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Trading strategies: Effectiveness and market volatility

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Trading Strategies: Effectiveness and Market Volatility

by

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Abstract

Trading Strategies: Effectiveness and Market Volatility

By

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Stock market models with six trading strategies are simulated. (1) Constant rebalancing investor, (2) Universal portfolio investor, (3) CPPI(Constant proportion portfolio insurer), (4) ORPI(Option replicating portfolio insurer), (5) Technical noise trader with CHRISMA and (6) Information noise trader are included to see their profitability and impact on market volatility. Limit orders, Market orders, and Stop orders are also used to see their impact on profitability and market volatility. Simulation results show that more CPPI leads to greater market volatility, next is ORPI, the third is Information noise traders and there is little or no impact of other strategies. Profitability results show Universal portfolio and Constant rebalancers are generally winners and Portfolio insurers are losers. Especially CHRISMA type of Technical noise traders are the worst. More investors using Market orders impact relatively more on market volatility and trading volume. Market orders enhance Information noise traders profitability.

Preface

I would especially like to thank my academic father and Marvin Speiser Distinguished professor Harry Markowitz for his enthusiasm, intellectual guidance and generous assistance. Also, I would like to thank the other members of my committee, Terry Martell, Robert Ariel and Steven Krull, as well as the participants at the Baruch Finance Seminar Series. Of course, any remaining errors are my own.

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Chapter 1

Purpose and Organization

I. Introduction

I.A. Recent History

This paper will try to extend the market structure model used in the recent work by Kim and Markowitz [1989], Krull [1990], and Wang [1992] to examine the efficacy of certain trading strategies. The Kim and Markowitz paper consists of a simple market with two types of investors and two securities. The investors are portfolio rebalancers and portfolio insurers using constant proportion portfolio insurance (CPPI for short). The securities are cash and stock (or market portfolio). The Kim and Markowitz paper asks the effects on market volatility of the CPPI trading strategy. They show a significant increase of market volatility by increasing CPPI.

The Krull paper consists of a simple market with four types of investors and four securities. The investors are portfolio rebalancers, portfolio insurers using CPPI and option replicating portfolio insurance (ORPI for short), index arbitragers, and speculators. The securities are cash, stock 1, stock 2, and futures. He extends the Kim and Markowitz analysis of market volatility of trading strategies to another type of portfolio insurer(ORPI) and so-called program trading. He also shows an increase in market volatility. He extends his paper by analyzing the effectiveness of those strategies.

The Wang paper extends the Krull paper with careful consideration of the margin requirements in stocks and futures. He also asks the market volatility question again and gets similar results.

This paper will include *technical noise traders* who use technical analysis, for example-moving averages, etc.- and *information noise traders* who have the advantage of knowing some pieces of economic news several days before the public does. *Universal portfolio trader* who follows a new rebalancing technique proposed by Cover[1991] also will be included with *rebalancing trader*, *CPPI*, and *ORPI*. The model will try to see whether different types of traders affect stock prices, price level and volatility differently and whether they earn different returns.

Universal portfolio traders follow Cover's [1991] *Universal portfolio* dynamic trading strategy. This grows asymptotically as fast as an "*optimal constant rebalanced portfolio*" which we would get if we knew future stock prices in advance. We will show the finite time performance of this Universal portfolio which was partially, but analytically, shown by Jamshidian [1991].

This model includes different order execution types (limit orders, market orders, or stop-loss orders) and transaction costs such as commissions. This model determines stock price *endogenously* within the model. And we will try to find trading strategies that are best for different investment goals.

I.B. Goals

The goals of this study are several. The Kim-Markowitz framework will be expanded to include:

1) More types of investors,

2) More types of orders, (All the previous papers have only one type of order{limit orders}; here we will have market orders and stop-loss orders too.)

3) Commissions.

This paper shows the effects on market volatility and profitability of the trading strategies-constant rebalancer, portfolio insurers(CPPI and ORPI), noise traders(Technical Noise trader and Information Noise Trader), and Universal portfolio investor. It also shows different order execution types-limit orders, market orders, and stop-loss orders.

The portfolio insurers will be modeled using the option replication strategy of Rubinstein and Leland [1981] and Rubinstein [1985], in addition to the CPPI(Constant Proportion Portfolio Insurance) method, as in Krull [1990].

The *technical noise traders* use technical indicators such as moving averages and trading volumes. The *information noise traders* (or news trader: as in Black [1990]) use one of two facts of economic information that the model generates and affect the prices.

The *Universal portfolio* trader will be also examined for a finite number of periods. Thus, the model contains 6 types of investors: 1) Constant Rebalancer, 2) CPPI (Constant Proportion Portfolio Insurer), 3) ORPI (Option Replicating Portfolio

Insurer), 4) Technical Noise Trader, 5) Information Noise trader (news trader), and 6) Universal Portfolio Trader.

In addition to using the pure simulation model, historical market data of price and volume also will be used to drive the model. Thus, price and volume here are exogenously determined. This analyzes the actions of the various investors again. In this case, we should ignore different types of orders. We compare the results using market data with that of the simulation model with endogenous prices.

In addition, we compare the alternative strategies and order types for effectiveness based on realized risks and returns. Sharpe's ratio or Treynor's ratio or Elton-Gruber's measure may be used. This may expose certain strategies as flawed (at least in the context of the model).

II. Organization of the paper

The organization of the paper will be as follows: Section II reviews the volatility literature with a discussion of related models. Section III briefly reviews the major characteristics of the previous models. Description of the proposed methodology including descriptions of securities, order execution types, and investors to be modeled also will be in Section III. Section IV describes the proposed methodology including the description of the real data. Finally, section V will consist of results, a summary and comment about future research directions.

Chapter 2

Review of the Literature

I. Introduction

There is an argument that the stock market has excess volatility. Summers [1986] and Poterba and Summers [1988] determine that market fluctuations are much larger than rational valuation methods would suggest. Grossman and Shiller [1981] and Shiller [1981] find that stock price volatility is much more than what could be explained by variation in dividend or real interest rates.

II. Excess Market Volatility

Edwards [1988] reviews some theories advanced to explain recent increases in market volatility. They include increases in speculative activity caused by the presence of (1) professionally managed *speculative trading programs* and (2) '*fashions and fads*' which show capricious actions on the part of investors. Another possibility is (3) '*rational bubble*' theory. The tests of Krull [1990], Kim and Markowitz [1989], and Anderson and Tutuncu [1988] are mainly concerned with portfolio insurance that falls in the first group above. This paper deals with not only the first group but also considers the second and third group by introducing the noise traders.

French and Roll[1986] look at a period when the U.S. stock market was closed

Wednesdays. They find that the market is less volatile on these days than Wednesdays when it is open. By focusing on Wednesdays, they control for the intensity of release of public information. This result may reflect the incorporation of private information into prices during open hours, but it may also reflect the failure of arbitrage to accommodate intraday demand shifts.

Roll[1988] shows that most idiosyncratic price moves in individual stocks cannot be accounted for by public news. He finds that individual stocks exhibit significant price movements unrelated to the market on days when there is no public news about these stocks. A similar and more dramatic result is obtained for the aggregate stock market by Cutler, Poterba, and Summers[1989], who find that the days of the largest aggregate market movements are not the days of most important fundamental news and vice versa. The common conclusion of these studies is that news alone does not move stock prices; uninformed changes in demand move them too. We claim that these come from *noise traders.*

The model contains noise traders and sophisticated investors. Noise traders falsely believe that they have special information about the future price of the risky asset. They may get their pseudo-signals from technical analysts, stockbrokers, or economic consultants and irrationally believe that these signals carry information. Or, in formulating their investment strategies, they may exhibit the fallacy of excessive subjective certainty that has been repeatedly shown in experimental contexts. Noise traders select their portfolios based on such incorrect beliefs. In response to noise traders' actions, it is optimal for sophisticated investors to exploit noise traders' irrational misperceptions. Sophisticated traders buy when noise traders depress prices and sell when noise traders push prices up. Such active contrarian investment strategies push prices toward fundamentals, but not all the way.

III. Noise Trading Strategy and Asset Market Behavior

Many people claim to use technical trading rules capable of *"beating the market."* Most academicians and even some members of the financial community doubt the usefulness of such rules, pointing to the repeated failures of simple price-based filters to withstand the rigors of scientific study as evidence.

Most academic papers show that their rational investors can benefit at the expense of noise traders. But some papers including De Long, Shleifer, Summers, and Waldmann[1990a], show that noise traders affect prices and earn higher expected returns than the rational investors.

We present a simulation model in which noise traders affect prices, and check whether these noise trader beat the rational investors or vice versa. The system that at least one of our noise traders will use, which has been given the acronym CRISMA to represent its parts (Cumulative volume, RelatIve Strength, Moving Average), is completely *ex ante* in nature. Pruitt and White[1988, 1989] and Pruitt, Tse, and White[1992] report that they know of at least one active trader currently using the system. They claim that the CRISMA trading system appears to outperform the market over a significant interval of time, even after adjusting for round-trip transaction costs up to 2% per trade.

IV. Volatility and Mean Reversion in Asset Prices

When noise traders are present, the price of stock is excessively volatile in the sense that it moves more than fundamental value changes can explain. Accumulating evidence suggests that it is difficult to account for all the volatility of asset prices by fundamental news. Shiller's[1981] claim, that the stock market wildly violated variance bounds imposed by the requirement that prices be discounted present values, relied on controversial statistical procedures [Kleidon 1986]. But other evidence shows that asset price movements do not all reflect changes in fundamental values.

Roll[1984] considers the orange juice futures market, where the principle source of relevant news is weather. He shows that a substantial share of the movement in prices cannot be attributed to news about the weather that bears on fundamental values. Campbell and Kyle[1987] conclude that a large fraction of market movements cannot be attributed to news about future dividends and discount rates.

Such excess volatility becomes even easier to explain if we relax our assumption that all market participants are either noise traders or sophisticated investors who bet against them. A more reasonable assumption is that many traders pursue passive strategies, neither responding to noise nor betting against noise traders. When noise traders try to sell, only a few sophisticated investors are willing to hold extra stock, so prices must fall considerably for them to do so. The fewer the sophisticated investors, relative to the noise traders, the larger is the impact of noise.

If asset prices respond to noise and if the errors of noise traders are temporary, then asset prices revert to the mean. For example, if noise traders' misperceptions follow an AR(1) process, then the serial correlation in returns decays geometrically as in the "fads" example of Summers[1986]. He stresses that even with long time series, it is difficult to detect slowly decaying transitory components in asset prices.

Moreover, even if sophisticated investors accurately diagnose the process describing the behavior of noise traders, and if misperceptions are serially correlated, then the former will not be willing to bet nearly as heavily against noise traders. The risk of a capital loss remains and is balanced by a smaller expected return since the next-period price is not expected to move all the way back to its fundamental value. A high unconditional variance of prices can coexist with only a small opportunity to exploit noise traders.

