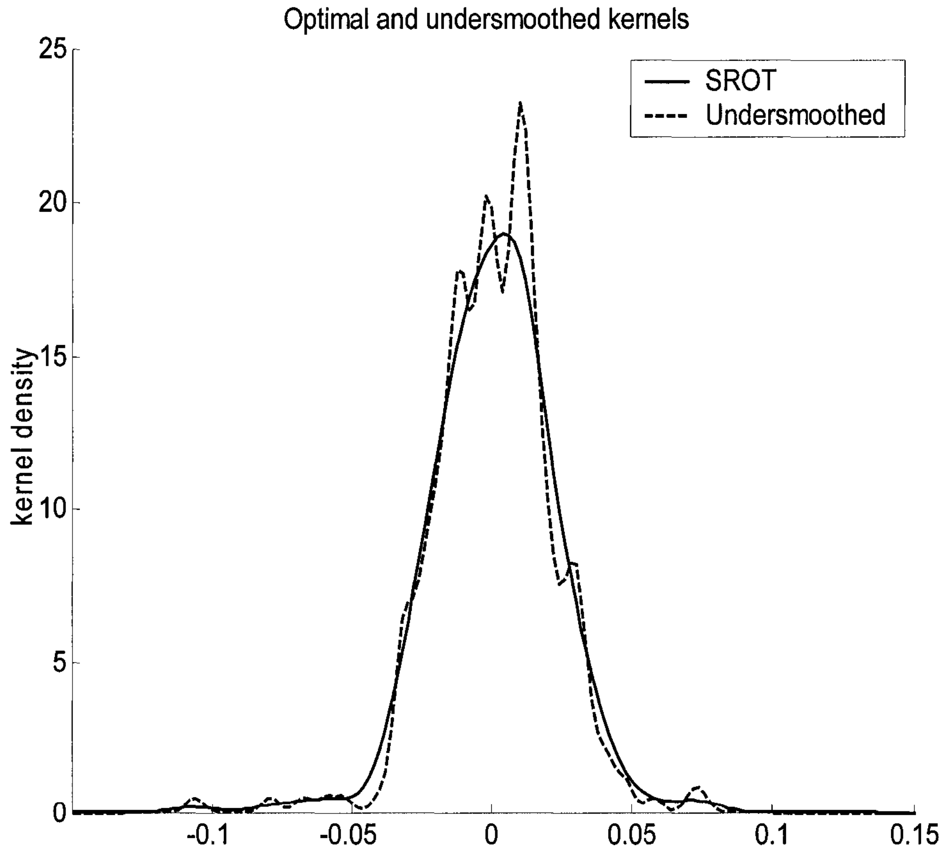
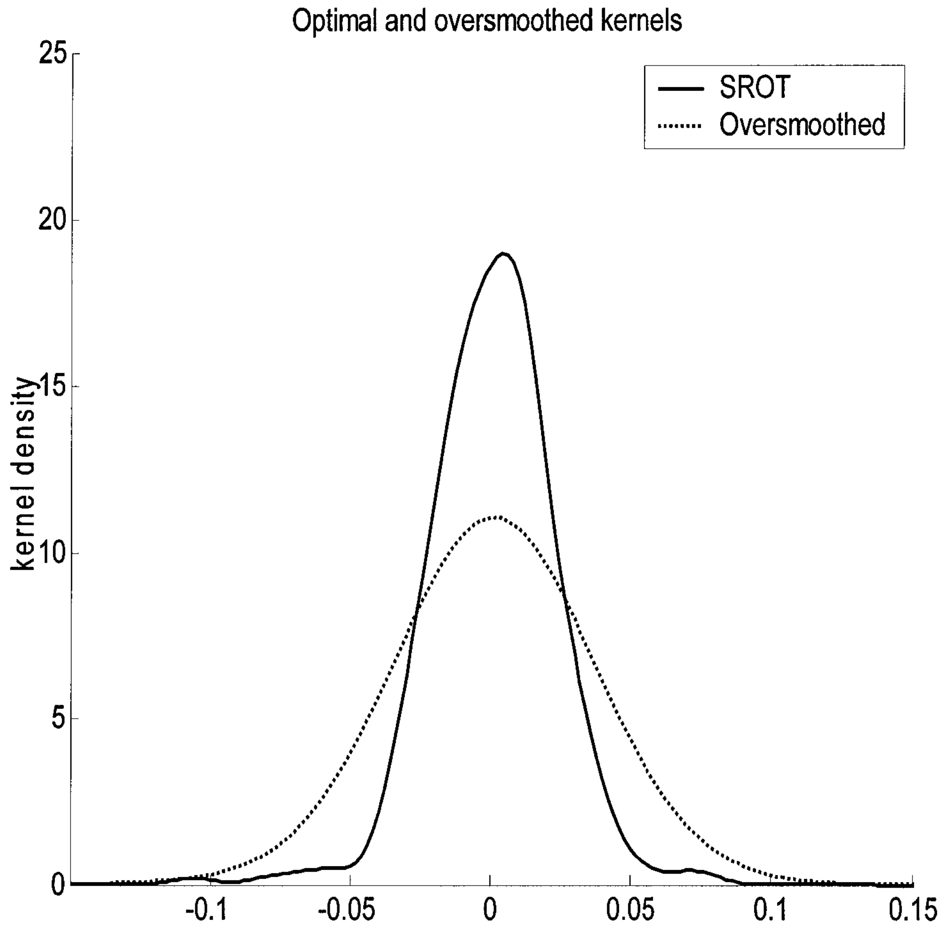


Fig. 2.6 Optimal and over-smoothed Kernels



Kernel density estimation is a good descriptive tool for seeing modes, location, skewness, tails and asymmetry. It has been and is being widely used in many diverse disciplines including engineering, statistics, archeology, computer science and genetics. Financial economists, as of the start of this study, have not shown great interest despite its advantages and high applicability to various estimation needs in the discipline.

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Description of Data

3.1.1 Sources of Data

There are two well-known sources of mutual fund data, one being Morningstar® Principia® by Morningstar Inc. The other is by the Center for Research in Security Prices (CRSP®), a financial research center at the University of Chicago Graduate School of Business. CRSP creates and maintains historical U.S. databases for mutual funds as well as stocks

(NASDAQ, AMEX, NYSE), indices and bonds. Non-surviving funds are usually removed from performance returns in mutual fund data. One advantage the CRSP has is that its US Mutual Fund Database is survivor-bias free as it contains live funds as well as funds that have been discontinued. It has one disadvantage, however, in that it is subject to omission bias.

Elton et al (2001) compared CRSP Survivor Bias Free U.S. Mutual Fund Database to Morningstar. They found that the CRSP database has an omission bias which causes the same effects as survivorship bias. Although all mutual funds were listed in CRSP, return data were missing for many funds. They found the CRSP return data to be biased upward.

Morningstar mutual fund data and profiles are publicly available online at the Yahoo! Finance website at http://finance.yahoo.com, where historical prices can be downloaded free of charge. Although this dataset has survivorship-bias as it does not provide data on dead funds, the historical prices are complete for the period they are available. For example, if a fund's historical prices are available as of April 1, 2000, they will be available for all periods until the current date. One exception is in the case of daily prices where there are some omissions. Weekly and montly historical prices are reported in full.

The profiles of the funds provide information on the current lead manager including his/her start date. Other relevant data reported include fund overview, fund summary, fund operations, fees and expenses and investment information. Fund overview provides information on the fund's Morningstar category and rating, net assets, year-to-date return and the fund's inception date. Fund summary explains the types of securities the fund buys, investment information including minimum initial and sybsequent investment amounts required.

3.1.2 The Choice of Funds

Institutional Mutual Funds are still a very small subset of mutual funds in terms of number of funds although growing interest by retirement plans (see Figure 3.2) has led to inception of numerous funds in this subset in recent years. However, funds started within the last five years do not have a long enough history for the purposes of this study. Some funds, despite their designation as Institutional Mutual Funds do (also) cater to the individual investors by selling shares through brokers; these funds typically have a much lower minimum initial and subsequent investment requirements, and as such are not included in this study.

All of the funds included invest primarily in domestic equities, have at least 5 years of historical prices available as of March 31st, 2005 (with a few exceptions of at least 4 years and 10 months), have minimum initial investment requirement of $500,000 (most over $1 million) and are named/designated as "Institutional". The fact that only funds with at least 5 years of life are chosen may lead to selection bias. Dead funds are not included, and therefore there is survivorship-bias in the sample. Mornigstar ratings and funds' fees and expenses are not considered. Investment styles are considered in classification of funds into nine categories.

3.1.3 Fund Categorization and the Choice of Benchmarks

The "style" of a fund or its manager refers to the approach fund managers use for security selection. A manager's investment style is considered to have an influence on his/her performance. Morningtar's styles classification allocates funds into different categories based on fund's investment methodology and the market capitalization of the companies in which it invests. It places the funds in large-cap, medium-cap or small-cap based on the market capitalization of the equities they hold. Funds are characterized as growth oriented, value oriented and blend. The combination of orientation and market capitalization yields nine categories: Large-Cap Growth, Mid-Cap Growth and Small-Cap Growth; Large-Cap value, Mid-Cap Value and Small-Cap Value; Large-Cap Blend, Mid-Cap Blend and Small-Cap Blend. As an example, a fund categorized as large-cap growth is placed as shown in Table 3.1 .

Table 3.1 Illustration of the Morningstar Style Box

				Size
				Large
				Medium
				Small
Orientation	Value	Blend	Growth	

Russell's[i] investment style Evaluation and Classification places the funds on a 4 quadrant matrix. The top left and right Quadrants on top represent Russell 1000 Value and Russell 1000 Growth, respectively, and includes funds that primarily invest in the securities included in Russell 1000 index, i.e. the 1000 securities with the largest market capitalization. The lower quadrants named Russell 2000 value and Russell 2000 Growth, include funds that primarily hold the securities included in the Russell2000 index, the smallest 2000 securities of the broad Russell 3000 index. The matrix is illustrated below.

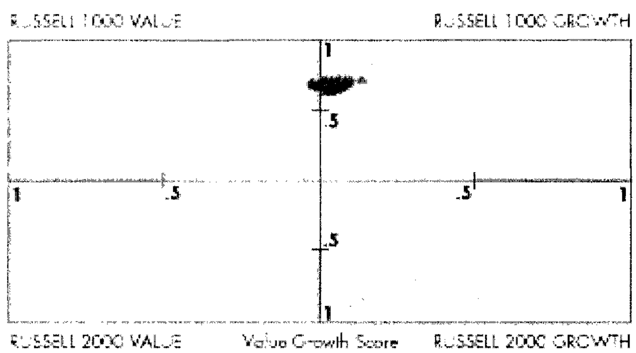


Fig.3.1 Russell Style Matrix

One advantage of this matrix is its versatility in that it illustrates a fund's orientation and market capitalization relative to other funds in the same category. As an example, of the two funds in Russell 1000 growth quadrant, the one with the higher market capitalization as determined by its holdings would be placed higher in the quadrant, the one with the more aggressive growth orientation would be to further the right.

Other classification methods have been offered. Goetzmann and Brown (1998)[ii] for example, offer a classification based on returns without using any information about the composition of the fund's portfolio. As such, they classify equity funds into eight major categories: Growth and Income, Growth, Income, Value, Global Timing, Glamour, International and Metal Funds.

If funds are divided into several categories, it makes little sense to compare the performances of all funds to a single benchmark, such as the S&P 500 index. Instead, each fund should be compared to a benchmark that is compatible with its classification. As such, this study uses nine different benchmarks one for each category of funds as shown in Table 3.2. Russell indexes are chosen because of their similarity in construction to Morningstar's style categorization where the historical fund prices are obtained, and for the stated purposes of the indexes[iii]: "to act as a performance standard for active managers."

Table 3.2 Fund classifications and appropriate benchmarks.

Fund Category	**Relevant benchmark**
Large-Cap Growth	Russell 1000 Growth index
Mid-Cap Growth	Russell 3000 Growth index
Small Cap Growth	Russell 2000 Growth index
Large-Cap Value	Russell 1000 Value Index
Mid-Cap Value	Russell 3000 Value index
Small-Cap Value	Russell 2000 Value index
Large-Cap Blend	Russell 1000 index
Mid-Cap Blend	Russell 3000 index
Small-Cap Blend	Russell 2000 index

3.2 Data Processing

3.2.1 Computing Returns

The historical prices obtained from Yahoo! Finance website were loaded into Microsoft Excel to compute raw returns. A weekly raw return is simply the weekly percentage change in the fund's closing price adjusted for dividends and splits. A fund's raw return at time t is given by

$$R_{pt} = \frac{\text{ACP}_{pt}}{\text{ACP}_{\text{pt-1}}}$$

where ACP_{pt} is the fund's adjusted closing price at the end of period t and ACP_{pt-1} is the fund's adjusted closing price at the end of period t-1 . The return on the benchmark (R_{bt}) is calculated in the same manner. A fund's risk premium (or excess return) is the difference between the fund's return and the yield on 3-month Treasury Bill (r_t) as proxy for the risk-free rate.

$$RP_{pt}=R_{pt}-r_t \qquad (3.2.1)$$

Similarly, a benchmark's risk premium is its excess return over risk-free rate:

$$RP_{bt}=R_{bt}-r_t \qquad (3.2.2)$$

Using this notation, the traditional 'alpha model' is expressed as follows:

$$(R_{pt}-r_t)=\alpha_p+\beta_p(R_{bt}-r_t)+\varepsilon_{t,} \quad \text{or}$$

$$RP_{pt}=\alpha_p+\beta p(RPpt)+\varepsilon_{t,} \qquad (3.2.3)$$

where

$$\beta p= \frac{Cov(RP_{pt}, RP_{bt})}{Var(RP_{bt})} \qquad (3.2.4)$$

but since $\rho_{pb} = \dfrac{Cov(RP_{pt}, RP_{bt})}{(\sigma(RP_{pt}))(\sigma(RP_{bt}))}$

portfolio beta is given by

$$\beta p = \frac{\rho_{pb}}{\sigma_m^2} \qquad (3.2.5)$$

where σ_m^2 is the market volatility.

For each one of the funds, return data were imported into Matlab® using the program's import wizard where each column of data were used to create vectors with column names. Data for each fund were saved separately as a Matlab Data file (mat-file). The names of the created vectors are listed in Table 3.3 .

Table 3.3 Vectors created in Matlab for MS Excel data.

Vector	Data
Ret	Return on fund
Bret	Return on benchmark index
Exert	Fund's Risk Premium, excess return over the risk-free rate

Ebret	Benchmark's Risk Premium, excess return over the risk-free rate
Dret	Fund's "Differential excess return", return over the benchmark, RP_{pt}-RP_{bt}

3.2.2 Kernel Density Estimation

A Matlab code written by Professor Salih N. Neftci was modified to estimate the kernel densities for each of the funds. The kernel function chosen was the Gaussian kernel. Tapia and Thompson (1978) note that the quartic kernel estimator is "nearly indistinguishable in its smoothness properties and has distinct computational advantages" in comparison to the Gaussian kernel. The current computer technology makes the computational advantage a minor concern. In fact, a Gaussian kernel can be estimated within seconds. Another kernel function commonly used is the uniform kernel which gives the same weight to all observations x_i around x. Other kernel functions, including the Gaussian, attribute more weight to observations that are near to x and less weight to the distant observations. There is very little difference among the kernel functions in terms of efficiency (see Table 3.4).