There is some evidence that stock prices indeed exhibit mean-reverting behavior. Fama and French[1988] and Poterba and Summers[1988] show that long-horizon stock returns exhibit negative serial correlation. Prices reverting to the mean also implies that measures of scale have predictive power for asset returns. When prices are above p'---high relative to their historical average multiple of dividends or earnings---prices are likely to fall in their model.

In fact, Campbell and Shiller[1987], Fama and French[1988], and other studies find that dividend/price ratios appear to contain substantial power for detecting transitory components in stock prices.

Chapter 3

Trading Strategies and Methodology

I. Introduction

The previous Kim-Markowitz, Krull, and Wang's model consists of two or three trading strategies; rebalancing, CPPI, and ORPI. This model includes three more trading strategies: information noise trader, technical noise trader, and universal portfolio trader. This paper also will examine the different execution orders for effect on market volatility test and profitability of trading strategies.

II. Investors and Trading Strategies

This model also includes *"test traders"*[1], given only a token wealth so as to have no impact on prices as a result of their alternate strategy. Following sections describe the above six types of trading strategies.

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[1] I thank to Professor Robert Ariel for this interesting suggestion

II.A. The Constant Rebalancer

The constant rebalancers try to maintain a fixed ratio of stock to cash. In our runs we assume this ratio to be half cash and half stock. This is accomplished by selling stock when stock value goes over a certain selling target of their portfolio or by buying stock when it goes under a certain buying target at a review time. The amount bought and sold is the amount needed to attain the target level(e.g. half-cash half-stock).

In general, a *portfolio* $b = (b_1, b_2, b_3, \ldots, b_m)'$, $b_i \geq 0$, $\Sigma\, b_i = 1$, is the proportion of the current wealth invested in each of the m stocks. Let $x = (x_1, x_2, \ldots, x_m)' \geq 0$ denote a stock market vector for one investment period, where x_i is the price relative for the i-th stock. Then $S = b'x = \Sigma b_i x_i$, where b and x are considered to be column vectors, is the factor by which wealth increases in one investment period using portfolio b. Consider an arbitrary sequence of stock vectors $x_1, x_2, x_3, \ldots, x_n \in R_+^m$. Here x_{ij} is the price relative of stock j on day i. A Constant rebalanced portfolio strategy b achieves wealth at time n

$$S_n(b) = \prod_{i=1}^{n} b'x_i, \qquad where \;\; x_i = [x_1, x_2, x_3, \ldots, x_m]' \; at \; day \; i \tag{1}$$

where the initial wealth $S_0(b)(=1)$ is normalized to 1. This assumes complete rebalancing and no transaction costs.

II.B. The Universal Portfolio Investor

Cover [1991] develops a new algorithm for a dynamically rebalanced portfolio selection strategy that asymptotically grows nearly as fast as an *'optimal constant rebalanced portfolio'* which would obtain if investors knew future stock prices in advance. The weighıs of the universal portfolio are determined by present and past stock prices and do not depend on future unknown prices.

Jamshidian [1991] explicitly shows, in a continuous-ti.ne Brownian world, the relative performance of the *universal portfolio* compared to the optimal constant rebalanced portfolio, equally weighted constant rebalanced portfolio, and evenly diversified buy-and-hold portfolio.

The *universal portfolio strategy* is the performance weighted strategy specified by

$$b_1^* = \left(\frac{1}{m}, \frac{1}{m}, \frac{1}{m}, \ldots, \frac{1}{m}\right), \quad \textit{at time } 1: \quad \textit{where } m \textit{ is number of stocks} \tag{2}$$

$$b_{k+1}^* = \frac{\int b S_k(b)\,db}{\int S_k(b)\,db}, \quad \textit{at time } k+1 \tag{3}$$

$$\textit{where} \qquad S_k(b) = \prod_{i=1}^{k} b' x_i\,, \tag{4}$$

and the integration is over the set of (m -1) dimensional portfolios

$$B = (b \in R^m : b_i \geq 0, \sum_{i=1}^{m} b_i = 1) \tag{5}$$

The wealth S_n resulting from the universal portfolio is given by

$$S_n^* = \prod_{k=1}^{n} b_k^{*t} \times x_k \tag{6}$$

Thus the initial universal portfolio b^*_1 is uniform over the stocks, and the portfolio b^*_k at time k is the performance weighted average of all portfolios b ∊ B.

Jamshidian [1991] also shows that the *universal portfolio* is a strategy that does some profit taking as one stock appreciates relative to other, that is, it sells some shares of the more appreciated stock and buys shares of the less appreciated. It always maintains more wealth invested in the more appreciated stock, so the profit taking is not extensive.

To be explicit in our analysis of two security case(stock and cash), we have quantized all integrals, resulting in the replacements of

$$S_n^* = \max_b S_n(b) \quad by \quad S_n^* = \max_{i=0,1,\ldots,20} S_n(i/20) \tag{7}$$

$$b_1^* = \left(\frac{1}{m},\frac{1}{m},\ldots,\frac{1}{m}\right) \; by \; b_1^* = \left(\frac{1}{2},\frac{1}{2}\right) \; and \; b_{k+1}^* = \frac{\int b S_k(b)db}{\int S_k(b)db} \; by \; b_{k+1}^* = \frac{\sum_{i=0}^{20} \frac{i}{20} S_k\left(\frac{i}{20}\right)}{\sum_{i=0}^{20} S_k\left(\frac{i}{20}\right)} \tag{8}$$

The resulting wealth factor

$$S_n^* = \prod_{k=1}^{n} b_k^{*t} \times x_k \tag{9}$$

is calculated using

$$b_k^* = \frac{\sum_{i=0}^{20} \frac{i}{20} S_{k-1}\left(\frac{i}{20}\right)}{\sum_{i=0}^{20} S_{k-1}\left(\frac{i}{20}\right)} \tag{10}$$

Telescoping still takes place under this quantization and it can be verified that S^*_n in (9) can be expressed in the equivalent form

$$S_n^* = \frac{1}{21}\sum_{i=0}^{20} S_n\left(\frac{i}{20}\right) \qquad (11)$$

Thus S^*_n is the arithmetic average of the wealth associated with the constant rebalanced portfolios.

II.C. The CPPI(Constant Proportion Portfolio Insurers)

CPPI chooses a floor at the beginning of a plan. The floor is the minimum value that the insurers wish to maintain and the cushion is the maximum loss they wish to ensure. As stock prices rise, more stock can be purchased while maintaining the floor, and as prices fall, stock must be sold to protect the floor.

At the beginning of each insurance plan, the relationship between the floor and cushion is defined as:

$$Cushion_0 = Asset_0 - Floor_0 \quad , \quad Floor_0 = (1 - \delta)\times Asset_0 \qquad (12)$$

where δ = $Cushion_0/Asset_0$.

Whenever the stock value changes, the new relationship between the cushion and floor at time t can be written as:

$$Cushion_t = Asset_t - Floor_0 \qquad (13)$$

After a floor is chosen, the CPPI rule requires the target stock exposure at any time t to be a constant *multiplier*(M) of the cushion:

$$\textit{Target value of stock}_t - M \times \textit{Cushion}_t \qquad (14)$$

Thus, stock appreciation requires buying more and depreciation requires selling more, the magnitude depending on the *multiplier*.

II.D. The ORPI(Option Replicating Portfolio Insurers)

Portfolio insurers of this type will hold cash and replicate a call option. The amount of stock to be purchased will be the hedge ratio, N(D1), determined from the Black-Scholes [1973] call option pricing model, times the portfolio value. Thus, at high market levels, N(D1) will approach one (fully invested in stock) and at low levels of stock price, it will approach zero (all in cash). N(x) is the cumulative normal distribution function. D1 is defined below. The exercise price will be set to be '*at-the-money-option*' at the beginning of each insurance plan(this can be altered by input). Since quarters are assumed to have 65 days, a year will be defined as 260 days. Volatility may be derived from 'real world' experience or from model history.

D1 is defined as:

$$\frac{(\ln(\frac{P}{E}) + (r - d + 0.5 \times s^2) \times t)}{s\sqrt{t}}. \qquad (15)$$

where P is the stock price, E is the exercise price, r is the risk free rate, d is the continuously compounded dividend rate to be paid before maturity, s is the standard deviation (volatility), and t is the time to maturity of the plan. The hedge of an insurance plan under the assumption of a zero risk free rate and no dividends will start out with

$$D1 = 0.5s\times\sqrt{t} \qquad (16)$$

II.E. The Information Noise Trader

The Information Noise Trader of this model trades based on one of two facts of true information. An information generator produces two facts of information at the same time randomly with mean of certain days(for example 20 trading days). Each fact of information has a value between low and high(for example 0.9 and 1.1) distributed uniformly. One of these facts of information is observed only by the *information noise traders* and they observe only one of the two. Certain days(for example 3 days) after, this trader observed the information, the price will fully reveal the two facts of information only if the price has not been adjusted fully. If price has already over-reacted, there will be no adjustment.

For example, suppose that the current stock price is $100, one information is 1.05(observable) and the other information is 1.07(non-observable). Then after 3 days, if price is $106, then it will immediately jump to $100x1.05x1.07 = $112.35. But if price is $115(greater than $112.35), because of possible overreaction, there will be no adjustment.

The information noise traders invest half of their cash to buy if the information they observe is greater than (1 + commissions). If they observe news that is less than (1-commission rate), then they short-sell stock(amount equivalent to half of their cash). They start to unwind their position after 3 days. If the logarithms of the two signals have different signs, one greater than 0, the other less than 0, the investor's decision could be quite wrong. This can happen, even though they observe one piece of information. So I call them also noise traders.

II.F. The Technical Noise Trader of the CRISMA Trading System

Recent empirical findings report patterns of volume and price variability. (See, for example, Wood, McInish, and Ord[1985] and Jain and Joh[1986]) One of the technical trading strategies that exploits such patterns is the CRISMA(Cumulative Relatlve Strength Moving Average).

The CRISMA[2] trading system identifies "target" securities by using the three most commonly employed technical filters. Graphs of these filters, based upon a stock's relative strength compared to the S&P 500, cumulative volume, and 50-day and 200-day moving averages of prices, attempt to measure and "triple confirm" upward momentum.[3] Buy recommendations are issued on potential securities only

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[2]see Pruitt and White[1988, 1989] and Pruitt, Tse, and White[1992] for the recent use and performance of this strategy

[3]The cumulative volume graph is obtained by subtracting the volume of security down-trades from the volume of security up-trades.

when a fourth and final "penetration filter" has been satisfied. Later, sell recommendations are issued when one of two criteria is met.