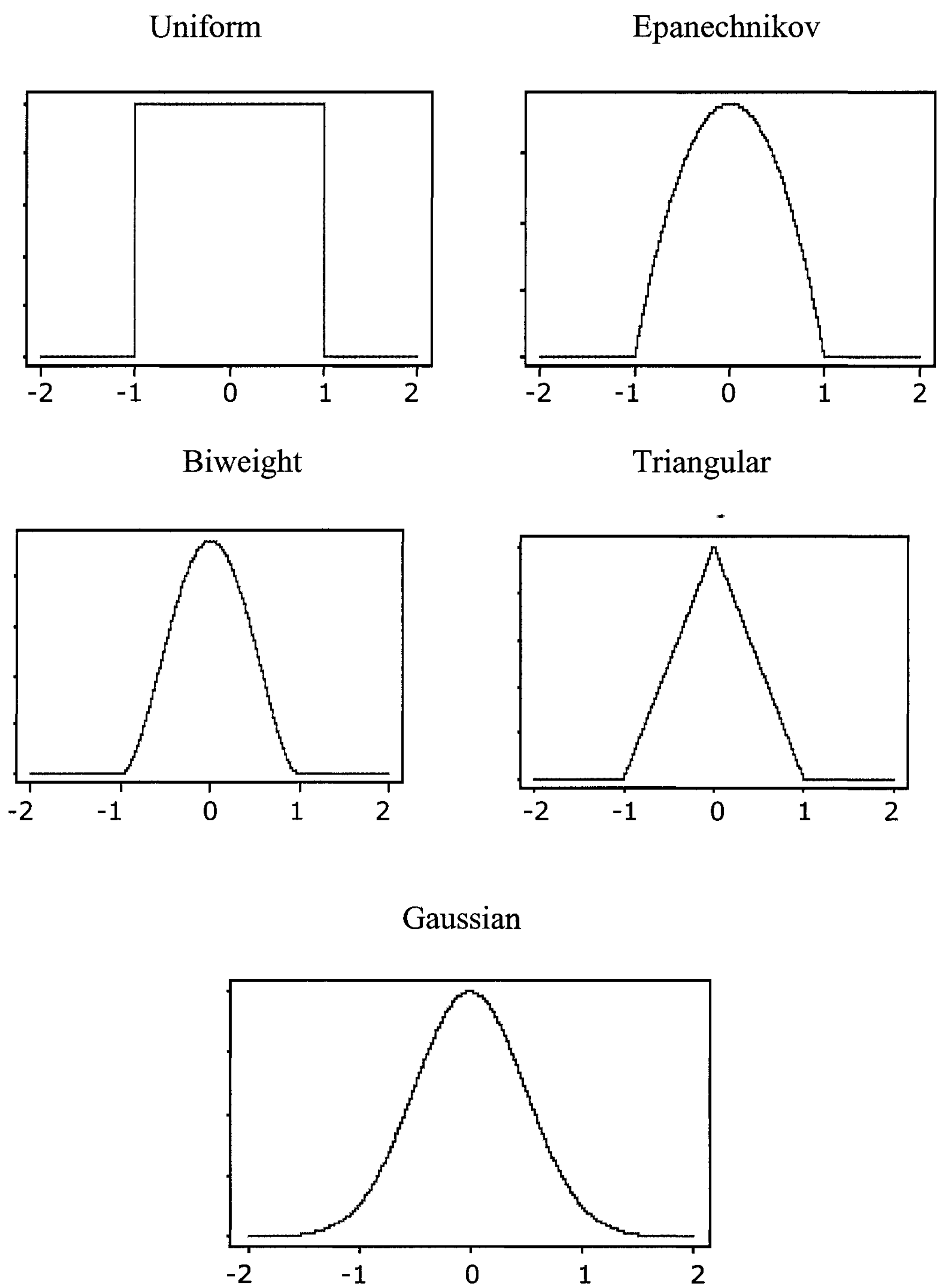
The choice is essentially one of purpose and preference. Silverman (1986) contends that "it is perfectly legitimate, and indeed desirable, to base the choice of kernel on other considerations.." This study plots the kernel densities

Table 3.4 Kernel Functions and their efficiencies.

Kernel Function	Efficiency
Epanechnikov	1.000
Biweight	0.994
Triangular	0.986
Gaussian	0.951
Uniform	0.930

of all funds in a given category in the same figure, and the Gaussian kernel provides the best distinction among different densities especially in the tails which are of interest in performance evaluation and certainly in this study (see Figure 3.2).

Fig. 3.2 Kernel Functions and their Shapes



The method of choice for bandwidth selection (h) was Silverman's Rule of Thumb which follows naturally from the choice of the kernel. Silverman (1986) finds this 'ideal' smoothing parameter (h_{opt}) from the view of minimizing the approximate mean integrated square error (MISE) by using simple calculus as shown by Parzen (1962)[iv]. The value of h_{pot} for Gaussian kernel depends on n, the number of observations, and σ, the standard deviation of the sample.

The code was reproduced for each fund with differentiating features, most notably, the name of the data file to loaded and the color and style of the plot. The 'hold plot' option was invoked to plot the densities of all funds in a category in the same figure. Although the data files contained the differential returns, these were not used at this time. Instead, the benchmark returns were plotted in the same figure as the funds for ease visual exploration.

The figures for each of the categories revealed differences in the densities of the funds and the benchmark. Some fund densities had heavier tails indicating they had a higher probability of realizing extreme returns. The area under the left tail and right tail of each fund's density was calculated using the trapezoidal method (with unit spacing) in Matlab. This is similar to computing the area under a curve using the Riemann-Stieltjies integral. Neftci (1996) [v]finds Riemann-Stieltjies integral "useful when integration is with respect to the increments in f(x) rather the x itself". Since the fund's (portfolio's) price depends on the prices of the securities it holds, this is a case where Riemann-Stieltjies integral will be useful. As such, this method is appropriate for computing the area under the tails of a fund's kernel density.

The end points for the tail areas were -0.4 and -01 for the left tail and 0.1 and 0.4 for the right tail. In other words, integration within these end values would give a fund probability of realizing between -40% and -10% return and between 10% and 40% return, respectively. In addition to areas under the tails, the median value of kernel density was computed for each fund and the benchmark. Data for all funds in a category and the benchmark were collected in an Excel worksheet. Using Excel's regression function, left tail and right areas were regressed on median values in turn.

In addition to regression results, kernel density plots of all funds in a category are presented for all categories in the figures section in the Appendix. Although the areas under the tail and the subsequent regression analysis reveal numerical insights, the plots themselves are useful for exploration and as visual aids.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Kernel Density Estimation Results

Weekly returns were obtained of institutional mutual funds in nine categories as per Morningstar style classification. Weekly returns were also obtained of the appropriate benchmark for each style category. Table 3.2 showing style classification and appropriate benchmarks is reproduced below for convenience. The returns were used to compute the kernel density estimates of all funds in a given category as well as the benchmark for the category.

Table 3.2 Fund classifications and appropriate benchmarks.

Fund Category	**Relevant benchmark**
Large-Cap Growth	Russell 1000 Growth index
Large-Cap Value	Russell 1000 Value Index
Large-Cap Blend	Russell 1000 index
Mid-Cap Growth	Russell 3000 Growth index
Mid-Cap Value	Russell 3000 Value index
Mid-Cap Blend	Russell 3000 index
Small Cap Growth	Russell 2000 Growth index
Small-Cap Value	Russell 2000 Value index
Small-Cap Blend	Russell 2000 index

The returns were imported into Matlab® and kernel density estimates were obtained using a special code modified from a code written by Professor Salih N. Neftci. The Gaussian kernel function and Silverman's Rule of Thumb method were chosen as the kernel function and the smoothing method, as explained in chapter three. For a given category, a kernel density estimate for each of the funds and the benchmark index was obtained and plotted on the same figure in Matlab by invoking the 'hold plot' function. This allowed the comparison of kernel densities and examination of tails on the figure before carrying out the tail analysis and regression analysis. These figures are presented in the following pages.

Since the study aims to identify fund manager's who perform significantly better or worse than the benchmark and other funds in the category, the tail areas are of primary interest. In all of the nine categories, funds differed in terms of 'area under the left tail or right tail' where the left tail represented weekly returns between -40% and -10%, and the right tail represented weekly returns between 10% and 40%. As expected, the densities in the extreme tail regions such as between -0.4 and -0.3, and 0.3 and 0.4 were either zero or extremely small. However, these regions were included for the purpose of completeness.

There were differences among the categories in terms of 'concentration' of heavy tails, but in general, heavy tails were present between -0.15 and -0.1 on the left and between 0.1 and 0.15 on the right. The horizontal axis is set accordingly to highlight this fact. In addition, tail areas are plotted separately and presented in the Appendix.

The kernel density estimation results indicate that, for all categories, there are differences in the returns of funds in a given category. In some cases, such as the Large-Cap Growth category, the differences are more pronounced than in others, such as the large value category. These might be explained by the higher volatility in the returns of growth funds as managers in this category are more likely to take risks than managers characterized by long run value orientation.

Tail areas for the regions of interest were calculated using the 'trapz' function in Matlab as explained in Chapter 3. The probability values obtained from these tail areas as well the median values of kernel density estimates for all funds were imported into Microsoft Excel for regression analysis. Regression results indicate that funds are different in their returns. The null hypothesis that returns of all funds within a category come from same population can be rejected for all categories tested. Regression analysis results are presented in the Appendix.

4.2 **Discussion**

Kernel density estimation offers several advantages in capturing fund return characteristics without specifying a functional form or underlying distribution. Thus, nonparametric density estimation eliminates the need for restrictive and possibly tenuous assumptions and thus offers insight to the construction of theoretical and empirical models. Whereas the emphasis in parametric estimation is on obtaining the best estimator of a given parameter, in nonparametric estimation the emphasis is on obtaining a good estimate of the *entire density function.* Intuitively, kernel estimation allows the data to specify the distribution and functional form. The parametric versus nonparametric trade-off is one of efficiency versus incorrect model specification. Recent advances in the theoretical properties of kernel density estimation, computational efficiency and the availability of large, accurate data sets have resulted in a tremendous increase in the realized relative efficiency of kernel estimators.

Traditional and current performance evaluation methods assume a parametric structure of the return data when doing so requires perfect information. No such assumption is necessary with nonparametric estimation methods. Kernel Density Estimation can be used as an exploratory tool in determining performance differences among managers. The findings can be analyzed using more rigorous methods such as appropriate regression analyses.

It should be noted that a study is only as good as the dataset on which it is based. The data used here was Morningstar data obtained from the Yahoo! Finance website. Since only data of living funds are available, survivorship-bias cannot be eliminated. Survivorship-bias free data are available by CRSP, however, that database suffers from an omission bias which causes the same effects as survivorship bias (Elton et al, 2001). Although all mutual funds were listed in CRSP, return data were missing for many funds. Until there is a database available that is free of both survivorship-bias and omission bias, one faces a trade-off. In this study, the Morningstar dataset was preferred to CRSP dataset due to the completeness of the data for the period of interest and applicability to the Morningstar style box.

CHAPTER FIVE

CONCLUSIONS AND FURTHER RESEARCH

5.1 Conclusions

This study is one of performance evaluation of mutual funds, which may be the most studied topic in Finance/Financial Economics. However, it is unique in the sense that it studied a very special subset of mutual funds, the institutional mutual funds. These funds are more like pension funds than mutual funds because of their target investors, the institutions and the retirement market. Despite the increasing size of retirement and institutional funds, these funds have not received the attention they deserve in the academia. This study aimed to remedy this problem.

This study is also unique in that it uses a method hereto unused in performance evaluation of fund managers, the kernel density estimation. This method, which has become extremely popular in other disciplines, owing in part to recent developments in computational technology, has been largely ignored by academicians in Finance/Financial economics, despite its high applicability. The second aim of this study was to illustrate the advantages of Kernel Density in financial research.

5.2. Areas For Further Research

This study has shown that Kernel Density Estimation, which has become extremely popular in diverse disciplines, can be used in performance evaluation of mutual fund managers. A special subset of mutual funds, the institutional mutual funds were used owing to their distinguishing characteristics from other mutual funds. However, the method can be applied to all fund and portfolio evaluation. In particular, it could be used to test whether institutional mutual funds are different from other mutual funds of the same style category as might be expected because of the close monitoring of institutional mutual fund managers as well as the difference in fund flows.

The dataset used had survivorship bias and the alternative dataset omission bias. This study could be repeated with the alternative dataset to see if the same results would be obtained. If a dataset that is free of survivorship bias and omission bias can be obtained in the future, the study can be repeated with this superior dataset.

Figure A.1. All Large Growth Funds vs Russell1000

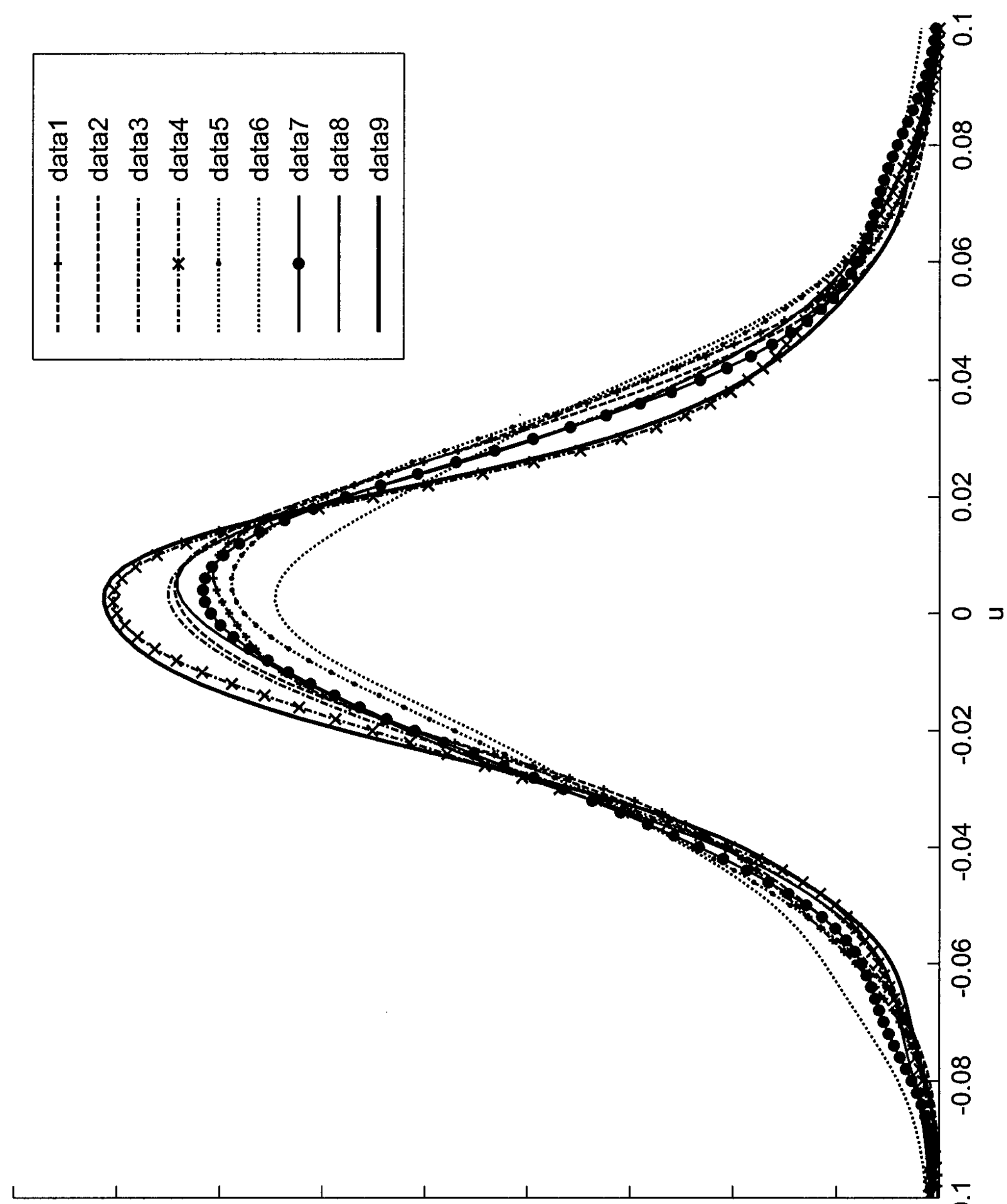
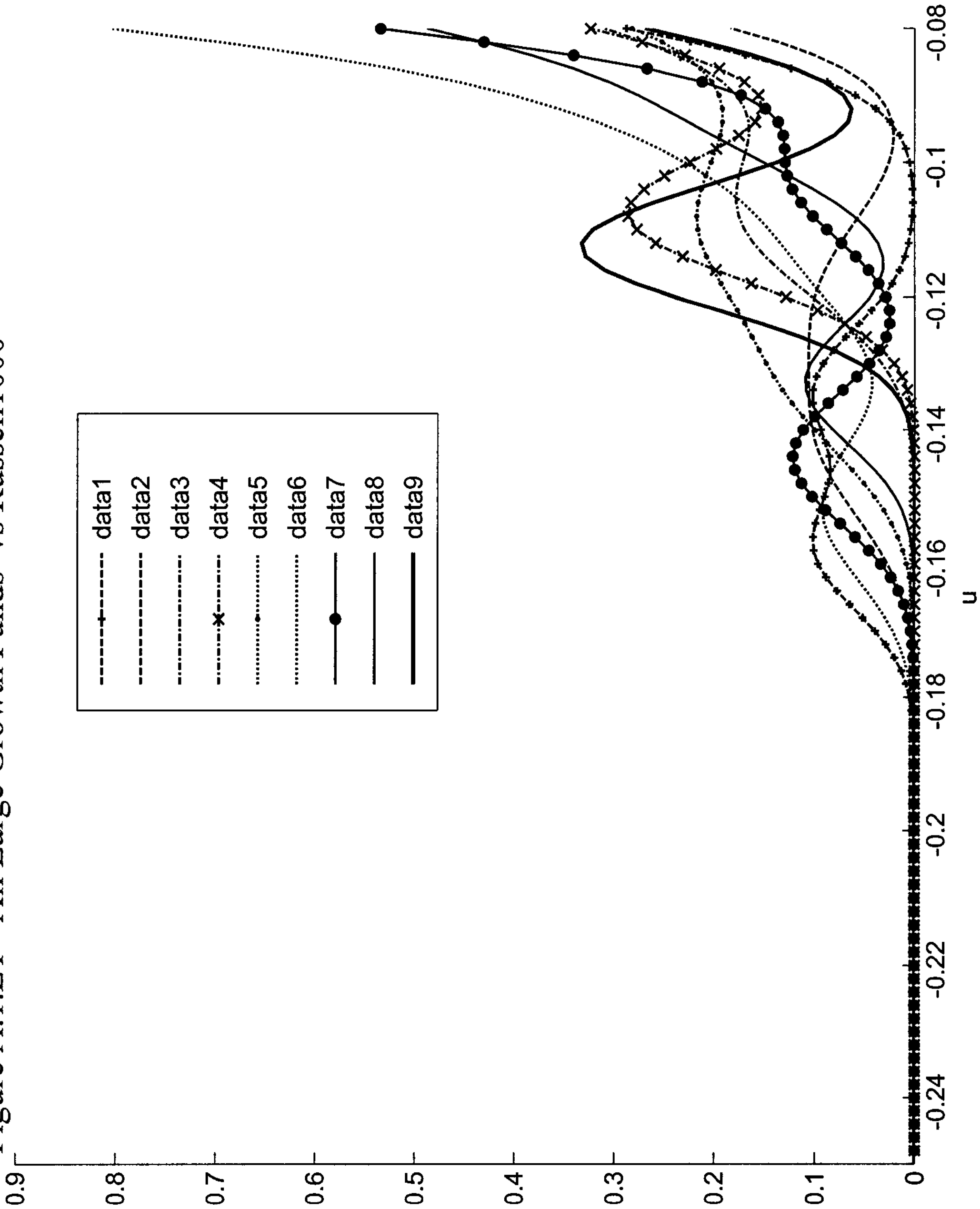