For a stock purchase recommendation to be issued, a stock initially must meet three specific criteria. First, the 50-day price moving average graph must intersect the 200-day price moving average graph from below when the slope of the latter graph is greater than or equal to zero. Of course, this phenomenon occurs only when a stock's price is rising relative to previous time periods.

Second, the relative strength graph, from beginning to ending point over the previous four weeks, must have a non-negative slope. This filter assures that the stock's price performance over the most recent period has been at least equal to that of the market as a whole.

Finally, the cumulative volume graph from beginning to ending point over the previous four weeks must have a positive slope. This filter obviously is based upon their claim that increases in trading volume are associated with rising stock price levels.

If these three criteria are satisfied, a stock is purchased when its price reaches 110% of the level established by the intersection of the 50 and 200 day moving average graphs.[4] This "penetration" filter attempts to reduce the likelihood of

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[4]Although they are rare, there are exceptions to the system's mechanics: 1) If the price of the stock does not rise to the purchase point within five weeks of crossing the 200-day price moving average graph, it is eliminated from consideration; 2) If the stock price has already risen above 110% of the price level established by the 200-day moving average at the time when all three criteria are satisfied, it is not purchased until the price has fallen to 110% of the 200-day price moving average; and 3) If the stock price has already risen above 110% of the price level established

"whipsaws," the accidental issue of false signals. Purchased stocks are sold when either their prices decline below the 200-day price moving average graph or rise above 120% of the level established by the intersection of the 50-day and 200-day price moving average graphs.

Although it might appear to call for substantial time to perform the analysis, one of the beauties of the system lies in that it is easy to identify the small number of stocks meeting the "triple confirmation" filters by a weekly glance through an investor stock guide. Once a stock meeting all three filters has been identified, all one need do is record the date of initial qualification, calculate the 110% and 120% price levels, and then track the stock's price to determine whether and/or when it should be bought or sold.

CRISMA's use of 50-day and 200-day moving average comes from the real market fluctuations. But our simulated market may have quite different price behavior. Thus, using the same 50-day and 200-day moving averages may mislead. Various time length moving averages will be tested to scale the rule properly. Especially, past real market data shows a roughly 3 to 1 ratio of return to volatility--i.e., an annual variance of 0.04 and annual return of 0.12--will be carefully considered.

This paper will try to show some implications of our simulation model for

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by the intersection value of the 50 and 200-day moving average graphs when all three criteria are satisfied, and subsequently rises to 120% of the 50 and 200-day price moving averages intersection value without dropping to at least the 110% level, the security is eliminated from further consideration.

financial markets (see also Black[1986, 1990]). We will try to examine whether, in the presence of noise traders, (1) asset returns exhibit the mean reversion documented by a great deal of empirical work, (2) asset prices diverge on average from fundamental values as suggested by Mehra and Prescott[1985].

II.G. The Test traders

We also will introduce six types of test traders with only a token wealth. They accept prices as exogenous, thus they can trade when they want. So, these test traders have no impact on market prices or volatility. This paper will ask whether profits by test traders are different from that of regular traders.

III. Order Execution and Market Imperfections

Black[1990] claims that different types of orders(limit orders or market orders) may be optimal for different types of investors(liquidity trader, noise trader, information trader).

Therefore this study will include the three different types of order execution types-limit orders, market orders, stop-loss orders, to see the effects of these types. Also some market imperfections such as commissions will be explicitly included. The other form of transaction costs-price impact-is generically included in this kind of simulation model.

Trading procedures in the model must be explained. When an investor receives a signal to buy or sell, an estimate of the current market price is obtained. This estimate is the average of the (highest) bid and (lowest) asked price if both exist. If only bids exist, the estimated price is 1.01 times the highest bid; if only offers exist, the price is 0.99 times the lowest offer. If neither bid nor offer exist, the price is the last sale price (set to 100 at the start of the simulation). Orders unfilled after 1 day are reconsidered. If an investor wants a market order he just specifies the quantity and takes whatever the price is now. If a counter-party does not exist, the model places its order in the order book with price unspecified. If the next counterpart is also a market order, the model uses the last sale price as the trading price.

Also, this model consists of two securities that include non-interest paying cash and one non-dividend paying stock. Investors review their portfolios on a random basis that is exponentially distributed with a mean of five trading days-equivalent to 1 calendar week. Also randomly based cashflows are included. All investors begin with a $100,000 portfolio and receive cash randomly with exponentially distributed mean times of ten days and uniformly distributed between -8,000 and +9,000. This supplies a slight upward drift by including more inflows than outflows on the average (generally, all numeric parameters can be altered by input).

IV. Methodology

First, some previous simulations will be duplicated with the information generator. Thus, even in simulation runs with rebalancers only, we expect volatility will not fall as low as in Kim-Markowitz, Krull, or Wang because of news fluctuations. As in Krull [1990], trading begins in equilibrium as opposed to out of equilibrium in Kim-Markowitz. Another modification will be to track portfolio values, returns, risks, Sharpe's ratio, Treynor's ratio and Elton-Gruber[1991] measure of the trading strategies to observe strategy profitability and effectiveness.

IV.A.Real Market Data As the Input

Here we will not include *Information Noise Trader* because we do not have an information generator that affects the price. All prices will be given exogenously. Thus, there will be no price impact and no liquidity problems. Investors simply buy and sell to follow their trading strategy or to adjust their portfolio due to cash inflows or outflows.

Historical prices were determined by a combination of traders following their chosen strategies. Thus by applying presumed actual strategies to historical prices, we may determine how traders of a particular type would have acted. This will be accomplished by using the half-hourly Dow-Jones Index reported weekly in *Barron's*, which has trading volume data. Thus, we can keep the technical noise traders who use trading volume as one of their signals. Ex-post tests (use today's price to determine trades and execute at today's price) and ex-ante tests (use today's price to determine trades but trades at tomorrow's price) will be used.

IV.B. Performance measures

We will use the Sharpe measure, Treynor measure, beta, and Elton & Gruber measure to compare the profitability of strategies. Unlike the Sharpe or Treynor measures, Elton & Gruber measures market timing ability without considering any risk. Their measure is

$$EG = E(\gamma(s)x) - E(\gamma(s))E(x) = Cov(\gamma(s),x) \tag{17}$$

where $\gamma(s)$ is proportion of stock out of total wealth, x is return of stock, and s is signal received by investors.

This measure can be calculated only when we know the composition of a portfolio. Our simulation gives the composition of stock and cash, thus we can apply this measure for this study.

Chapter 4

Results of the Simulation

I. Introduction

This chapter will present the detailed results of our simulation with various trading strategies. In the previous chapter we have defined the various trading strategies and execution orders. The effects of those trading strategies and orders on market volatility and profitability will be discussed accordingly.

II. Simulation Results on Market Volatility

Table 1 shows the basic specifications of the input. Table 2 compares the All Rebalancer case with and without the information generator. As we see in Table 2, unlike the previous papers, with an information generator volatility does not fall to an unreasonably low level; rather it maintains a certain level of volatility even after a long period. It may make this model more realistic and interesting.

II.A. Trading Strategies and market volatility

Tables 3A through 3E report the volatility effects of various trading strategies. We have total of 150 investors for each simulation. By increasing the number of other types of investors, we reduce the same number of rebalancers. Thus, we always maintain 150 total investors. As we expect, by increasing number of portfolio insurers we get greater volatility, and more by CPPI than ORPI as reported in Krull [1990] (see Table 3A and 3B). Noise traders, including technical noise traders and information noise traders also increase volatility. This may show, at least partially, that excess volatility of the market comes from trading strategies. But the impact is not as great as that of portfolio insurers(see Table 3C and 3D). Universal portfolio investors have little effect on volatility, like constant rebalancers (see Table 3E).

Table 3F shows repetition of previous results. Ten simulations with different random seeds are reported for each type of investor. Each strategy has 100 investors and 50 rebalancers are assumed for each repetition simulation. This result also reaches the same conclusion as the previous tables 3A through 3E.

II.B. Effects of Different orders on market volatility

Table 4A and 4B shows the volatility effects of different order execution types. Table 4A shows that Market orders cause most volatility, and Stop orders second, Limit orders third. In general, more market order type investors increase trading volume and volatility. Table 4B also shows the following results: 1. The first and second parts show that Market orders cause more volatility than Stop orders. 2. The second and third parts show that Market orders cause more volatility than Limit orders 3. The first and third parts show that Stop orders and Limit orders have similar effects on volatility. Thus, we say that more market order type investors increase trading volume and volatility.

Table 4C shows the 10 repetition results of the impacts by different orders. Table 4B and Table 4C shows little differences, thus we can say that the results are relatively robust. Throughout all ten repetitions, market orders cause the most volume and the greatest volatility. Thus, we say more market orders lead to more trading volume and more volatility in general.

III. Profitability of strategies

III.A. Profitability of six strategies

Table 5A shows the effectiveness of the various trading strategies and order types. Their results show the following results:

1. Technical traders are losers in every sense (return, Sharpe ratio, Treynor ratio). 2. Portfolio Insurers get smaller return than both types of rebalancers (constant rebalancers and universal portfolio investors) and information noise traders. Their betas are also smaller, but Sharpe and Treynor ratios suggest that, even after adjusting for their risks, these are not superior to rebalancing techniques. 3. The Universal portfolio investor beats the constant half-half rebalancer. The constant rebalancers have smaller betas and smaller return than the universal portfolio investors. But their Sharpe measure suggest the universal portfolio investors are a little better than the constant rebalancers.

4. Among the information-noise traders, market orders were most effective as conjectured by Black [1990]. 5. In general, the universal portfolio is the best among

the above six strategies. Except for the market order information noise trader, universal portfolio investor beats all the others in a return sense and their Sharpe ratios are the best, too.

A newly developed timing ability measure, the Elton and Gruber measure(E-G) shows mixed results. E-G measure shows technical noise traders one of the best and information noise traders or universal portfolio investors one of the worst. This may say that this measure is not powerful or sensitive to time intervals. We used the quarterly data to measure. Weekly or daily data may give different results.

III.B. Profitability of test traders

Test traders have only a token wealth and they are price takers. We model them as without any impact on prices and liquidity constraint(they can trade when they want to trade). These may give different results for their profitabilities. Table 5B shows their performance. This shows a great similarity with market order investors of Table 5A. Thus, we say the same conclusion as before when there is cashflow.

Table 5C shows performance results of all investors when there is no cashflow. This gives pure trading performance. Unlike the previous case of with upward cashflow result, this shows better performances of test traders than regular big investors, except technical noise traders. Information test traders do far better than in the previous results. Thus, we say that liquidity constraint is an important factor for performance. Especially, performance of information traders depend on liquidity constraint very much. This also suggests the use of market orders for information traders as shown in Black [1990].

III.C. Repetitions on Profitability

Table 5D shows the 10 repetitions of the previous simulations with different random seed numbers. We used a last random seed number reported by a previous simulation as a beginning random seed number in each simulation. These runs show results like the previous ones. Thus, our results are not limited to one specific simulation. Rather they are robust for any simulations. Additional simulations on volatility questions were also done and show the same conclusions.

III.D. Profitability with different parameters

Table 5E through 5G show the profitability results with different parameters. Here we change the bid-ask spread factors, commission rates and moving averages. Default bid-ask factor factors are 1.01 times the price if there is no selling orders have been placed, and 0.99 times the price if no buying orders have been placed. Default commission rate is 1% per round trip. Default moving averages are 200 days and 50 days. These factors may affect the results.

III.D.1. Bid-Ask spread

We changed them to 1.05 or 1.075 instead of 1.01 and 0.95 or 0.925 instead of 0.99. We did 6 simulations, changing both and changing only one of the two. Table

5E reports the profitability and suggest that these factors have little impact on most of our profitability results. But there is one investor type(ORPI) whose performance has been improved much. When ORPI choose bigger ask spread when they are buying, it improved their performance. This suggest ORPI investors must be aggressive when they are buying. Though not reported, these factor changes had little impact on volatility or trading volume in our simulations.

III.D.2. Commission rates

Table 5F shows profitability under different commission rates. Commission equals the dollar amount of trade times the commission rate. Default commission rate is 1% per round trip. We did 7%, 5% and 2% commission rate. Their results show that there is little or no differences with different commission rates. This suggest that commission rate is relatively less important in trading decisions.

III.D.3. Moving averages

CHRISMA suggests 200 day moving average and 50 day moving average for their trading rule. This works when there is 3 to 1 ratio of return and standard deviation. Our simulation world may have different ratio. And this may mislead one concerning the profitability of the CHRISMA technical trading rule. We used many other combinations of moving averages and report some of them in Table 5G. This shows a little difference in magnitude, but their relative rankings are still the worst.

III.E. Time path of profitability

Figure 1A(limit orders) shows the time path of the profitability of the various strategies using limit orders when there is no cashflow. It shows that the Universal portfolio investor and Constant rebalancer are the winners. The universal portfolio is slightly better than the others. Portfolio insurers and technical noise traders are the losers.

Figure 2A(market orders) shows a similar result, but the Information noise trader did much better than in the limit order case. Figure 3A(stop-loss order) has a result similar to that of figure 1A, but the Information noise trader is worse than in the limit order case. From the above figures, we may say that the Information trader should use *market orders* as Black [1990] claims.

Figure 1B(limit orders) shows profitability when there is -8,000 to +9,000 cashflow. The performance of information noise traders is improved much and becomes the best. Figure 2B(market orders) and figure 3B(stop orders) are also drawn with cashflow. Figure 2B shows the most remarkable performance of information traders. Thus, we say information traders should use market orders for their performance.

Figure 4A and 4B show the time path of the profitability of the various test traders without and with cashflow, respectively. They show that the Information noise traders are the winners. The universal portfolio is the second and the rebalancers the third. Portfolio insurers and technical noise traders are the losers. Unlike the previous results, test traders of information noise investor type perform better than the universal or rebalancer. This may say investors with information advantage must act carefully not to impact prices too much. This will reduce or eliminate their advantages. Liquidity factor that exists for non test traders may play a great role in information noise traders case.

Figure 4A shows much better results for information traders than figure 4B. Figure 4A shows pure trading performance and figure 4B includes upward cashflow effects. The rankings of trading strategies are the same for both figures. But pure trading performance case(figure 4A) shows much better performance for information traders.

IV. Profitability Using Real Data

IV.A. Ex-post and Ex-ante tests

Table 6A and 6B use the 30 minute interval Dow Jones Industrial Index and NYSE trading volume reported by Barron's. The ex-post test(use current price to determine trades and trade at current price) and Ex-ante test(use current price to determine trades and trade at the next price) show a result similar to that of the simulation. The ex-post test shows results very similar to the ex-ante test. This may come from there being only a 30 minute interval between each data point, so that there is not much difference between the two prices.

IV.B. Time path of Ex-ante profitability

Figure 5 shows the price and trading volume of the Dow Jones Industrial average and NYSE trading volume in 30-minute intervals. Figure 6 and Figure 7 show the time path of all the strategies' performances. Here we cannot include the Information noise trader, because we cannot detect the information timing and size from historical data. The Universal portfolio investor is the leader and Constant rebalancer(50/50) and 50/50 Buy and Hold follow. CPPI performed slightly behind and ORPI next. Unlike the simulation result the difference is very small, because the Dow Jones Index was not volatile enough to benefit the Universal portfolio investor. The commissions generated by rebalancers and Universal portfolio investors show not much transaction for these investors.

Chapter 5

Conclusions and Implications

I. Summary and Conclusions

Kim-Markowitz[1989], Krull[1990], and Wang[1992]s models have been modified and extended to see the effects of various trading strategies on market volatility and profitability. Different order execution types have been used including some market imperfections like commissions.

Previous papers suggest that different trading strategies, especially portfolio insurance, increases market volatility. Some papers also suggest more noise trading leads to more volatility. Previous studies show little about profitability of strategies. This paper examines the profitability of the trading strategies with different types of orders. Black[1990] suggests different orders may be optimal for different investors.

Our results suggest portfolio insurers cause more market volatility than other types of investors. Another type of investor that affects market volatility may be information noise traders. Different market orders show different impact on market volatility, but not much. Market orders are associated with slightly more volatility than other two. That also increase the trading volume as we expected.

Profitability results show universal portfolio investors are best in general. The constant rebalancer follows next. If information noise traders with partial information advantage use market orders for their trading, they become the best of all investors. This is consistent with the results conjectured by Black[1990].

An empirical test using 30-minute interval data shows very similar results as our simulation results. More repetition results and different parameter simulation results also show little difference. Thus, we conclude our simulation results may be robust even in the real market.

II. Implications of Results

The results of this paper have the following trading implications:

1. More portfolio insurers increases the market volatility more, in general.

2. Information noise traders also increases the market volatility. This also suggests that trading strategies are great factors on market volatility. Without any change in economic fundamentals like interest rate or recession, market volatility can change much.

3. Investors without any information advantage should use universal portfolio trading strategy introduced by Cover[1990]. This will generate the best result in profitability.

4. Investors with an information advantage, in our simulation information noise traders, use market orders to get the best results.

5. Our simulation shows little impact of transaction costs at least up to 7% per round trip.

6. Test trader results show the importance of liquidity. All investor types except technical noise traders perform better in test trader simulations. Especially, investors with an information advantage get better results with better liquidity as we expect.

III. Caveats and Future Research

III.A. Caveats

This paper assumes only 6 trading strategies. This limited number of trading strategies may limit our ability to interpret the results. In particular, technical noise traders use only one specific trading system, CHRISMA; this reduces the power of this paper also. Non interest bearing cash and non dividend paying stock may limit our interpretations but we believe these factors do not affect our result significantly. The one stock included can be extended to more stocks, but the one stock can be interpreted as a stock index.

Market makers or specialists who try to make a market more liquid do not appear here. This means that our market order investors cannot execute sometimes, and may lead to a more volatile market. Lack of derivative markets like options or futures limit strategies also.

III.B. Future Research

This paper has not considered the use of margin or the short sale uptick rule. More importantly, specialists and/or competing market makers were not included which might stabilize the volatility significantly. Those specialists can also make the market more liquid. This may reduce the difference between the information noise traders performance for non test traders and test traders. Also, the actual proportions of investor types in the real world are not readily known. Thus, various proportions of investor types should be tested. Technical noise traders with CHRISMA is just one of many techniques used in the real market. Further studies should consider other types of technical trading strategies.

Table 1 (Benchmark Specifications)

	Reba	CPPI	ORPI	Tech	News	UPI
1.Initial Portfolio($000)	100	100	100	100	100	100
2.Initial $Stock/$Total	0.5	0.5	0.5	0.0	0.0	0.5
3.How often review(days)	5	5	5	1	1	5
4.How often cash in/out	10	10	10	10	10	10
5.Minimum deposit ($000)	-8	-8	-8	-8	-8	-8
6.Maximum deposit ($000)	+9	+9	+9	+9	+9	+9
7. Target fraction of stock	0.5					vary
8.Rebalance if less than	0.46					vary
9.Rebalance if more than	0.55					vary
10.Length of insurance plan		65	65			
11.Target ratio of stock		2.0				
12.Buy if actual is less than		1.7				
13.Sell if more than		2.3				
14.Cushion at start		0.25				
15.Cushion at new plan		0.25				
16.Max ratio of stock		1.0				
17.Std. Dev. of market			0.2			
18.Length of 1st price MA				200		
19.Length of 2nd price MA				50		
20.Days of Volume MA				20		
21.Max of Information					1.1	
22.Min of Information					0.9	
23.Mean of News Arrival					20day	
24.Days Before PublicNews					3day	
25.Commission rates(%)	0.5	0.5	0.5	0.5	0.5	0.5

Table 2

All Rebalancers (150 rebalancers)
Comparison of Model without and with news

	Without News Generator			With News Generator		
Qtr	Price	Std.Dev[5]	Grand Std.Dev	Price	Std.Dev[6]	Grand Std.Dev
1	110	.02671	.027	110	.02808	.028
2	116	.01832	.023	116	.03035	.029
3	118	.01952	.022	122	.02280	.027
4	131	.01505	.020	128	.01938	.026
5	135	.01930	.020	136	.02601	.026
10	169	.01403	.017	162	.01670	.026
20	236	.01210	.016	230	.01050	.023
40	357	.00795	.013	339	.02097	.023
60	493	.00388	.011	449	.01767	.023
80	612	.00215	.010	581	.01725	.023
100	741	.00176	.009	659	.02852	.023

Left 3 column without news generator
Right 3 column with news generator

[5] Quarterly Period Standard Deviation

[6] Quarterly Period Standard Deviation

Table 3A
Grand Standard Deviation
CPPI Investors

	Number of CPPI Investors					
Quarter	0	5	25	50	75	100
1	.028	.017	.028	.090	.091	.147
2	.029	.018	.025	.089	.088	.135
3	.027	.021	.025	.087	.086	.125
4	.026	.022	.023	.080	.085	.116
5	.026	.021	.025	.075	.082	.109
10	.026	.020	.029	.060	.079	.095
20	.023	.023	.028	.052	.069	.086
40	.023	.023	.029	.049	.064	.078
60	.023	.024	.028	.046	.060	.076
80	.023	.024	.028	.045	.059	.074
100	**.023**	**.024**	**.030**	**.045**	**.058**	**.073**