Figure A.1.LT All Large Growth Funds vs Russell1000



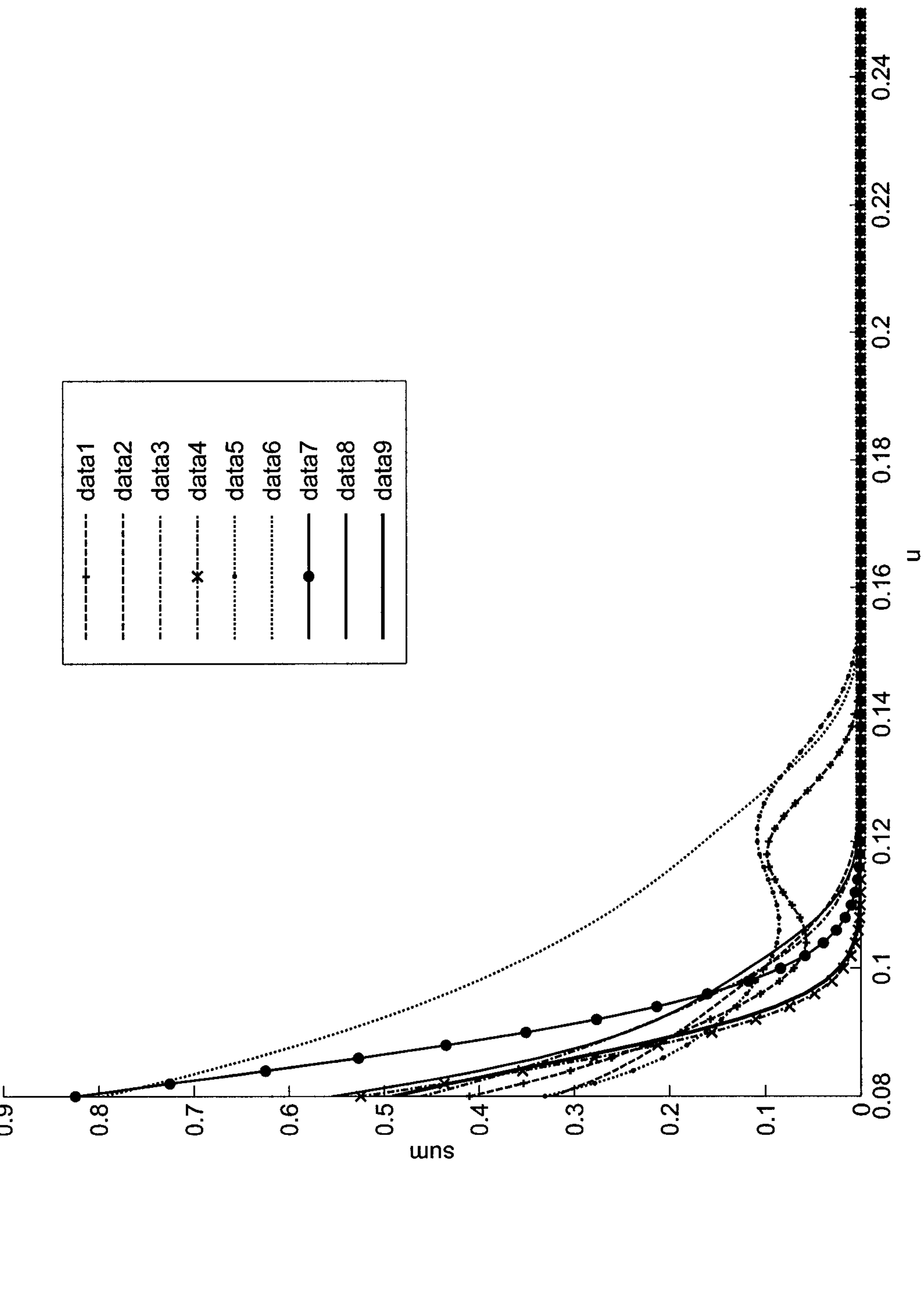
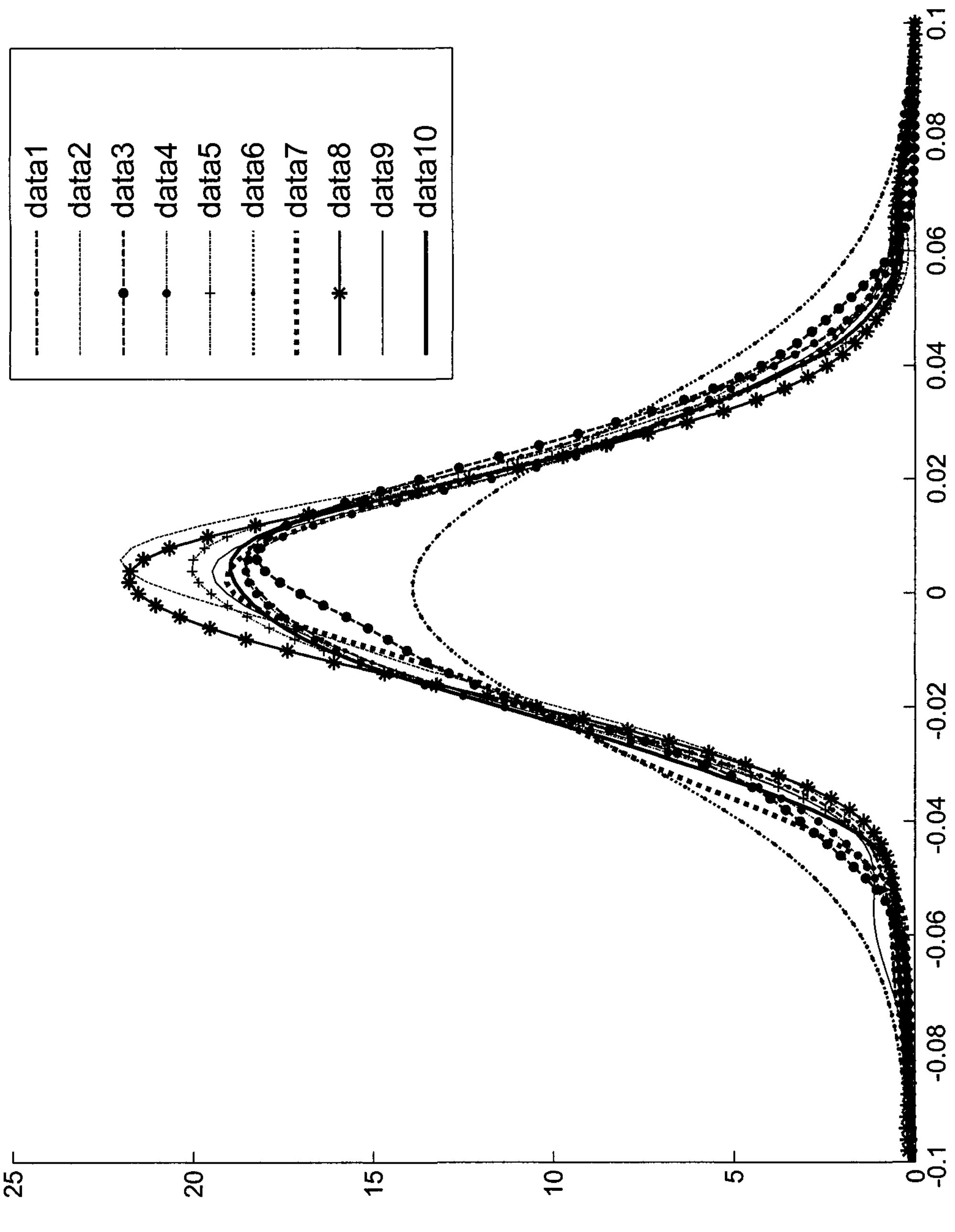


Figure A.1.RT All Large Growth Funds vs Russell1000

Fig. A.2 Large Value and Russell1000 LV



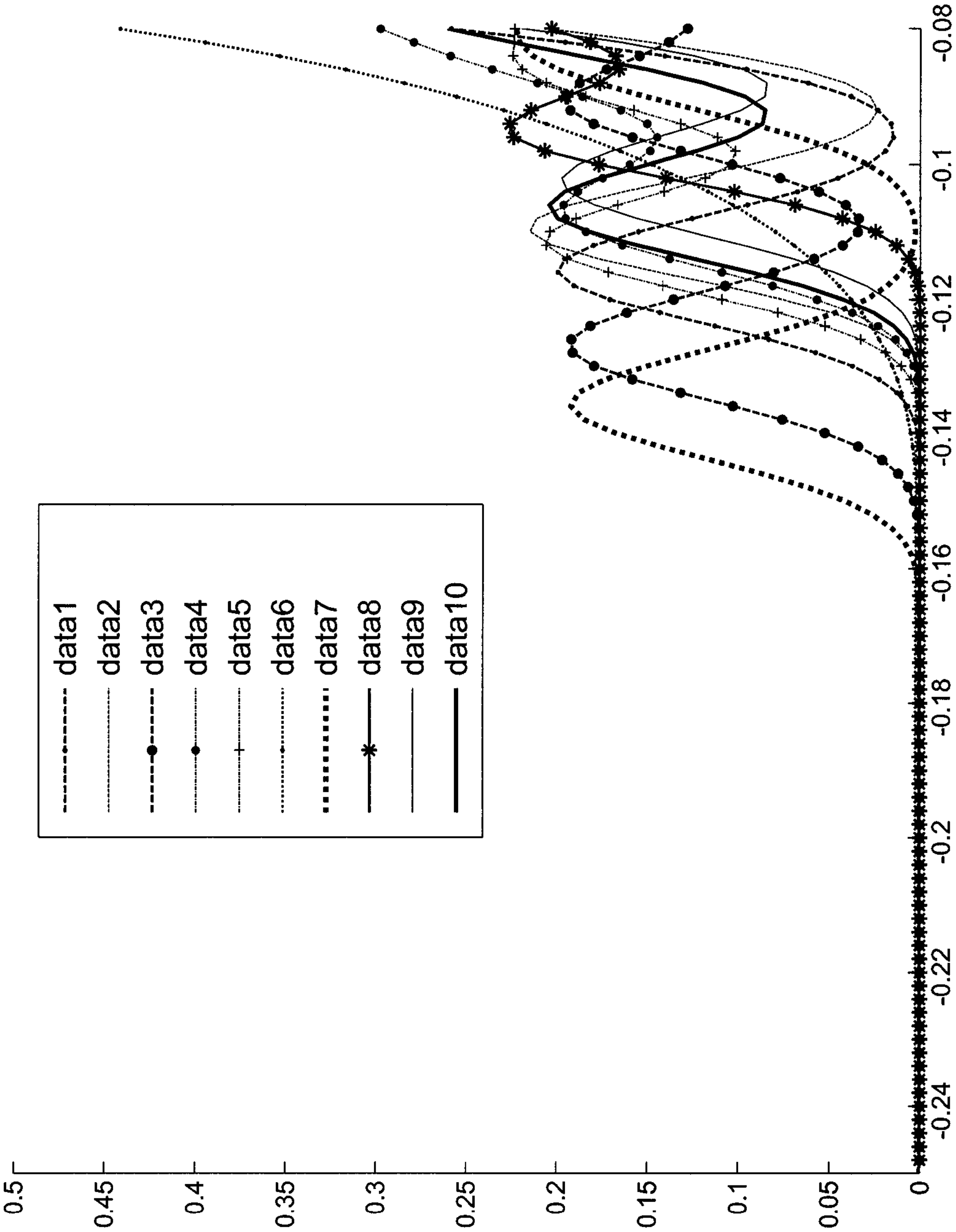

data1
data2
data3
data4
data5
data6
data7
data8
data9
data10
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.24
-0.22
-0.2
-0.18
-0.16
-0.14
-0.12
-0.1
-0.08