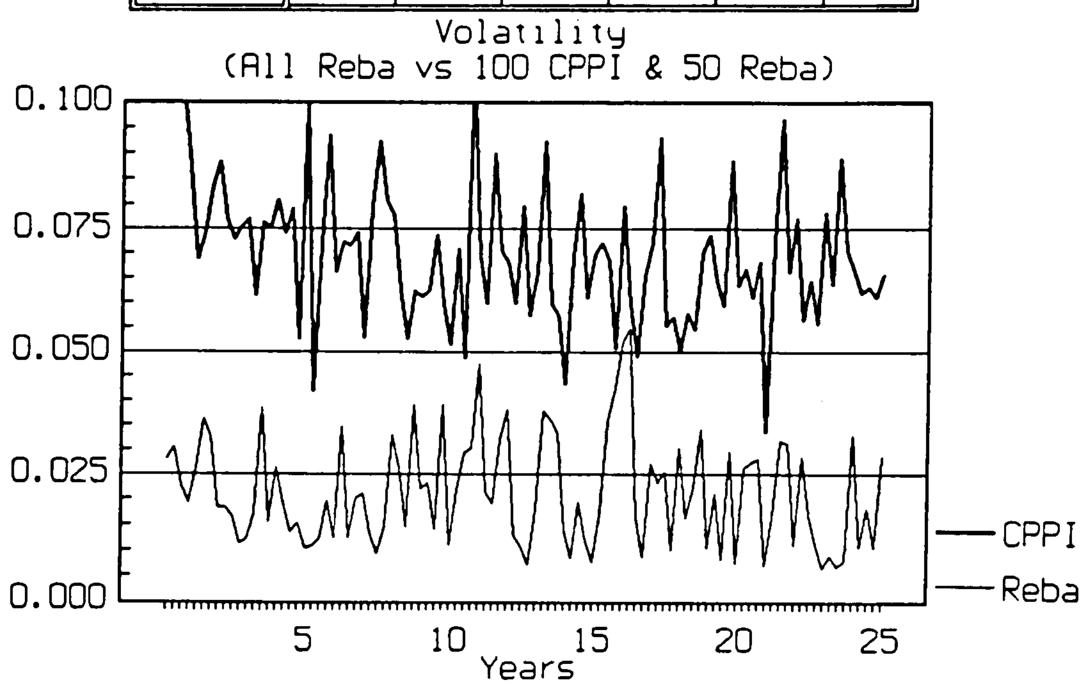


Table 3B
Grand Standard Deviation
ORPI Investors

	Number of ORPI Investors					
Quarter	0	5	25	50	75	100
1	.028	.031	.028	.026	.037	.040
2	.029	.027	.030	.036	.040	.040
3	.027	.031	.030	.036	.040	.044
4	.026	.031	.029	.036	.038	.044
5	.026	.030	.030	.035	.039	.042
10	.026	.026	.035	.032	.039	.044
20	.023	.024	.034	.035	.039	.045
40	.023	.024	.033	.037	.039	.044
60	.023	.025	.032	.037	.040	.043
80	.023	.026	.031	.037	.040	.043
100	**.023**	**.026**	**.031**	**.036**	**.040**	**.043**

Volatility
(All Reba vs 100 ORPI & 50 Reba)

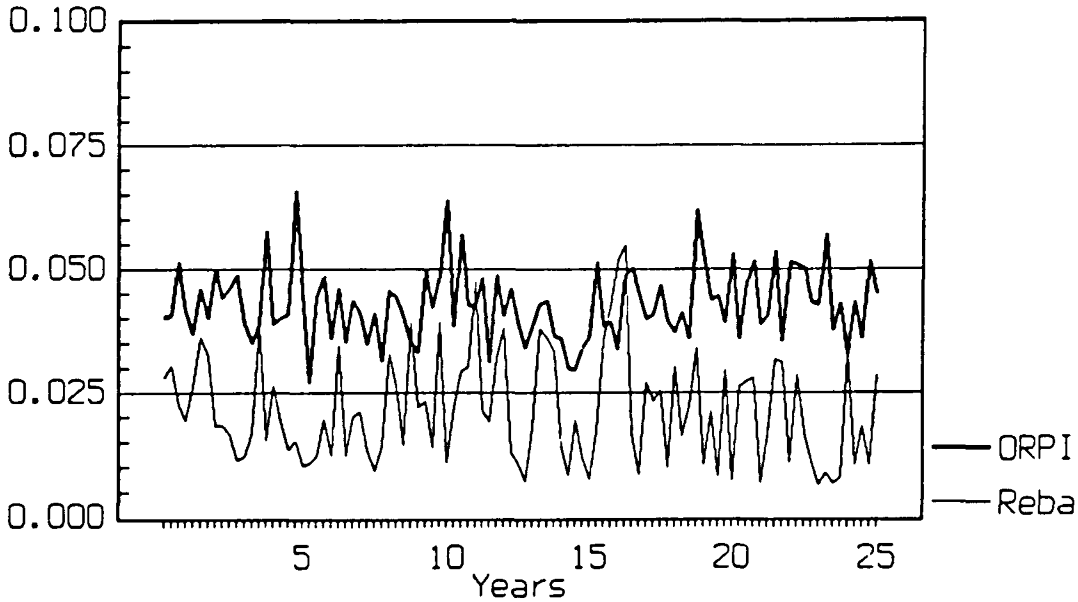
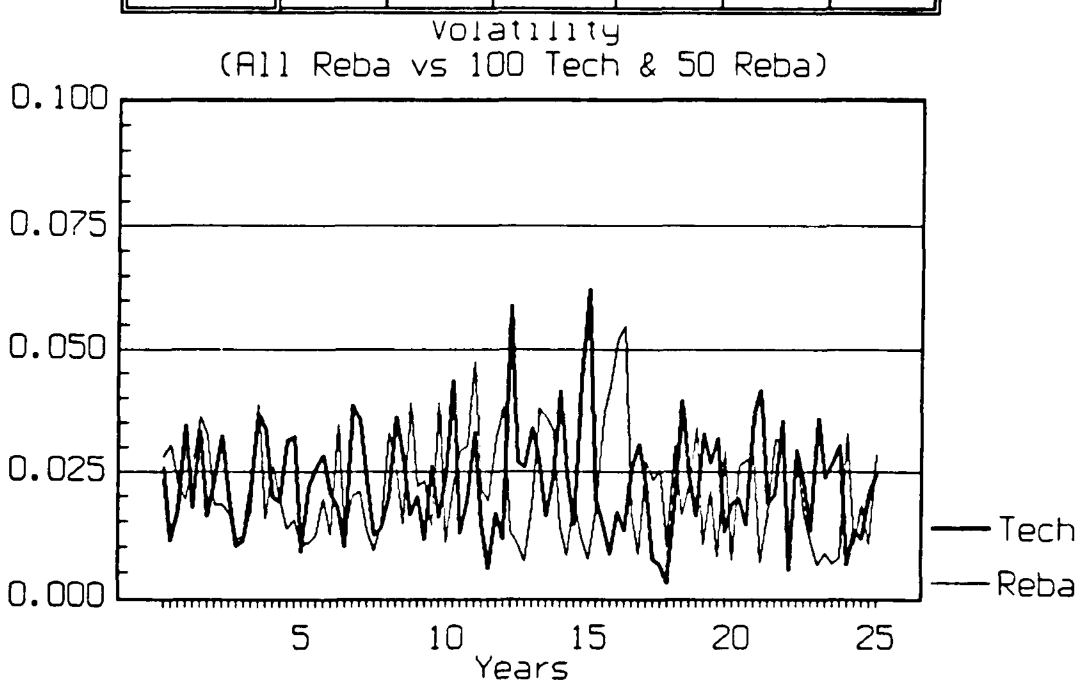


Table 3C
Grand Standard Deviation
Technical Noise Traders

	Number of Technical Noise Traders					
Quarter	0	5	25	50	75	100
1	.028	.031	.036	.027	.041	.026
2	.029	.032	.041	.035	.037	.020
3	.027	.030	.040	.031	.032	.019
4	.026	.030	.036	.031	.032	.024
5	.026	.029	.033	.030	.030	.023
10	.026	.028	.031	.029	.028	.024
20	.023	.026	.030	.028	.027	.024
40	.023	.027	.028	.029	.027	.024
60	.023	.026	.029	.029	.027	.027
80	.023	.026	.032	.027	.026	.028
100	**.023**	**.026**	**.032**[7]	**.027**	**.026**	**.028**



[7]Very high period standard deviation happened in 1 period

Table 3D
Grand Standard Deviation
Information Noise Traders

	Number of Information Noise Traders					
Quarter	0	5	25	50	75	100
1	.028	.019	.020	.035	.040	.049
2	.029	.020	.025	.029	.031	.039
3	.027	.022	.023	.025	.027	.036
4	.026	.022	.022	.022	.026	.034
5	.026	.023	.021	.025	.024	.034
10	.026	.022	.023	.022	.023	.027
20	.023	.025	.025	.023	.023	.028
40	.023	.025	.025	.024	.025	.031
60	.023	.024	.025	.024	.024	.031
80	.023	.023	.025	.024	.027	.034
100	**.023**	**.023**	**.026**	**.027**	**.026**	**.033**

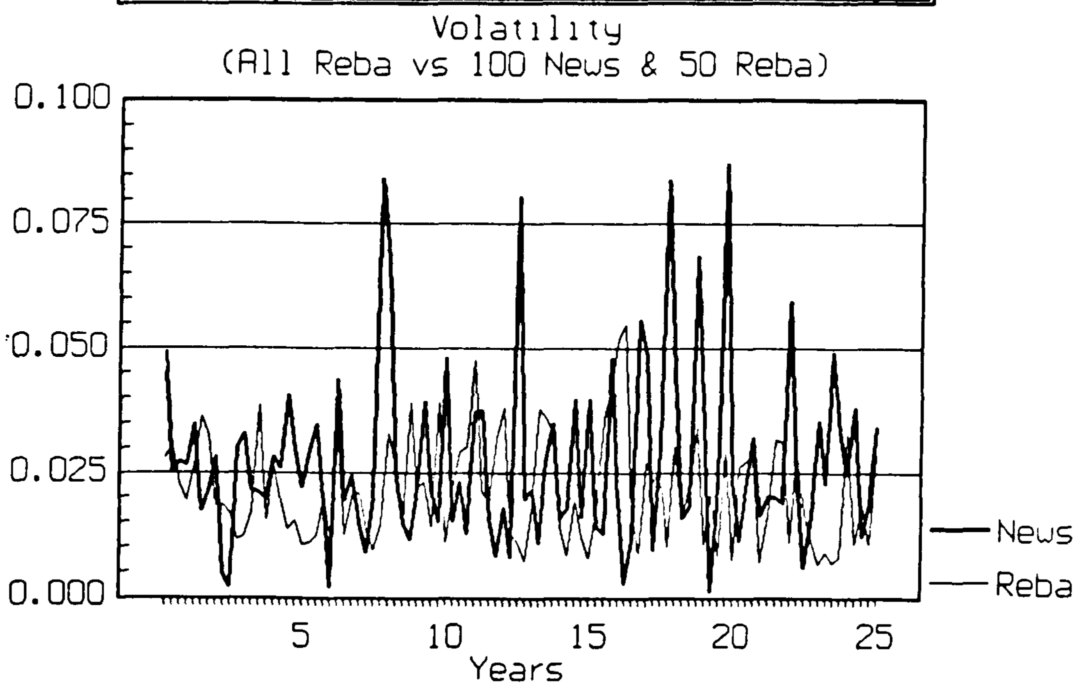


Table 3E
Grand Standard Deviation
Universal Portfolio Investors

	Number of Universal Portfolio Investors					
Quarter	0	5	25	50	75	100
1	.028	.019	.023	.023	.031	.022
2	.029	.020	.021	.023	.028	.026
3	.027	.022	.032	.023	.026	.026
4	.026	.022	.030	.024	.026	.025
5	.026	.023	.028	.024	.025	.025
10	.026	.022	.027	.025	.026	.025
20	.023	.025	.026	.025	.025	.028
40	.023	.025	.026	.025	.024	.029
60	.023	.024	.028	.026	.025	.028
80	.023	.023	.028	.025	.025	.028
100	**.023**	**.023**	**.028**	**.026**	**.025**	**.028**