Fig. A.2.RT Large Value and Russell1000 LV

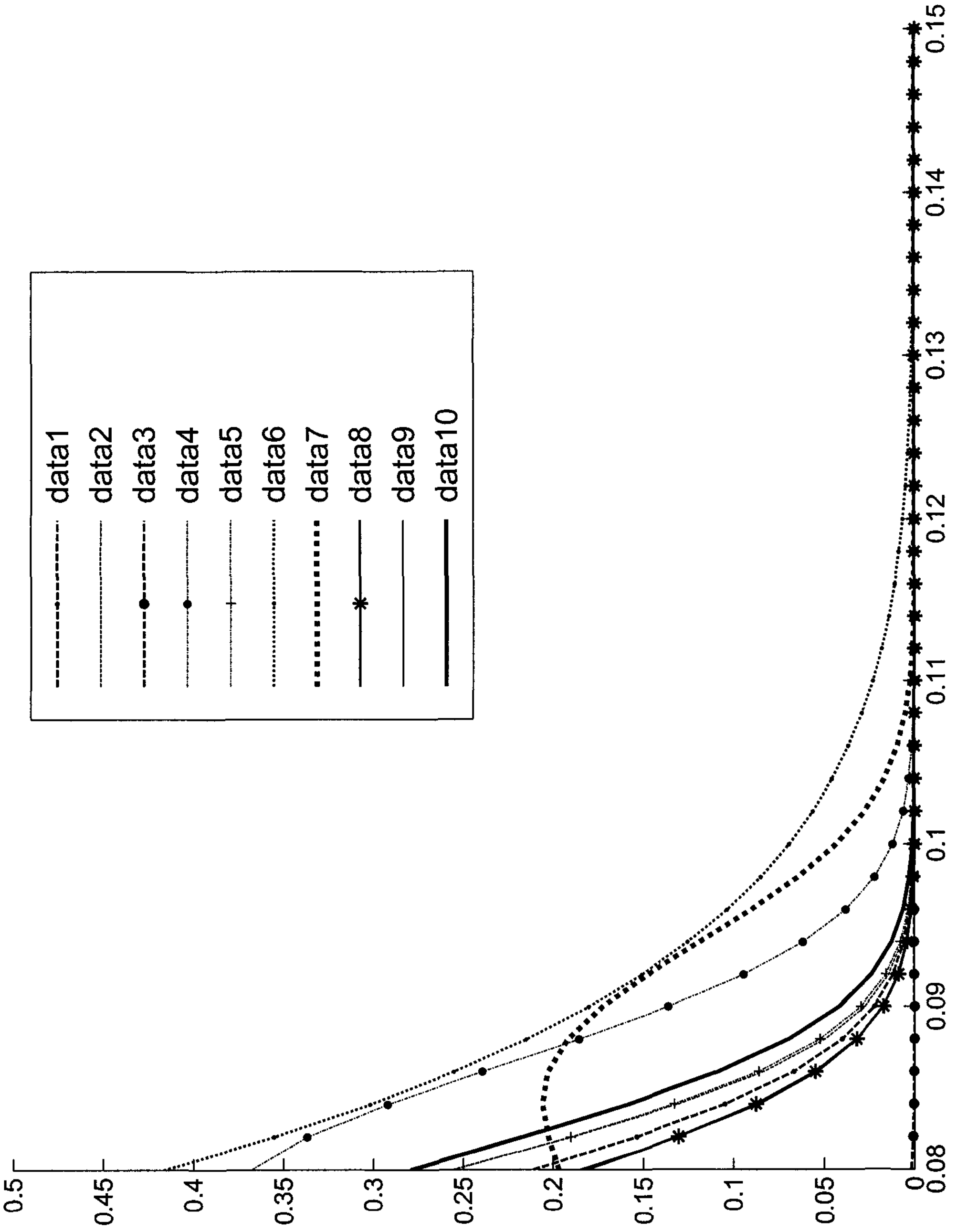


Fig. A.3. Large Blend Funds and Russell 1000 Blend

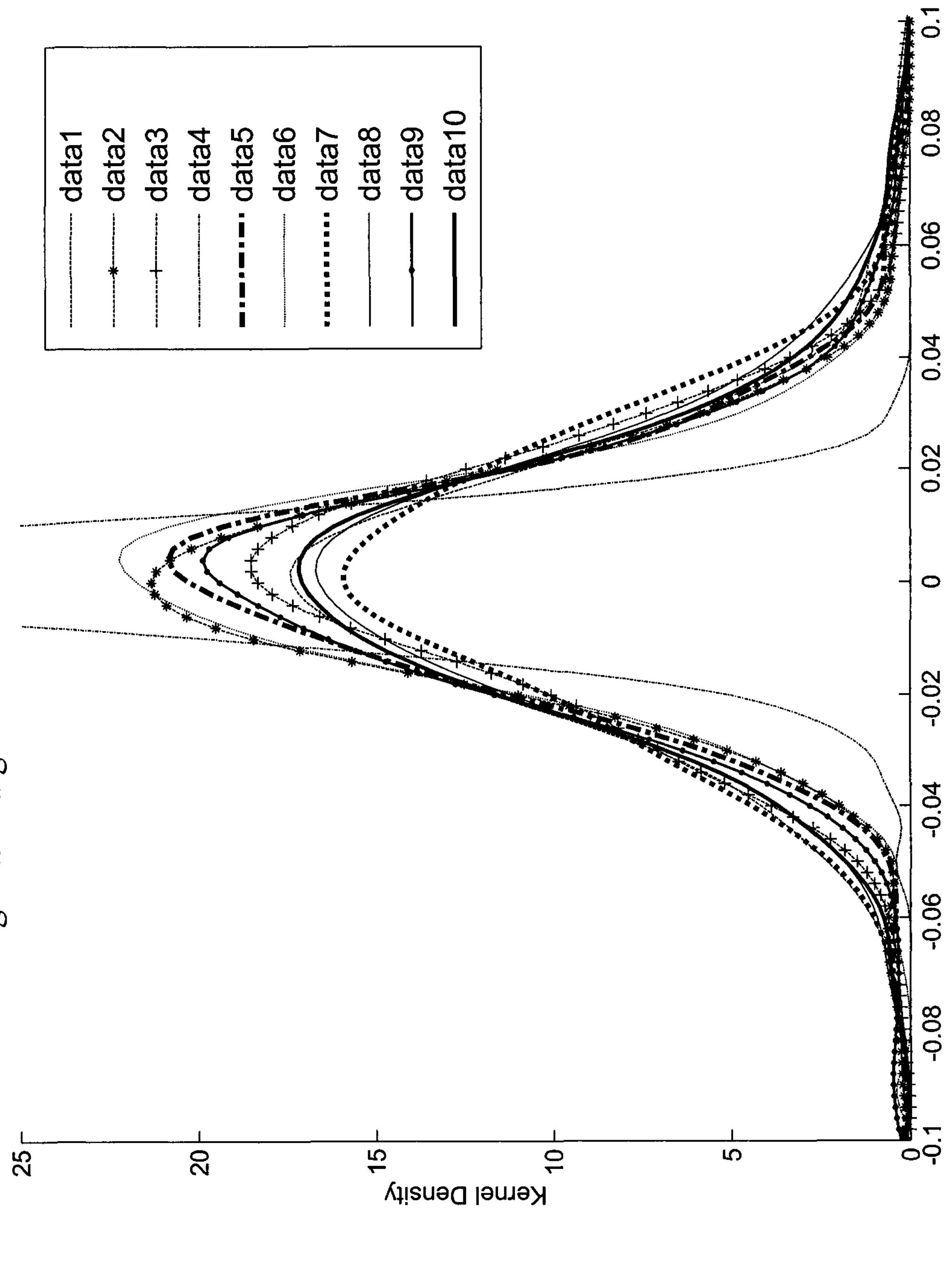
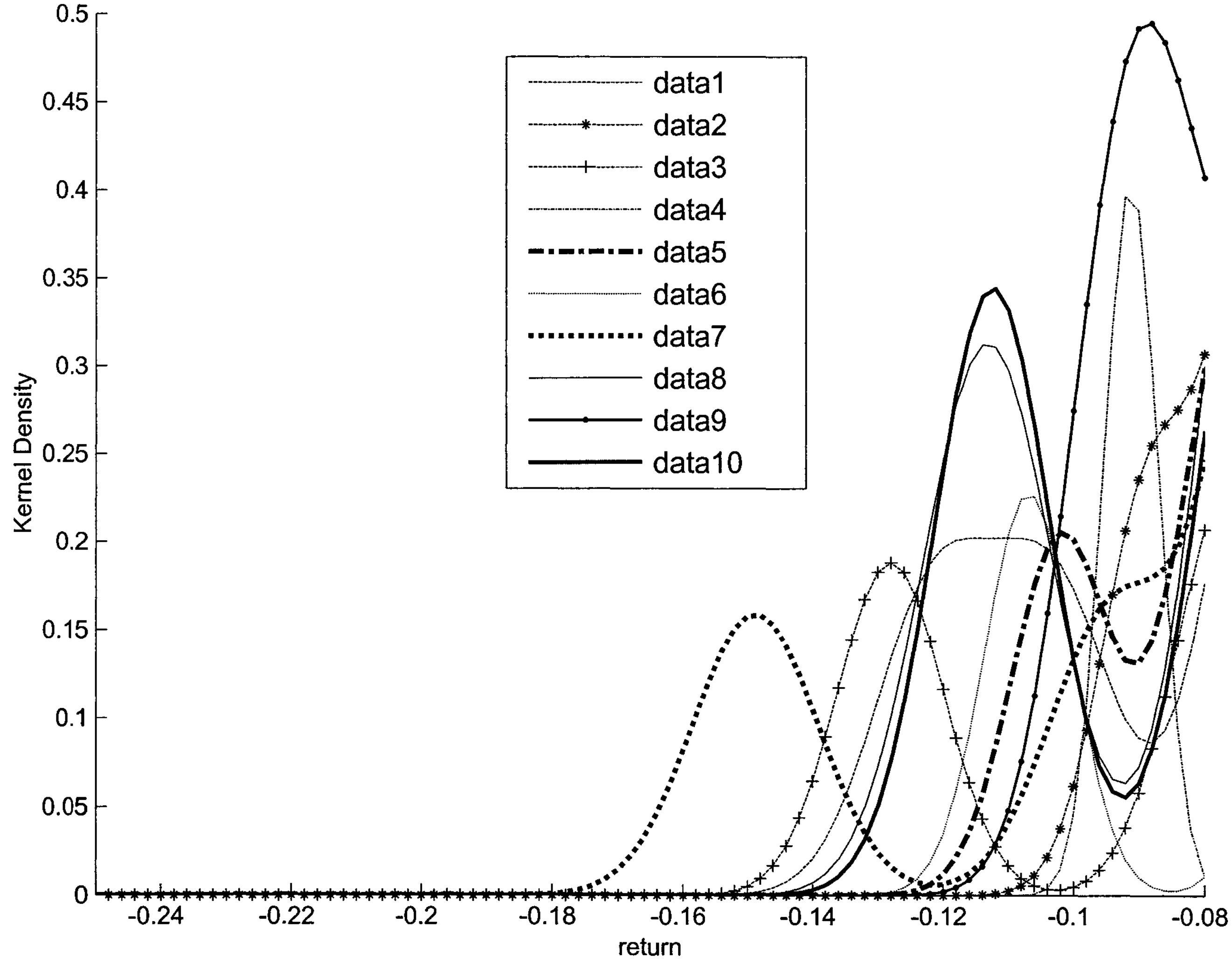


Fig. A.3.LT Large Blend Funds and Russell 1000 Blend



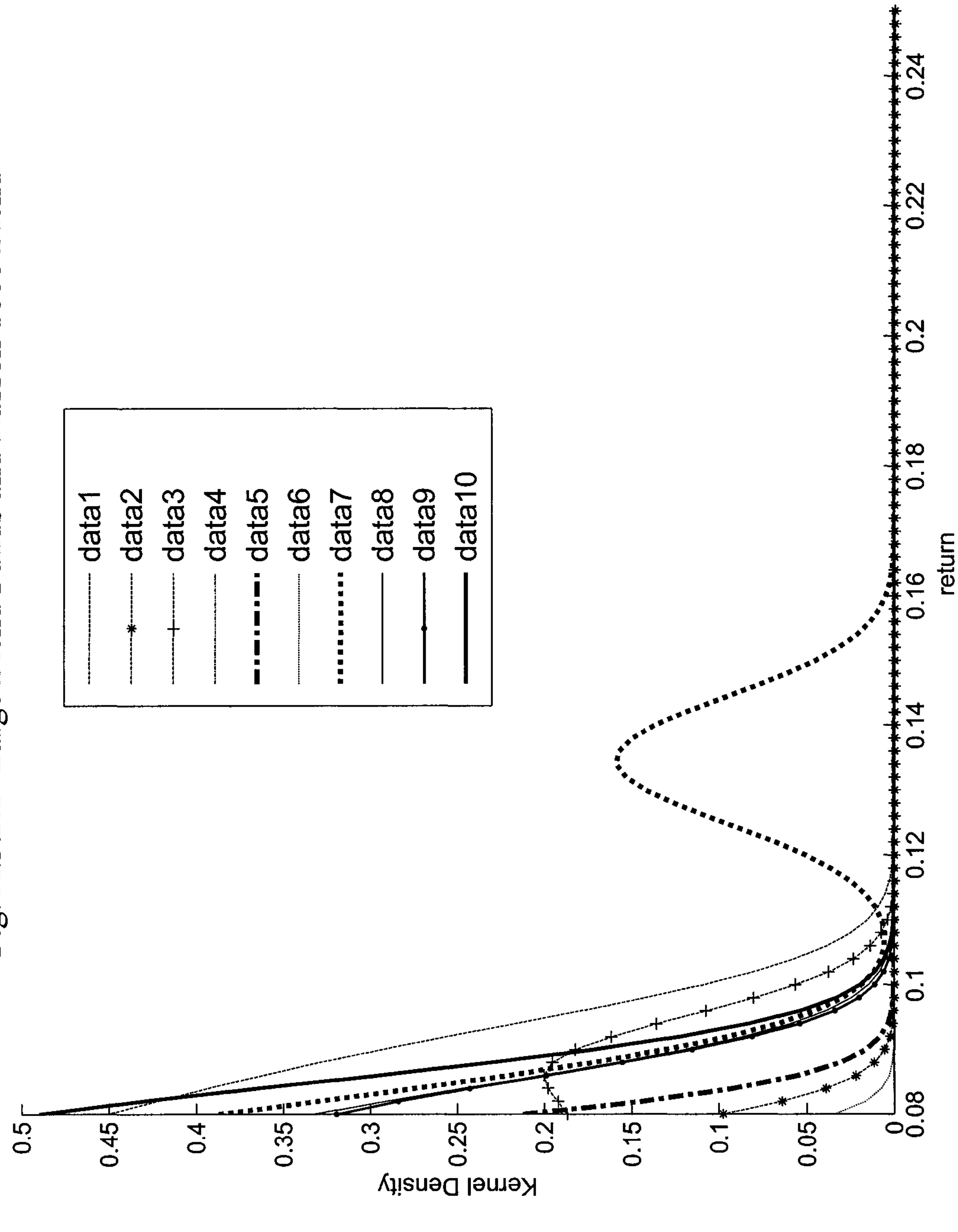


Fig. A.3.RT Large Blend Funds and Russell 1000 Blend

Fig A.4. Mid-Cap Growth Funds and Russell3000

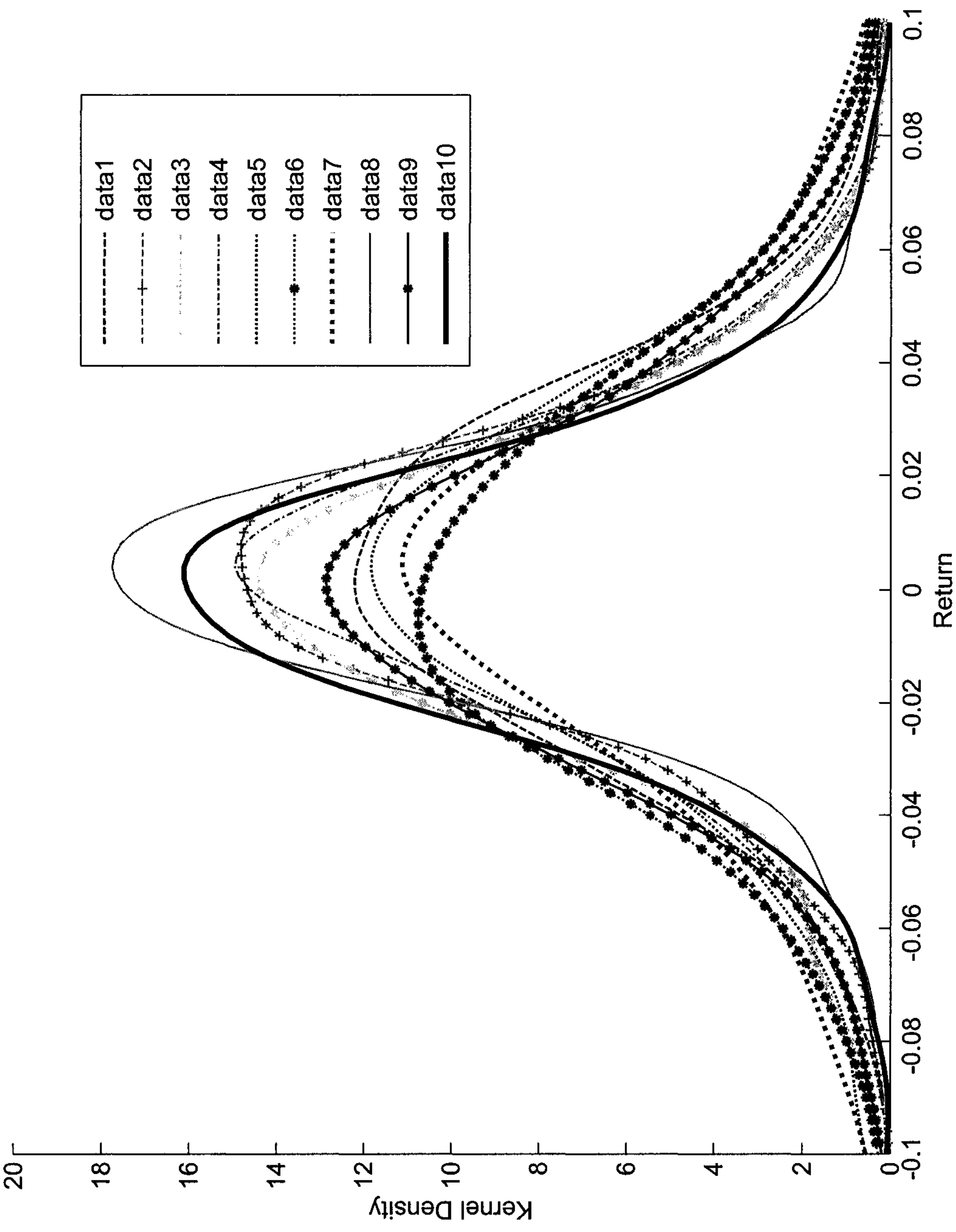


Fig A.4.LT Mid-Cap Growth Funds and Russell3000

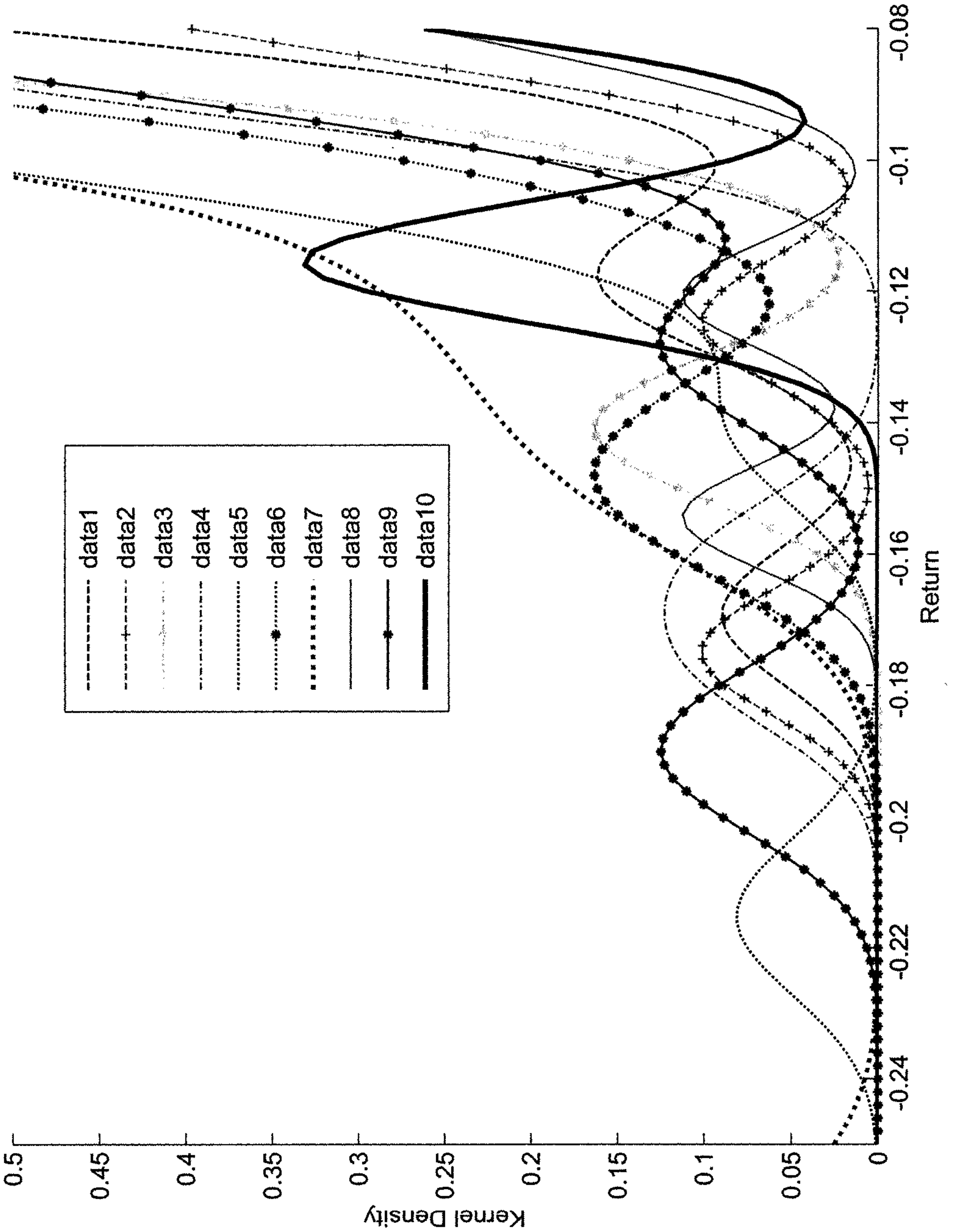


Fig A.4.RT Mid-Cap Growth Funds and Russell3000

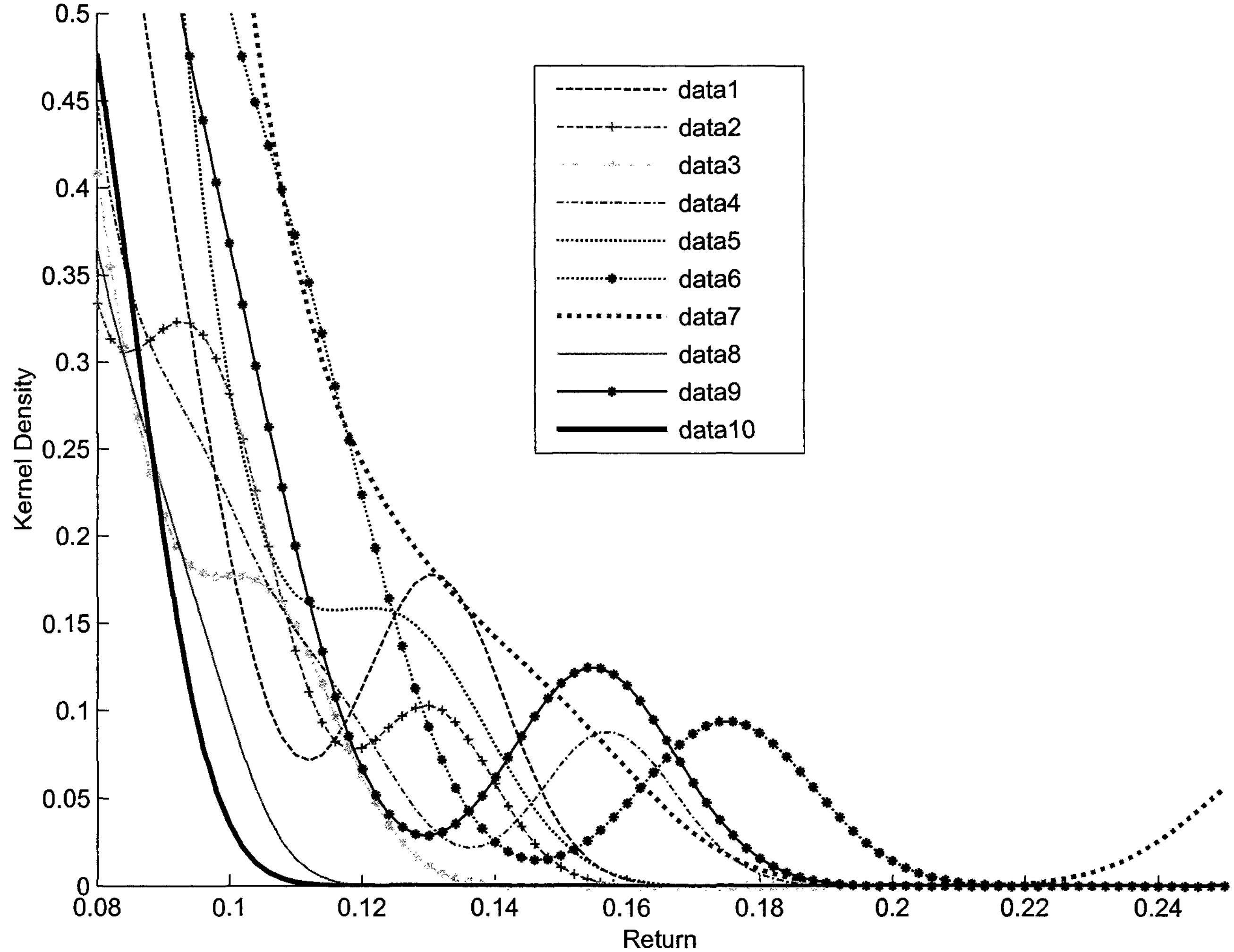