Volatility
(All Reba vs 100 Univ & 50 Reba)

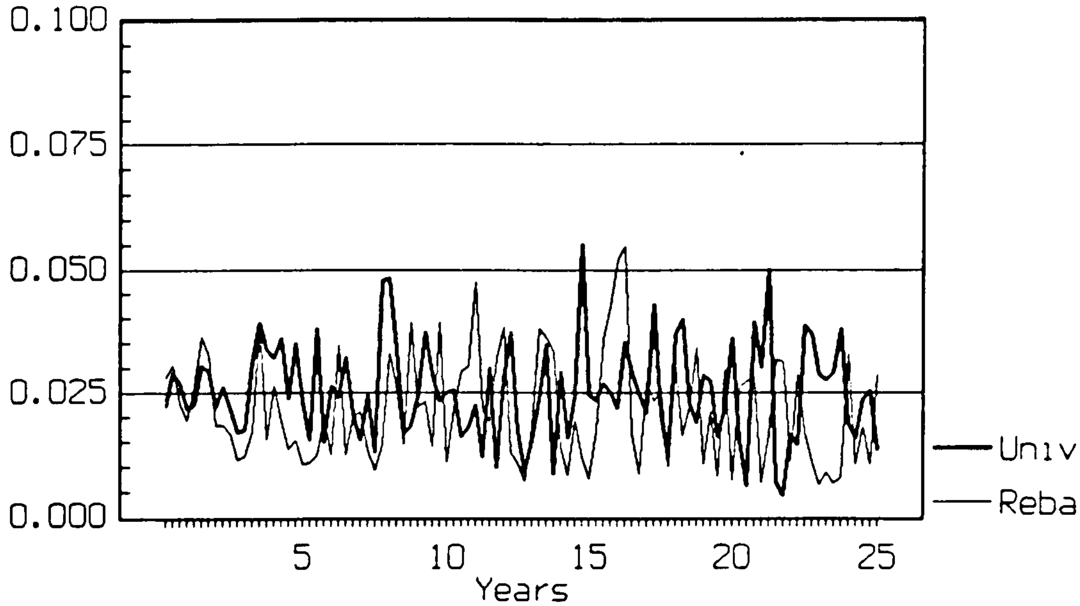


Table 3F

Grand Standard Deviation
10 Repetitions of All strategies
(100 each investors and 50 rebalancers)

Sim	Reb	CPPI	ORPI	Tech	Info	Univ
Sim0	0.022	0.065	0.043	0.025	0.032	0.023
Sim1	0.024	0.077	0.047	0.028	0.034	0.022
Sim2	0.023	0.069	0.039	0.032	0.038	0.028
Sim3	0.026	0.075	0.049	0.030	0.033	0.025
Sim4	0.028	0.073	0.050	0.027	0.039	0.027
Sim5	0.020	0.073	0.043	0.028	0.035	0.029
Sim6	0.027	0.063	0.041	0.031	0.033	0.026
Sim7	0.023	0.067	0.045	0.029	0.036	0.024
Sim8	0.025	0.071	0.037	0.028	0.037	0.022
Sim9	0.021	0.073	0.042	0.026	0.031	0.028
Average	0.0239	0.0706	0.0436	0.0284	0.0338	0.0254

Where
Reb: Rebalancers
Tech: Technical Noise traders
Info: Information Noise traders
Univ: Universal portfolio traders
Sim0 - Sim9 : 10 repetitions of simulation

Table 4A

Volume and Standard Deviation of Different Orders

	Limit Order			Market Order			Stop-loss Order		
Qtr	V	P	G	V	P	G	V	P	G
1	8	.025	.025	10	.037	.037	4	.023	.023
2	17	.035	.031	18	.040	.038	7	.025	.024
3	23	.023	.028	30	.050	.043	13	.042	.032
4	29	.033	.030	36	.038	.042	20	.034	.032
5	33	.024	.029	43	.054	.045	29	.035	.033
10	58	.028	.032	74	.053	.045	58	.027	.039
20	92	.023	.031	123	.031	.043	92	.052	.041
40	147	.027	.032	196	.054	.042	150	.029	.039
60	196	.025	.031	251	.028	.041	199	.029	.037
80	231	.031	.030	298	.047	.040	245	.039	.037
100	267	.049	.030	338	.039	.041	284	.030	.037

where
V: Volume x000 shares
P: Period Standard Deviation
G: Grand Standard Deviation to date

Table 4B

Volume and Standard Deviation of different Orders

	Limit & Market			Limit & Stop			Market & Stop		
Qtr	V	P	G	V	P	G	V	P	G
1	14	.062	.062	11	.046	.046	15	.055	.055
2	22	.034	.050	20	.049	.048	25	.049	.052
3	30	.048	.050	27	.051	.049	32	.058	.054
4	42	.058	.052	37	.041	.048	44	.059	.056
5	48	.042	.050	42	.038	.046	49	.043	.053
10	73	.026	.046	61	.030	.041	71	.033	.048
20	118	.038	.043	99	.038	.037	112	.030	.042
40	188	.041	.041	158	.032	.035	179	.048	.040
60	238	.026	.039	205	.023	.034	224	.022	.038
80	282	.025	.039	251	.025	.034	269	.030	.038
100	319	.016	.038	285	.032	.033	305	.047	.038

Half and half(75 investors each)) order type investors are in each simulation

where
V: Volume x000 shares
P: Period Standard Deviation
G: Grand Standard Deviation to date

Table 4C

Volume and Standard Deviation of Different Orders
(10 repetitions)

	Limit orders		Market orders		Stop orders	
	V	G	V	G	V	G
Sim0	261	0.029	342	0.042	257	0.035
Sim1	250	0.031	382	0.039	262	0.031
Sim2	272	0.029	327	0.041	271	0.035
Sim3	238	0.031	370	0.046	269	0.037
Sim4	291	0.030	352	0.043	251	0.033
Sim5	265	0.034	318	0.046	248	0.039
Sim6	262	0.032	339	0.041	249	0.033
Sim7	283	0.033	340	0.047	297	0.037
Sim8	258	0.028	312	0.045	283	0.034
Sim9	246	0.030	361	0.042	253	0.039
Average	262.6	0.0307	344.3	0.043	264.0	0.0353

where
V: Volume x000 shares
G: Grand Standard Deviation

Table 5A
Effectiveness of Strategies

Type	Beta	Sharpe	Treynor	E-G	Comm	Return[7]
Rebalancer-L	.95	.361	.016	3.95	39	903%
Rebalancer-M	.95	.361	.016	4.07	46	833%
Rebalancer-S	.95	.362	.016	4.40	41	903%
CPPI-L	.92	.176	.008	7.30	137	393%
CPPI-M	.90	.201	.009	8.00	139	476%
CPPI-S	.92	.187	.008	10.5	130	481%
ORPI-L	.97	.247	.012	7.81	291	596%
ORPI-M	1.09	.214	.010	11.1	302	578%
ORPI-S	.98	.208	.010	14.3	332	494%
TechNoise-L	.03	-.197	-.145	1.70	50	205%
TechNoise-M	.21	-.450	-.204	19.2	262	-12%[8]
TechNoise-S	.06	-.238	-.091	4.23	84	290%
InfoNoise-L	1.41	.221	.007	14.4	26	839%
InfoNoise-M	1.36	.223	.017	-12.3	26	1304%[9]
InfoNoise-S	1.50	.140	.021	-23.9	43	799%
Universal-L	1.15	.365	.016	0.23	100	1093%
Universal-M	1.15	.369	.016	0.46	105	977%
Universal-S	1.15	.365	.016	0.05	95	1069%

Sharpe: Sharpe's ratio:Excess return adjusted by standard deviation
Treynor: Treynor's ratio:Excess return adjusted by beta
E-G: Elton & Gruber's ratio:Measures covariances ($x10^4$)
Comm: Commission (x$100)

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[7] results from 100 quarters with upward cashflow

[8] Only negative return

[9] Best return among all the types of investors

Table 5B

Effectiveness of Test Traders
(Small wealth, no impact on prices)

Type	Beta	Sharpe	Treynor	E-G	Comm	Return
Rebalancer	.93	.365	.017	3.80	6	933%
CPPI	.89	.194	.009	9.89	29	428%
ORPI	1.03	.217	.011	4.61	53	636%
Tech Noise	.09	-0.325	-0.336	9.97	73	-20%
Info Noise	1.62	.273	.014	1.88	19	1276%
Universal	1.14	.369	.017	0.51	13	1076%

where
Sharpe: Sharpe's ratio:Excess return adjusted by standard deviation
Treynor: Treynor's ratio:Excess return adjusted by beta
E-G: Elton & Gruber's ratio:Measures covariances ($x10^4$)
Comm: Commission (x$100)
Tech Noise: Technical Noise traders
Info Noise: Information Noise traders

Table 5C

Effectiveness of All Investors
(Without Cashflow: Invest only with Initial Wealth)

Type	Limit	Market	Stop	Test Trader
Rebalancer	57%	55%	56%	288%
CPPI	-54%	-51%	-52%	134%
ORPI	-0.3%	-13%	-11%	160%
Tech Noise	-35%	-91%	-50%	-33%
Info Noise	25%	49%	-6%	714%
Universal	61%	58%	67%	368%

where
Tech Noise: Technical Noise traders
Info Noise: Information Noise traders

Table 5D

Effectiveness of All Strategies
Repetition of Simulations

(Return %)