Fig. A.5. Mid Cap Value Funds and Russell 3000 Value

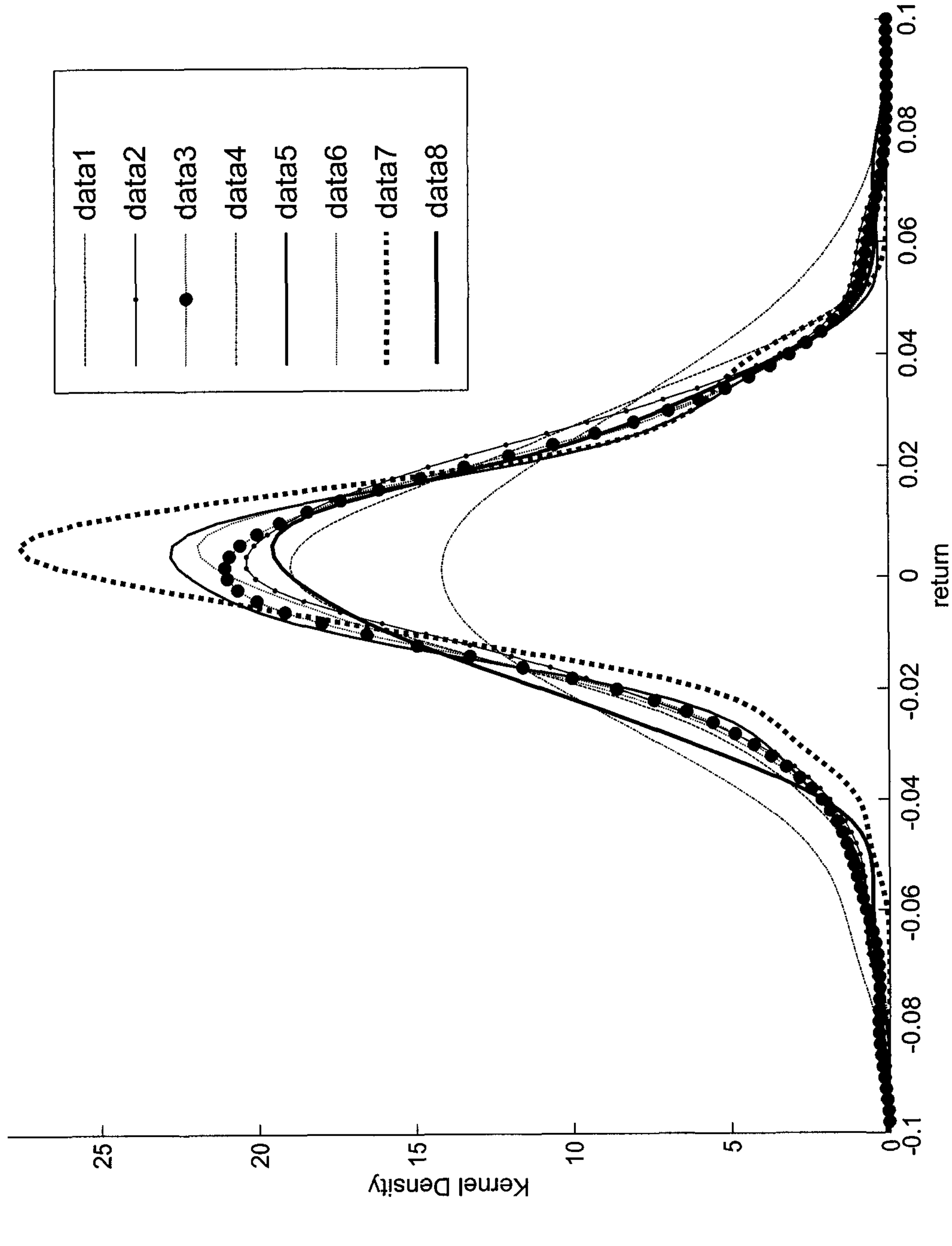


Fig. A.5.LT Mid Cap Value Funds and Russell 3000 Value

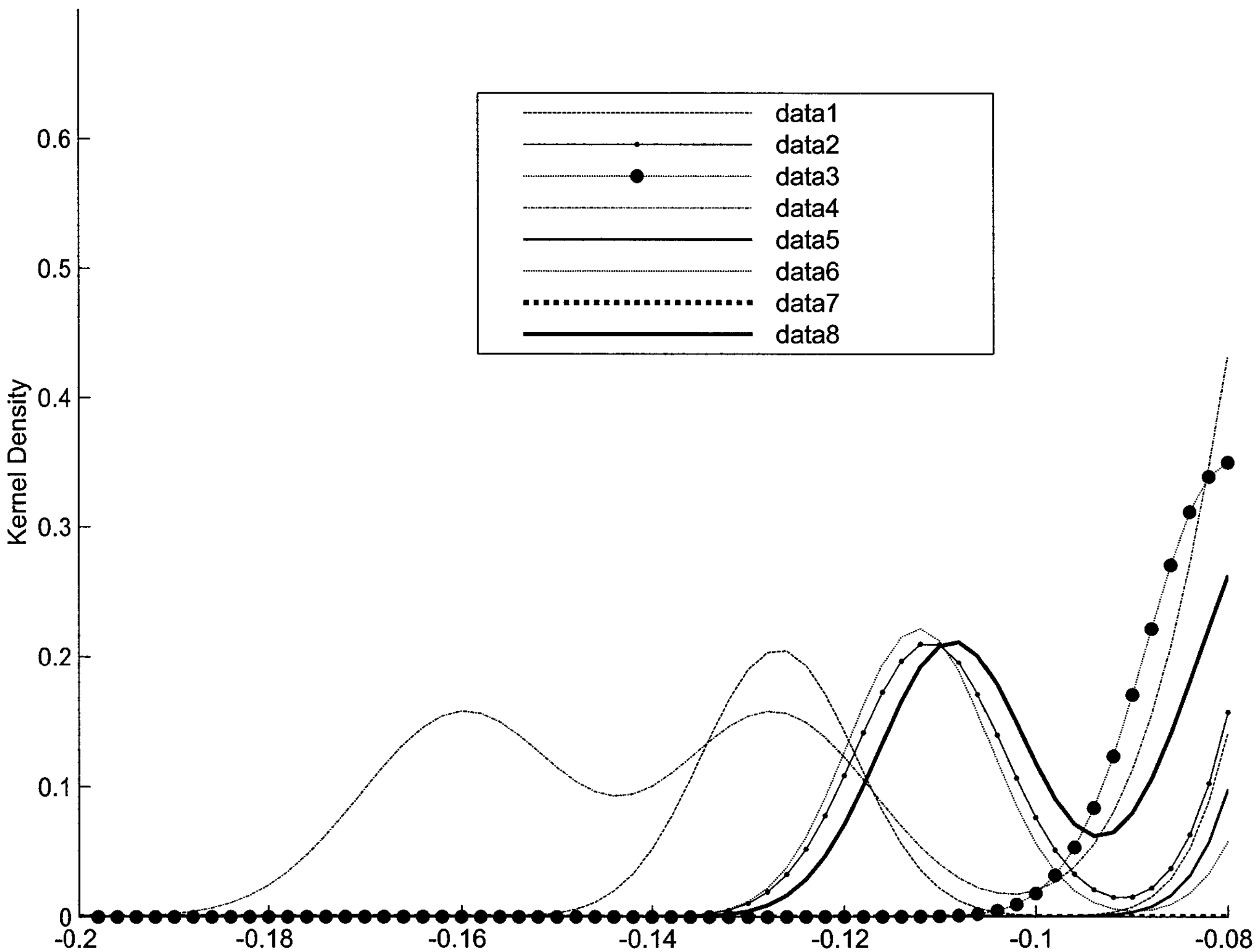


Fig. A.5.RT Mid Cap Value Funds and Russell 3000 Value

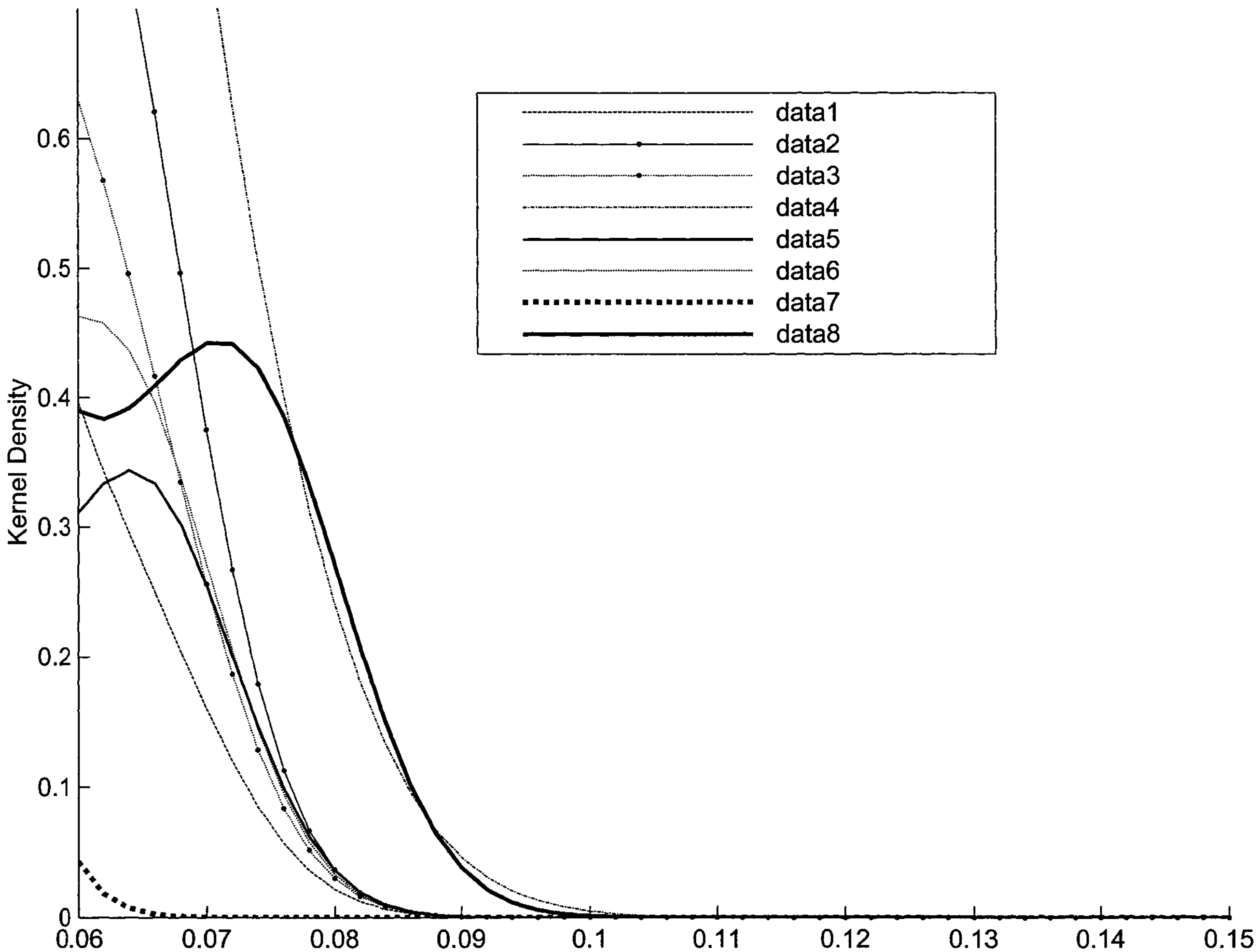


Fig. A.6. Mid-Cap Blend Funds and Russell3000

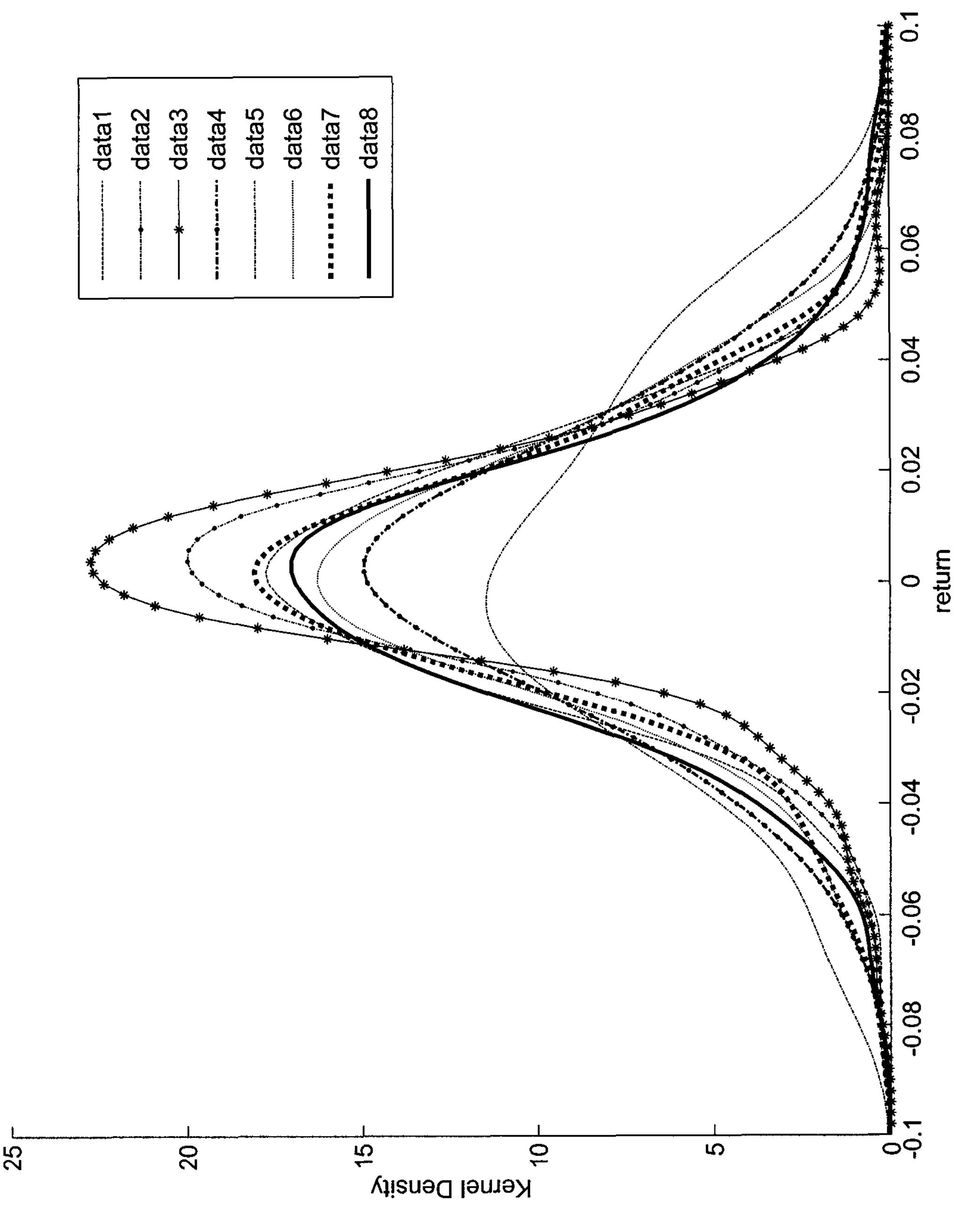


Fig. A.6.LT Mid-Cap Blend Funds and Russell3000

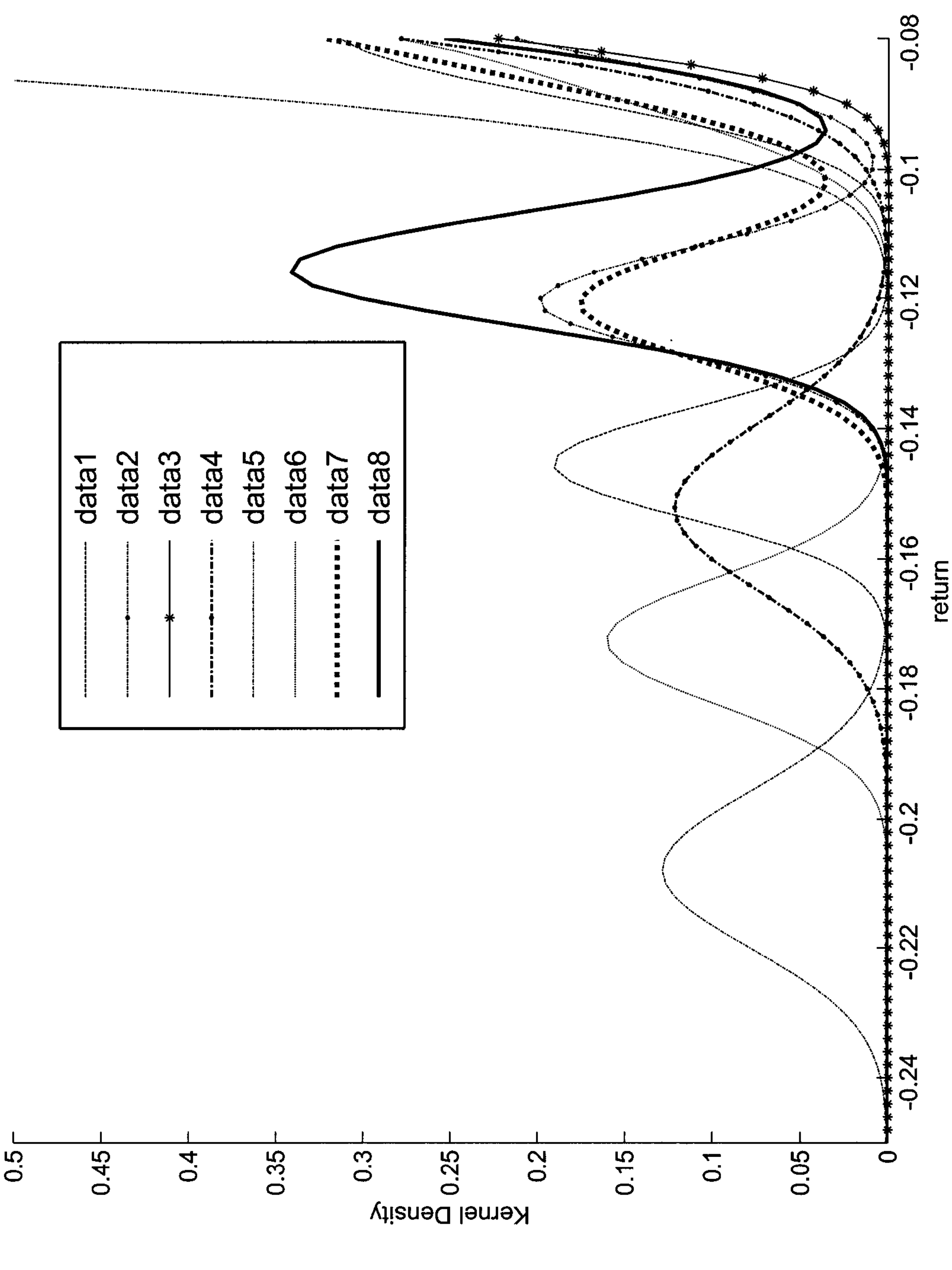


Fig. A.6.RT Mid-Cap Blend Funds and Russell3000

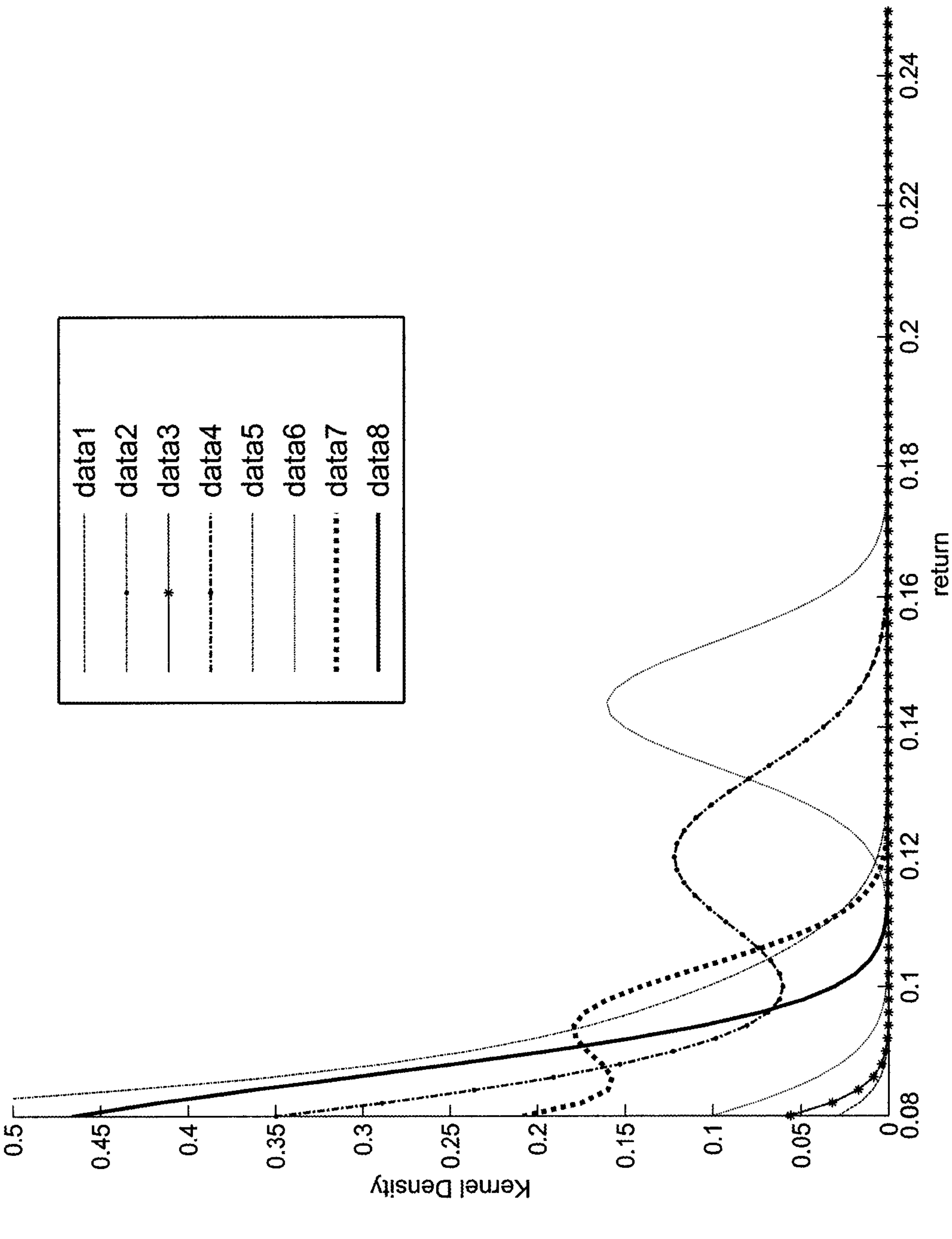


Fig A.7.RT Small Growth Funds and Russell2000 Growth Index

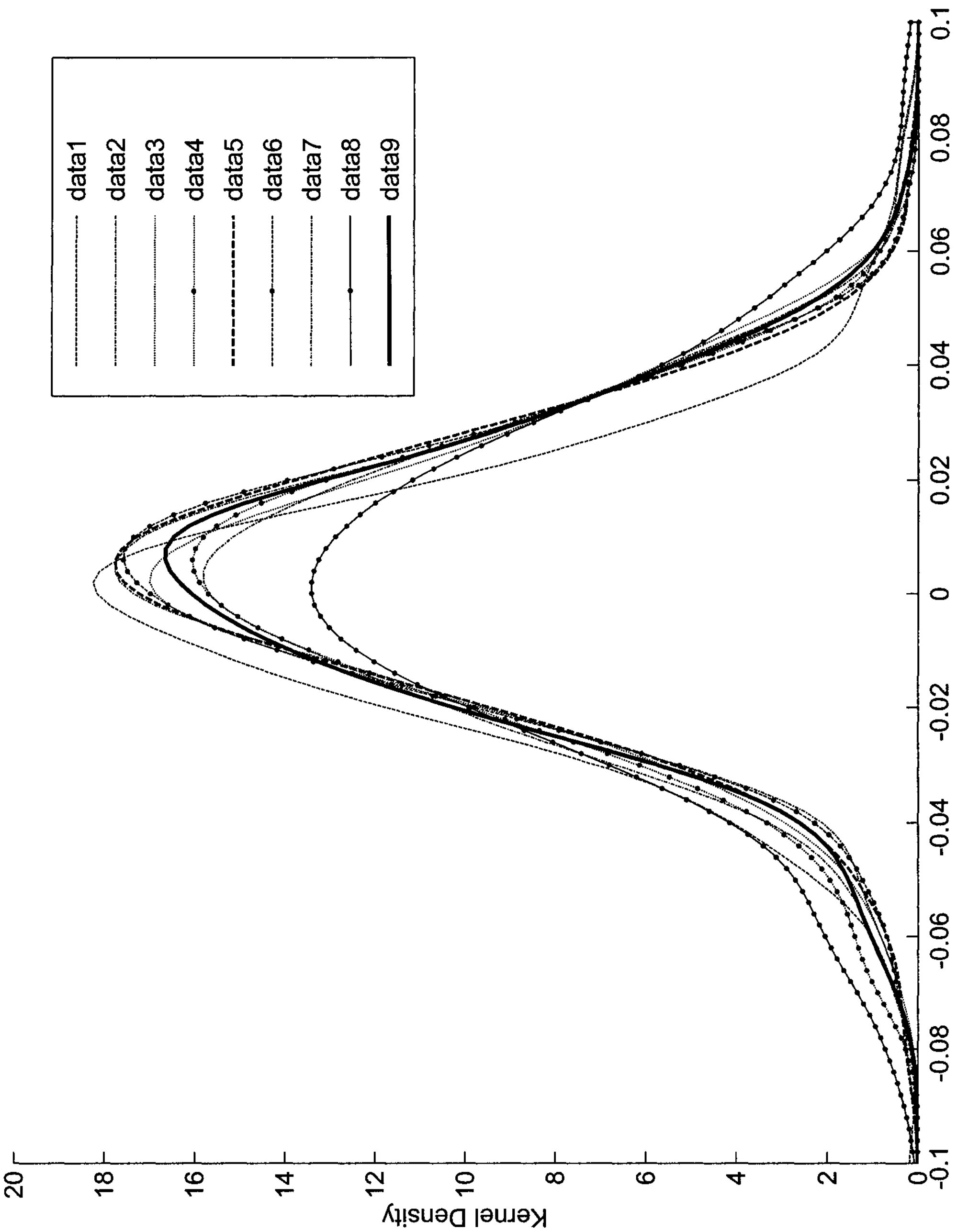


Fig A.7.LT Small Growth Funds and Russell2000 Growth Index

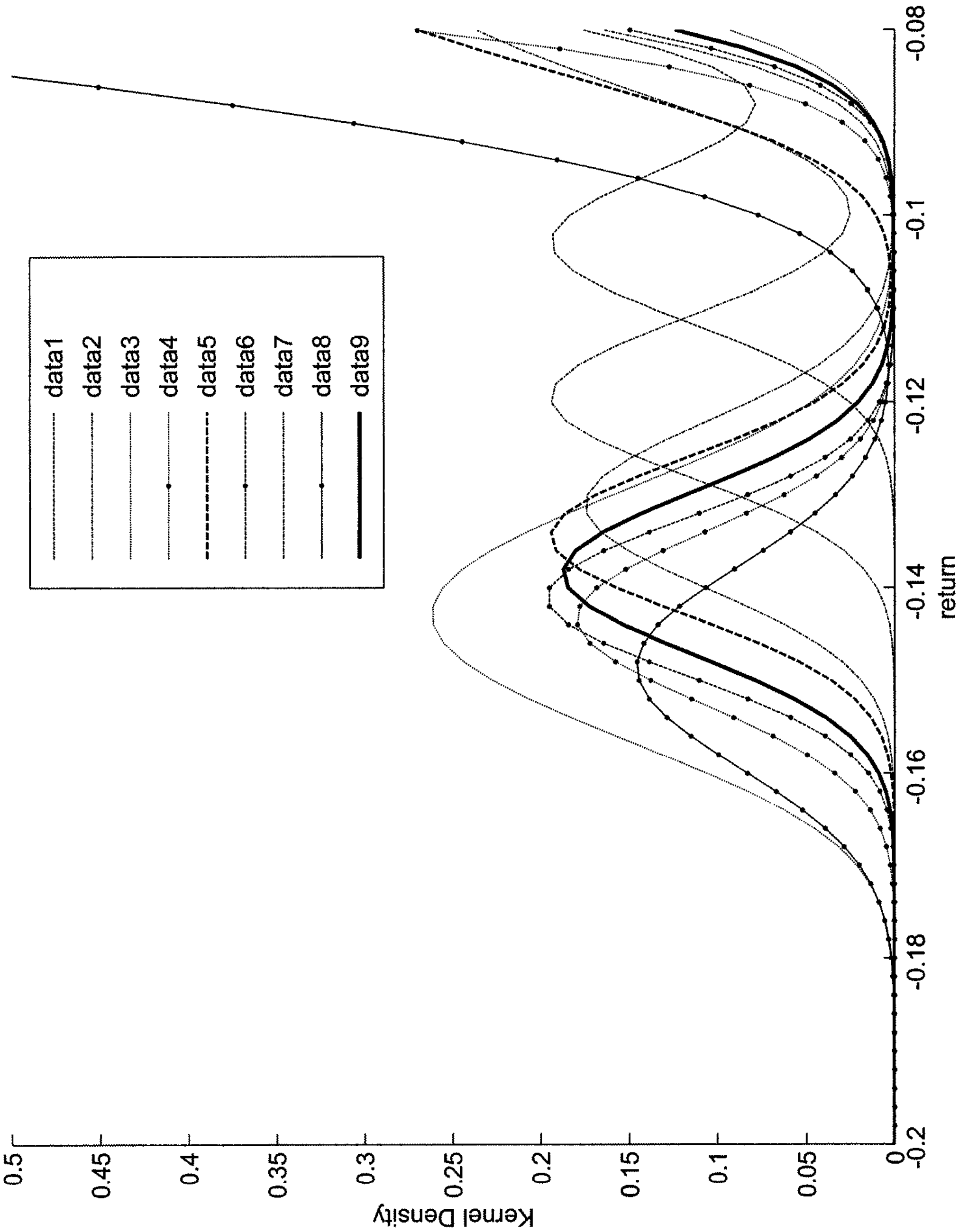
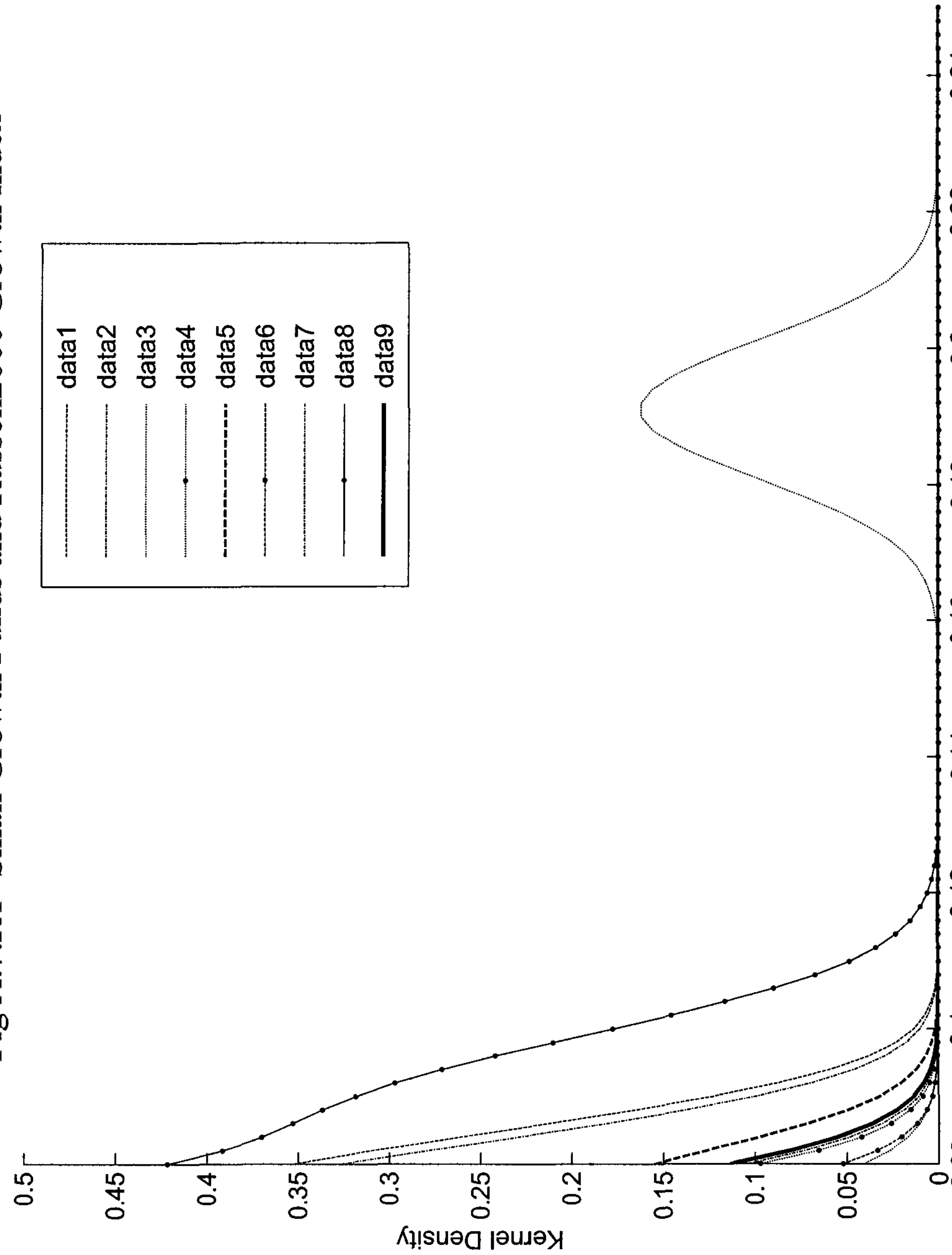