Type	Sim0	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Avg
Rebalancer:L	860	893	798	991	922	837	843	880	915	912	885.1
Rebalancer:M	831	918	719	892	898	929	912	926	1085	796	890.6
Rebalancer:S	924	902	742	817	1003	933	934	792	901	887	883.5
Rebalancer:T	895	875	729	919	937	896	922	960	1066	934	913.3
CPPI:L	446	319	388	564	538	428	561	517	540	381	468.2
CPPI:M	539	468	512	621	449	473	544	582	461	456	510.5
CPPI:S	514	440	396	488	508	382	465	497	583	471	474.4
CPPI:T	584	564	476	677	497	573	559	632	587	456	560.5
ORPI:L	518	652	564	672	581	576	681	637	450	702	603.3
ORPI:M	429	493	473	633	599	539	540	528	593	479	530.6
ORPI:S	551	701	589	653	463	629	476	583	581	495	572.1
ORPI:T	573	590	503	544	468	537	562	500	631	677	558.5
Tech Noise:L	67	46	158	152	80	182	215	127	51	190	126.8
Tech Noise:M	-93	-82	-90	-79	-87	-89	-85	0	-84	-73	-76.2
Tech Noise:S	-28	-47	6	31	4	-12	88	-39	-39	39	0.3
Tech Noise:T	66	-36	-22	1	52	-7	54	19	-40	-19	6.8
Info Noise:L	1398	1672	1470	1356	1565	1400	1706	1718	1997	1562	1584.4
Info Noise:M	1500	1701	1411	1719	1859	1709	1550	1603	1764	1596	1641.2
Info Noise:S	1502	1688	1103	1273	1233	1364	1795	1456	1555	1253	1422.2
Info Noise:T	1727	2035	1791	1780	1549	1469	1910	1758	1910	1415	1734.4
Universal:L	1186	1044	1126	1152	1221	1216	1175	1369	1228	1135	1185.2
Universal:M	1105	1305	1152	1129	1054	1244	1291	1380	1261	1215	1213.6
Universal:S	1231	1160	945	1199	1245	1182	1172	1340	1288	1211	1197.3
Universal:T	1208	1148	1145	1099	1105	1265	1298	1145	1312	1075	1180.0

where
Sharpe: Sharpe's ratio:Excess return adjusted by standard deviation
Treynor: Treynor's ratio:Excess return adjusted by beta
E-G: Elton & Gruber's ratio:Measures covariances ($x10^4$)
Comm: Commission (x$100)

Table 5E

Effectiveness of All Strategies
With different parameters

(Return %)

Type	Both 7.5%	Both 5%	Bid 7.5%	Bid 5%	Ask 7.5%	Ask 5%	Default 1% Both	Average
Rebalancer:L	986	1009	887	1033	1106	1072	903	885.1
Rebalancer:M	727	877	798	956	982	979	833	890.6
Rebalancer:S	888	1088	854	935	1041	900	903	883.5
Rebalancer:T	888	979	889	925	796	851	933	913.3
CPPI:L	166	229	312	382	209	341	393	468.2
CPPI:M	51	38	151	201	199	251	476	510.5
CPPI:S	112	319	333	512	316	346	481	474.4
CPPI:T	387	528	442	403	368	405	428	560.5
ORPI:L	419	568	452	509	1197	1276	596	603.3
ORPI:M	165	344	369	374	960	705	578	530.6
ORPI:S	231	333	341	383	783	988	494	572.1
ORPI:T	204	314	451	365	852	693	636	558.5
Tech Noise:L	-99	-99	222	154	-99	-80	205	126.8
Tech Noise:M	-99	-99	-99	6	-99	-99	-12	-76.2
Tech Noise:S	-99	-99	78	131	-85	-86	290	0.3
Tech Noise:T	-32	-68	-75	19	75	25	-20	6.8
Info Noise:L	992	1455	1422	1409	1698	1868	839	1584.4
Info Noise:M	917	1581	1542	2167	1607	1651	1304	1641.2
Info Noise:S	1177	1865	1279	1646	1857	1965	799	1422.2
Info Noise:T	1197	1488	1701	1867	1677	1788	1276	1734.4
Universal:L	1400	1522	1002	1174	1516	1345	1093	1185.2
Universal:M	923	1341	1105	1273	1535	1300	977	1213.6
Universal:S	1476	1638	1116	1443	1607	1445	1069	1197.3
Universal:T	1281	1520	862	1346	1493	1330	1076	1180.0

where
Both: Change Bid and Ask factor(0.99 to 0.95 or 0.925 and 1.01 to 1.05 or 1.075)
Bid: Change only Bid factor(0.99 to 0.95 or 0.925)
Ask: Change only Ask factor(1.01 to 1.05 or 1.075)
Average: Average of benchmark results(from Table 5D)

Table 5F

Effectiveness of All Strategies
With different commission rate

(Return %)

Type	7%	5%	2%	Default	Average
Rebalancer:L	875	935	826	903	885.1
Rebalancer:M	775	998	841	833	890.6
Rebalancer:S	787	936	903	903	883.5
Rebalancer:T	705	953	862	933	913.3
CPPI:L	282	367	353	393	468.2
CPPI:M	274	210	276	476	510.5
CPPI:S	294	558	445	481	474.4
CPPI:T	243	504	427	428	560.5
ORPI:L	443	425	495	596	603.3
ORPI:M	356	487	437	578	530.6
ORPI:S	407	389	456	494	572.1
ORPI:T	328	504	573	636	558.5
Tech Noise:L	68	-16	213	205	126.8
Tech Noise:M	-88	-99	-58	-12	-76.2
Tech Noise:S	-6	52	140	290	0.3
Tech Noise:T	-30	-59	98	-20	6.8
Info Noise:L	1282	1787	1410	839	1584.4
Info Noise:M	1251	2041	1795	1304	1641.2
Info Noise:S	927	1445	1456	799	1422.2
Info Noise:T	1221	1822	1476	1276	1734.4
Universal:L	1070	1018	964	1093	1185.2
Universal:M	945	1266	1144	977	1213.6
Universal:S	887	1277	1229	1069	1197.3
Universal:T	866	1233	1049	1076	1180.0

where
Commission rates for a round trip
Commission = $amount x commission rate
Default: Benchmark result with the same random seed
Average: Average of benchmark results(from Table 5D)

Table 5G

Effectiveness of All Strategies
With different Moving Average

(Return %)

Type	MA1	MA2	MA3	MA4	Default	Average
Rebalancer:L	882	986	910	959	903	885.1
Rebalancer:M	802	908	833	866	833	890.6
Rebalancer:S	816	916	891	894	903	883.5
Rebalancer:T	812	936	812	890	933	913.3
CPPI:L	363	343	373	390	393	468.2
CPPI:M	213	235	308	255	476	510.5
CPPI:S	559	526	635	605	481	474.4
CPPI:T	443	442	515	468	428	560.5
ORPI:L	612	612	534	650	596	603.3
ORPI:M	514	490	559	543	578	530.6
ORPI:S	546	682	578	460	494	572.1
ORPI:T	475	540	589	509	636	558.5
Tech Noise:L	214	212	222	214	205	126.8
Tech Noise:M	7	10	16	14	-12	-76.2
Tech Noise:S	306	213	339	415	290	0.3
Tech Noise:T	87	57	3	15	-20	6.8
Info Noise:L	1409	1508	1616	1618	839	1584.4
Info Noise:M	1740	1911	1758	2013	1304	1641.2
Info Noise:S	1609	1829	1752	1835	799	1422.2
Info Noise:T	1549	1761	1688	1801	1276	1734.4
Universal:L	949	1114	1081	1039	1093	1185.2
Universal:M	1081	1271	1174	1181	977	1213.6
Universal:S	1138	1353	1204	1253	1069	1197.3
Universal:T	1049	1232	1099	1157	1076	1180.0

where
MA1: 100 day MA and 25 day MA
MA2: 100 day MA and 50 day MA
MA3: 40 day MA and 10 day MA
MA4: 40 day MA and 20 day MA
Default: Benchmark result with the same random seed
Average: Average of benchmark results(from Table 5D)

Table 6A

Effectiveness of Strategies
Empirical Test with 30 minute Interval Data

	Ex-Post Test			Ex-Ante Test		
Investors	Return	Comm	Sharpe	Return	Comm	Sharpe
Rebalancer	11.51	6.98	.090	11.50	7.00	.090
CPPI Investor	10.44	17.86	.083	10.45	17.85	.083
ORPI Investor	3.05	64.19	.020	3.44	63.61	.022
Tech Trader	-.39	4.28	-.275	-.42	4.49	-.275
Universal trader	12.10	2.46	.094	12.09	2.47	.094
Buy and Hold	11.50			11.49		

Table 6B

Effectiveness of All Strategies
Empirical Test with 30 minute Interval Data
10 Repetitions of Simulations
Ex-post Test

Investor	Reb	CPPI	ORPI	Tech	Univ
Sim0	11.47	10.38	3.17	-0.57	12.21
Sim1	11.39	10.45	3.21	0.01	12.28
Sim2	11.57	9.28	3.19	-0.39	12.11
Sim3	11.48	10.21	3.18	-0.72	12.19
Sim4	11.52	10.21	3.18	-0.72	12.19
Sim5	11.63	9.77	3.08	-0.47	12.27
Sim6	11.61	10.46	3.14	0.07	12.01
Sim7	11.59	10.17	2.99	-0.26	12.11
Sim8	11.58	10.38	3.12	-0.45	12.37
Sim9	11.52	9.87	3.01	-0.37	12.47
Average	11.536	10.169	3.112	-0.0306	12.253

where
Reb: Rebalancers
Tech: Technical Noise traders
Univ: Universal portfolio investors

Figure 1A
Performance of Investors
(No Cashflow Limit Orders)