Fig A.7.RT Small Growth Funds and Russell2000 Growth Index



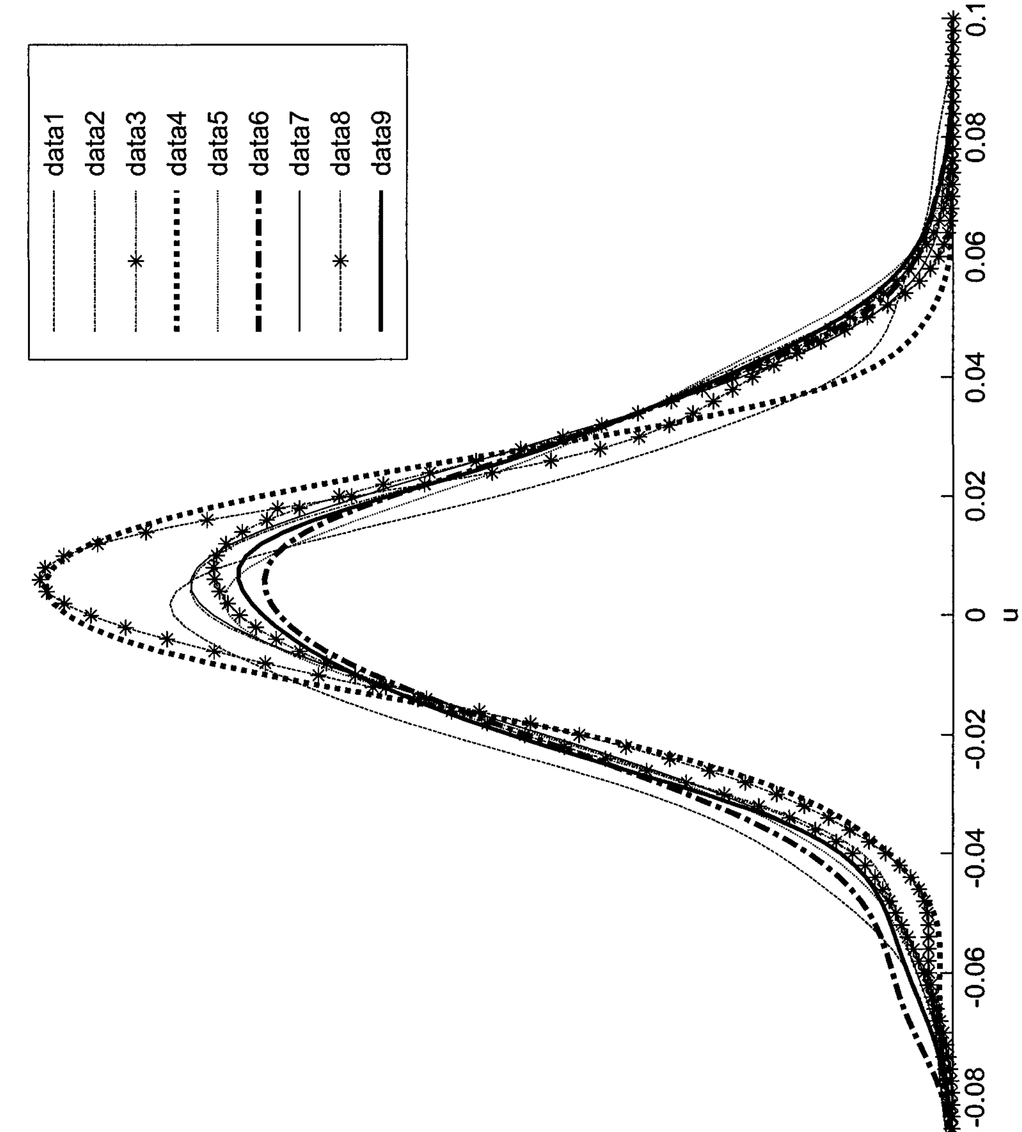


Fig. A.8. Small Value Funds and Russell2000 Value Index

Fig. A.8.LT Small Value Funds and Russell2000 Value Index

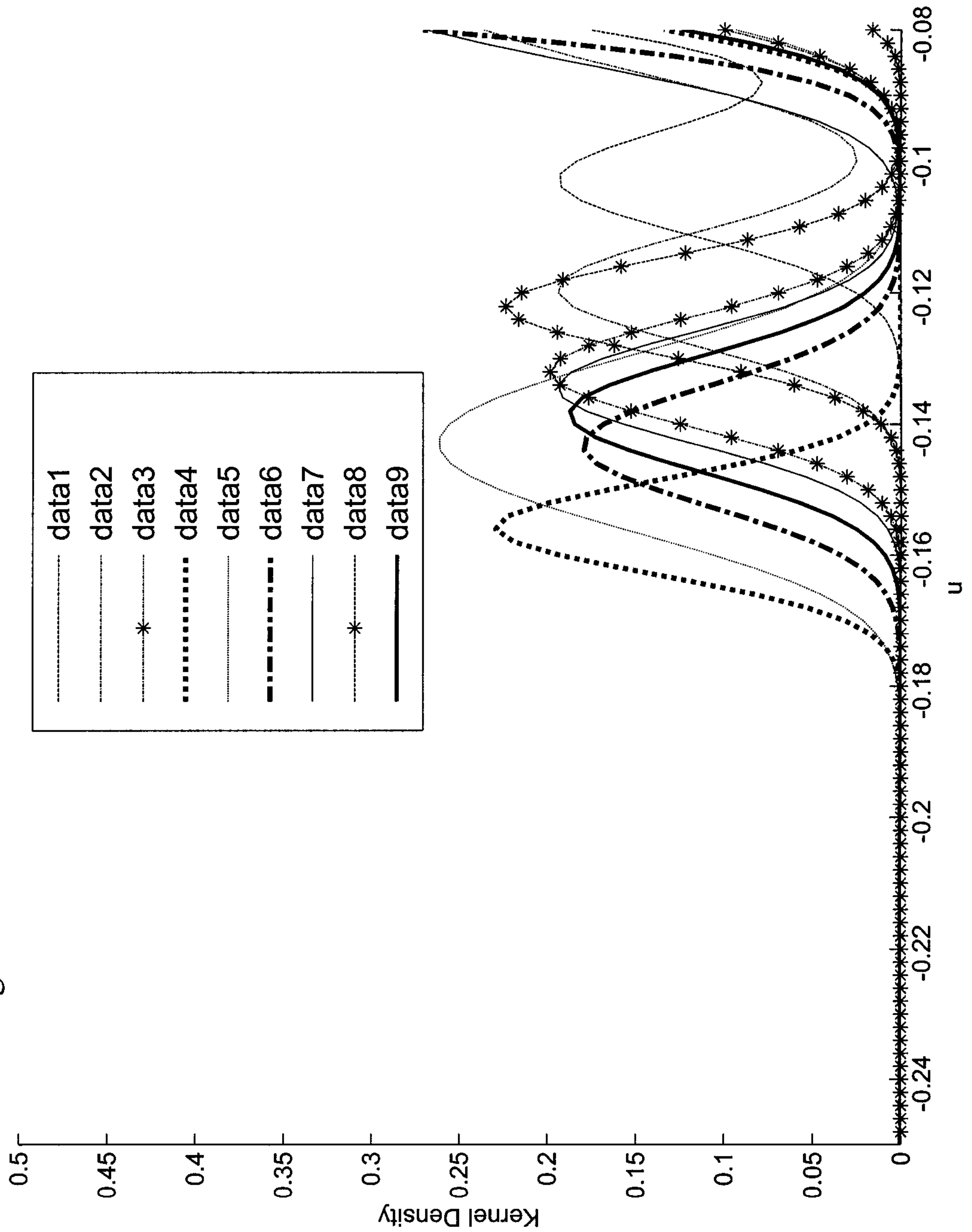


Fig. A.8.RT Small Value Funds and Russell2000 Value Index

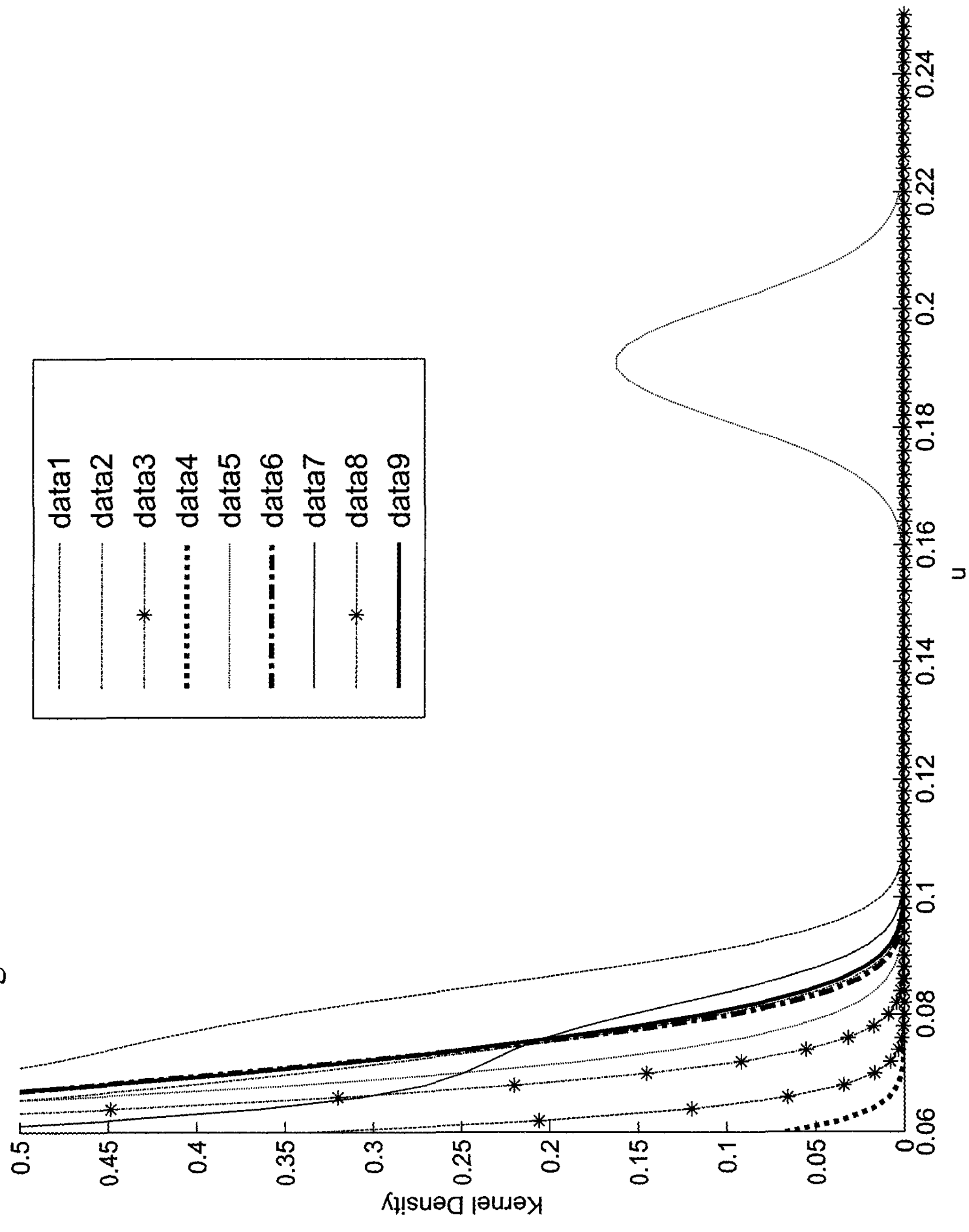


Fig. A. 9 Small Blend and Russell2000 Blend

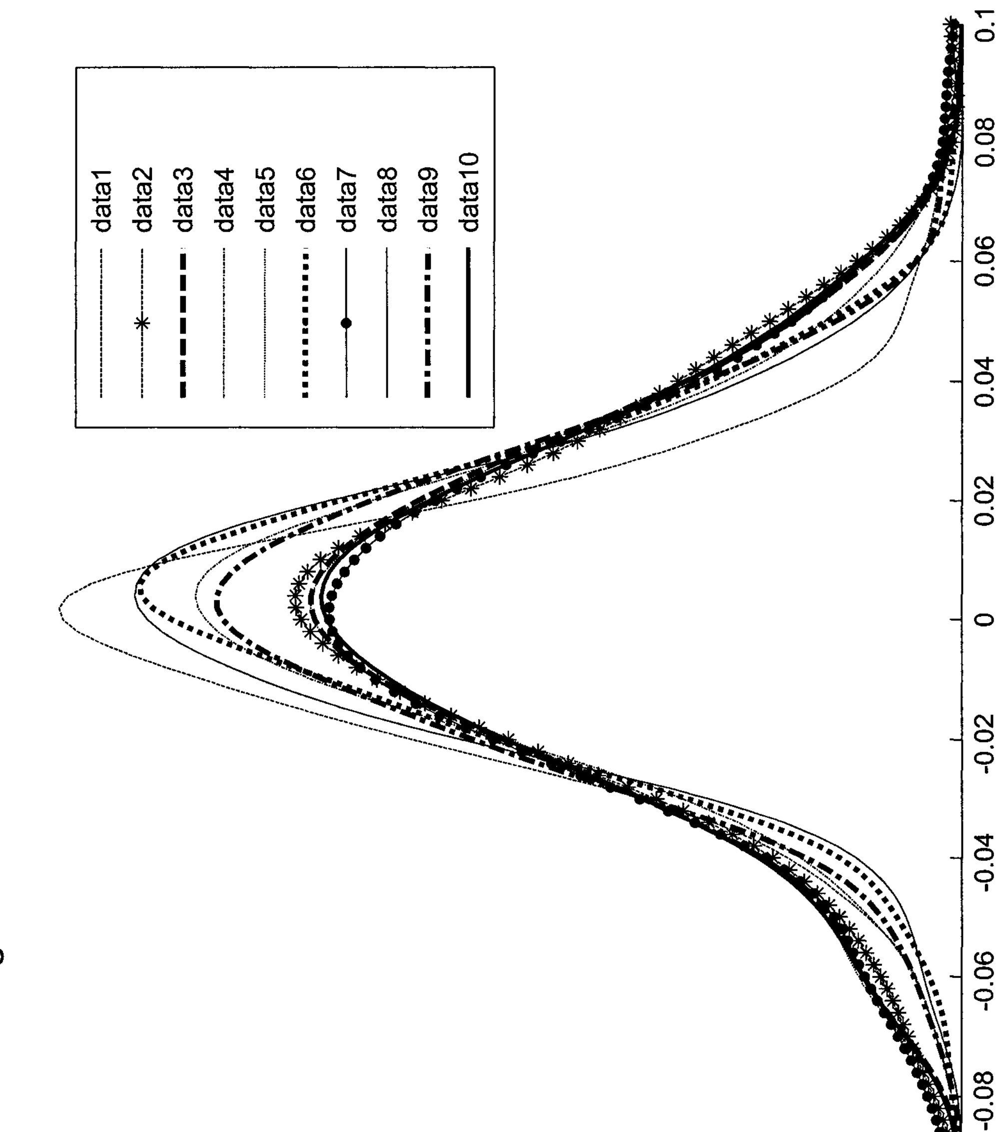


Fig. A. 9LT Small Blend and Russell2000 Blend

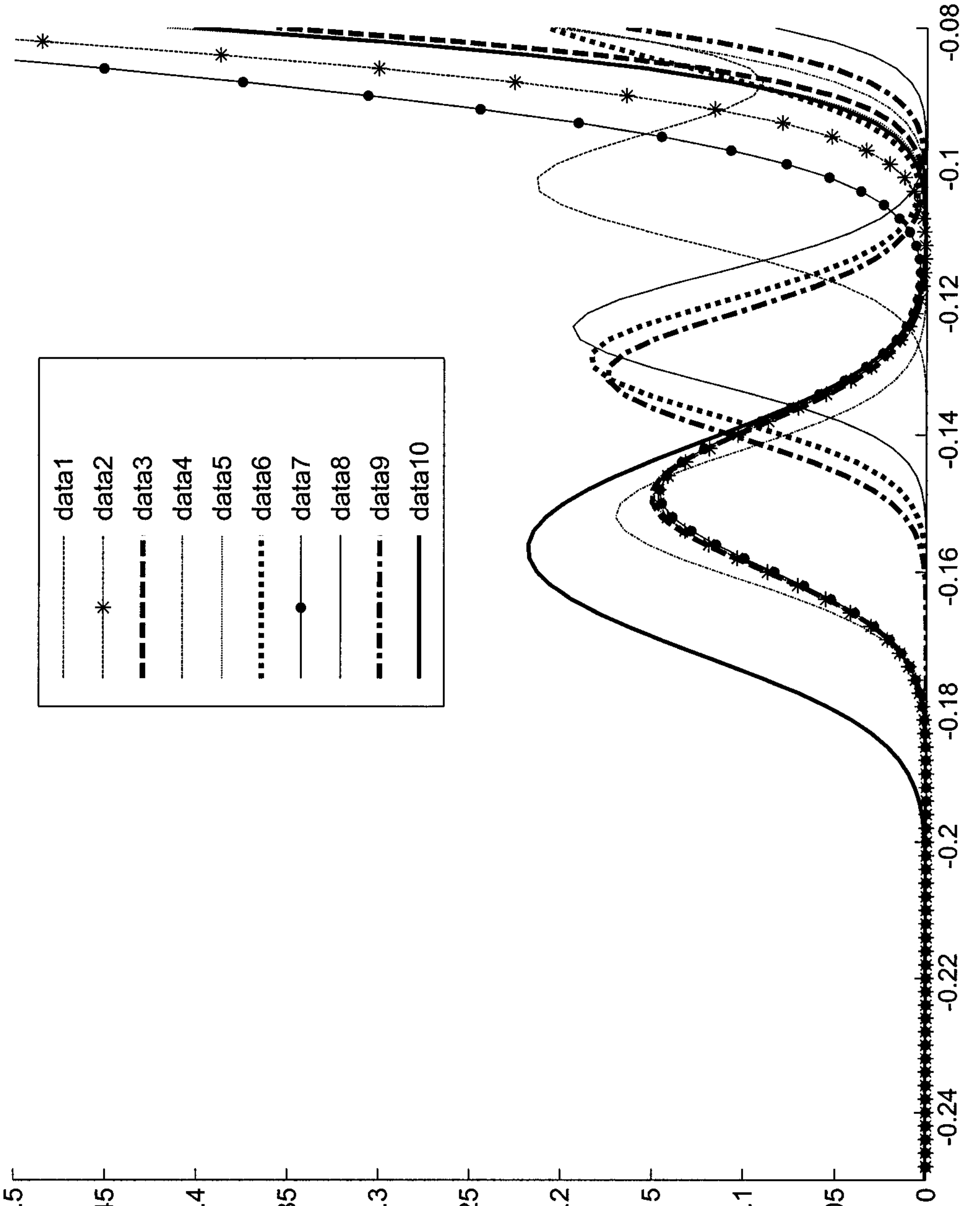
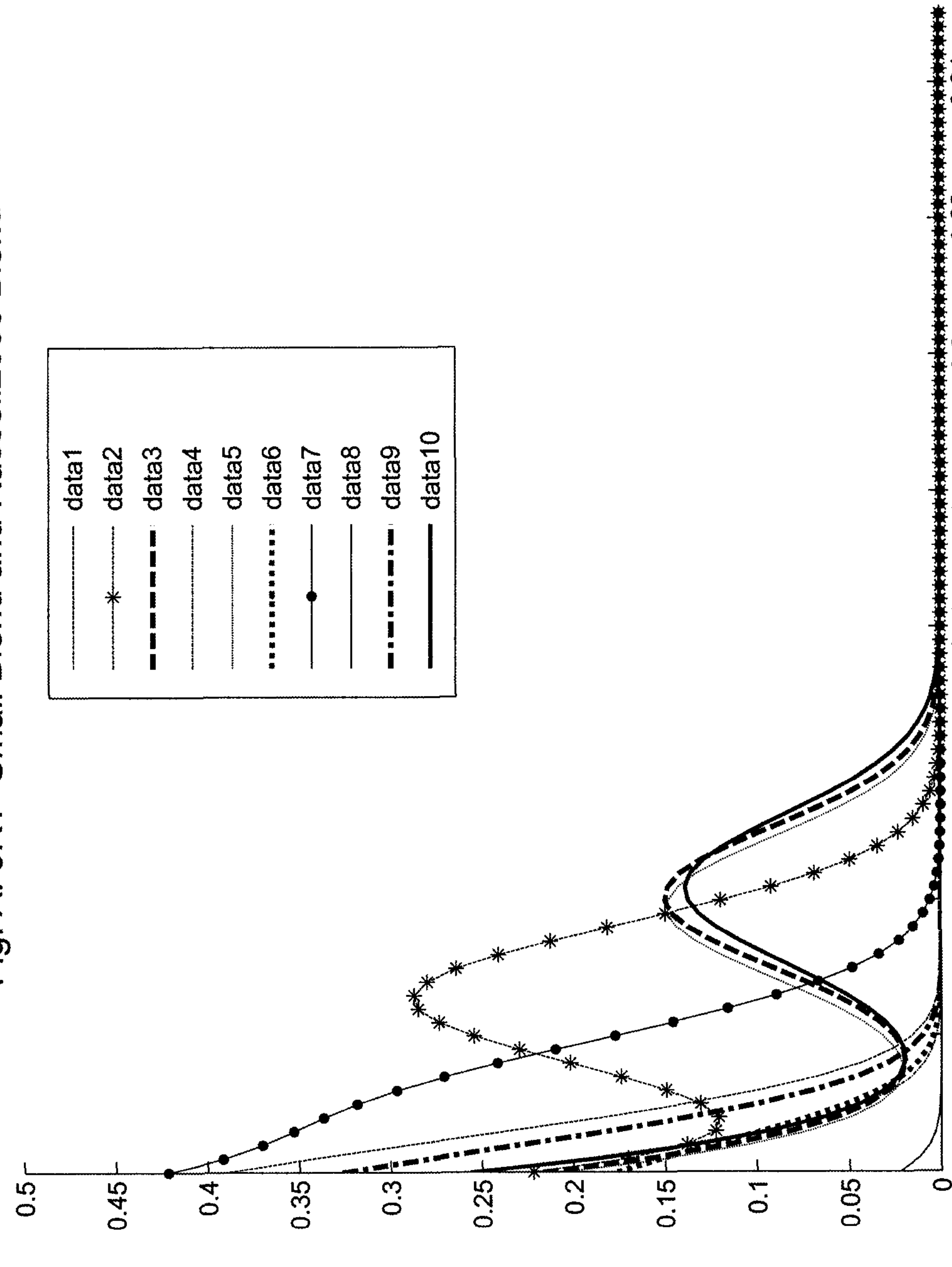


Fig. A. 9RT Small Blend and Russell2000 Blend



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