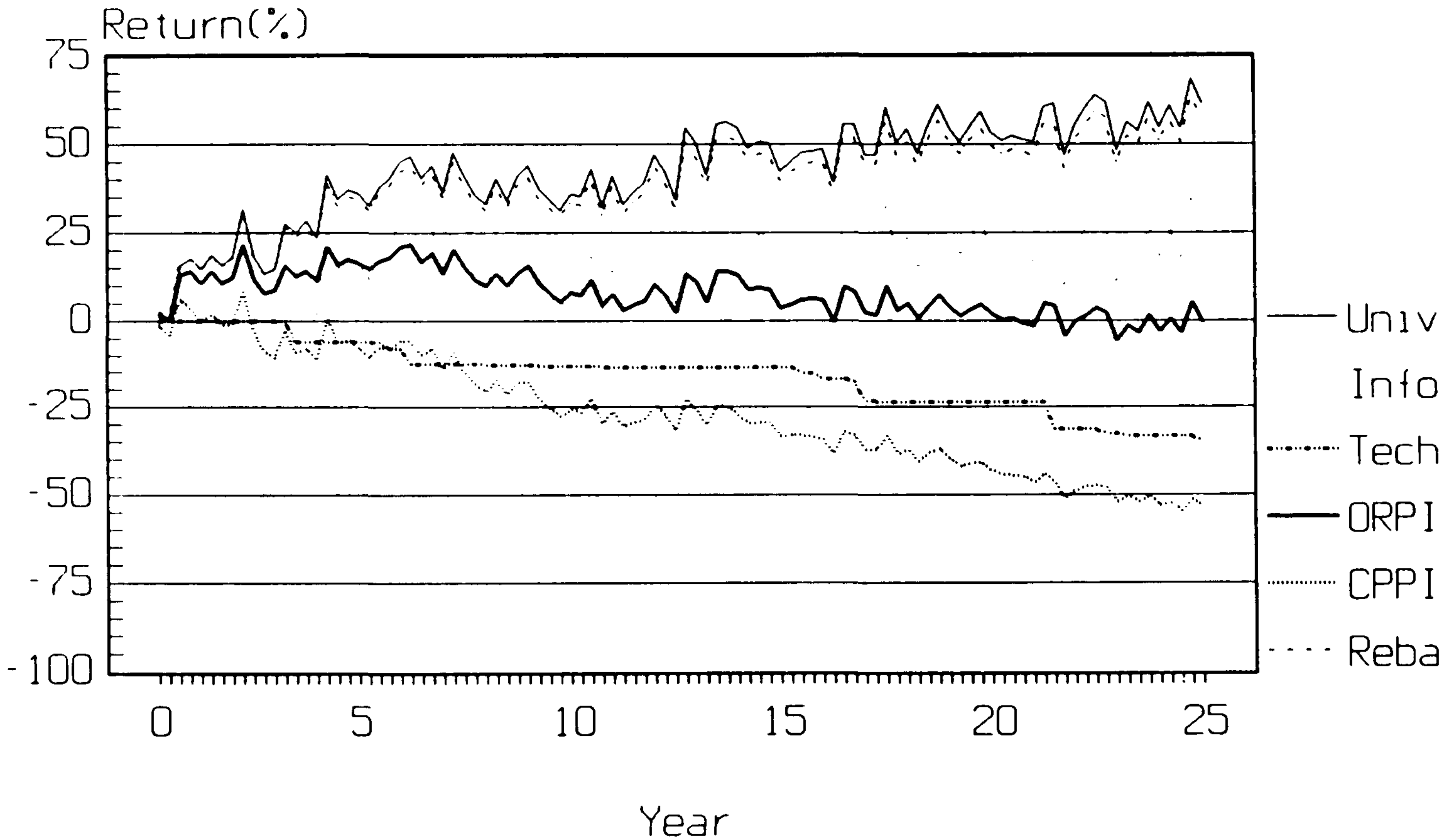


Figure 1B
Performance of Investors
(With Cashflow Limit Orders)

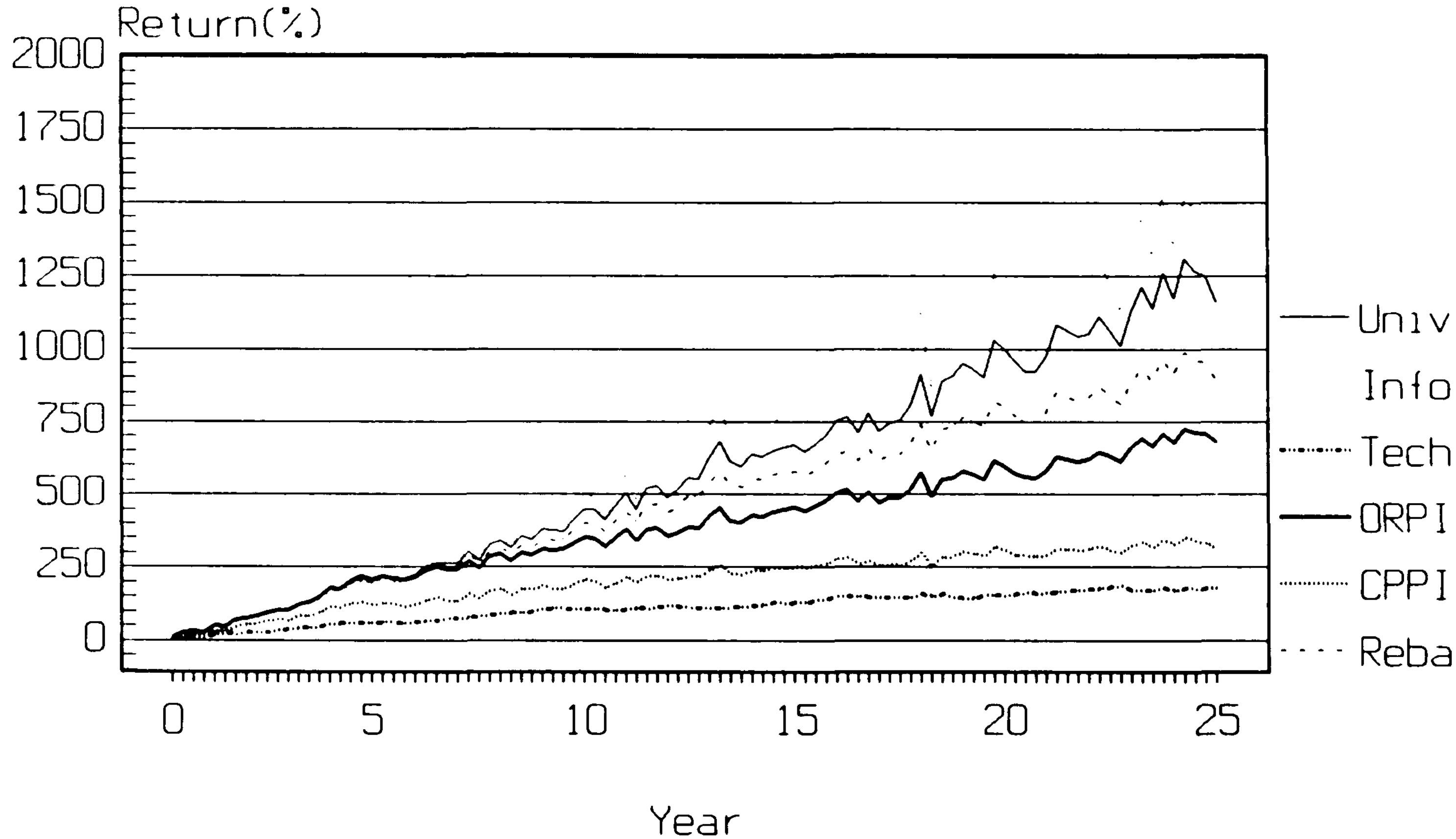


Figure 2A
Performance of Investors
(No Cashflow Market Orders)

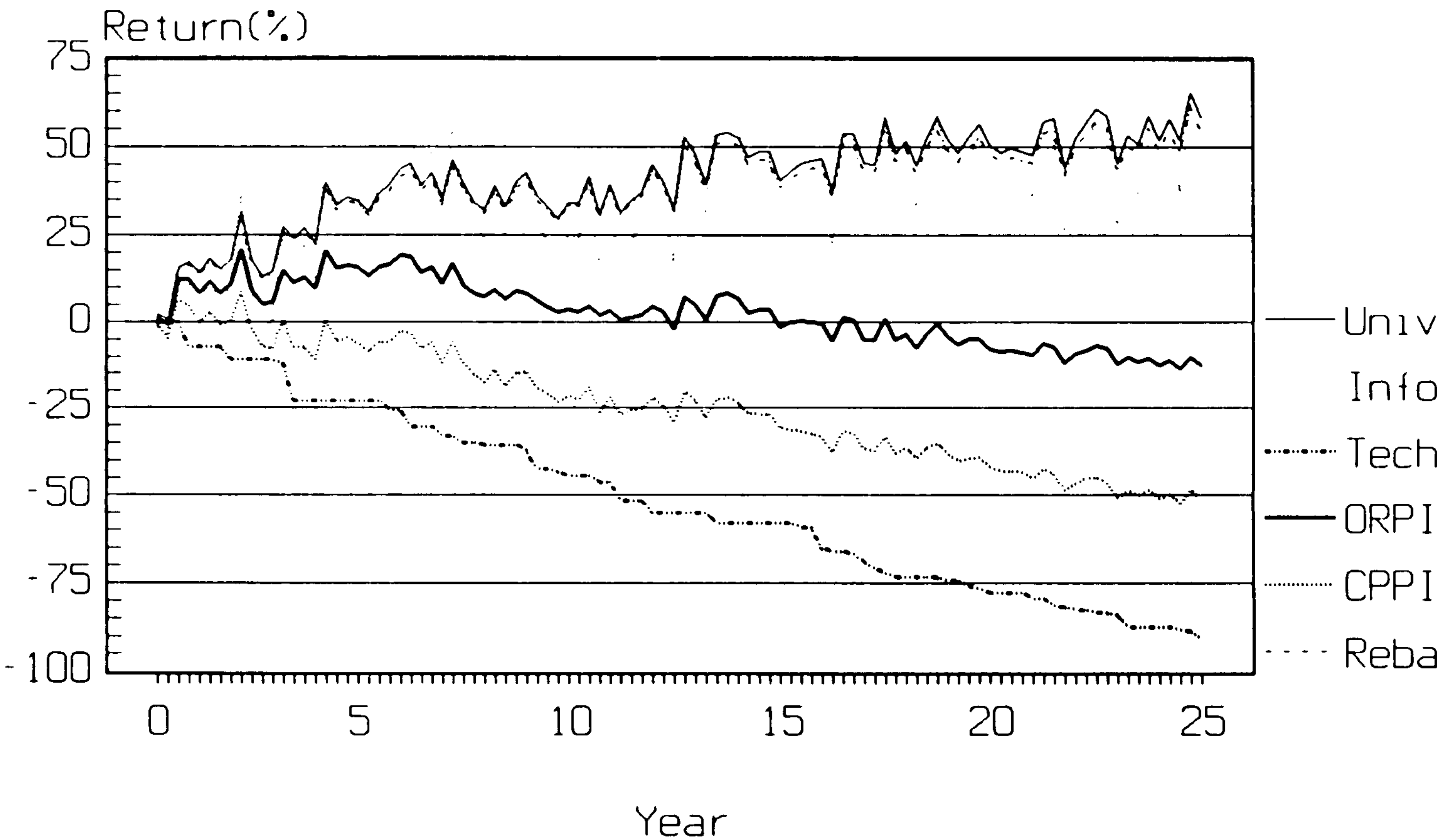


Figure 2B
Performance of Investors
(With Cashflow Market Orders)

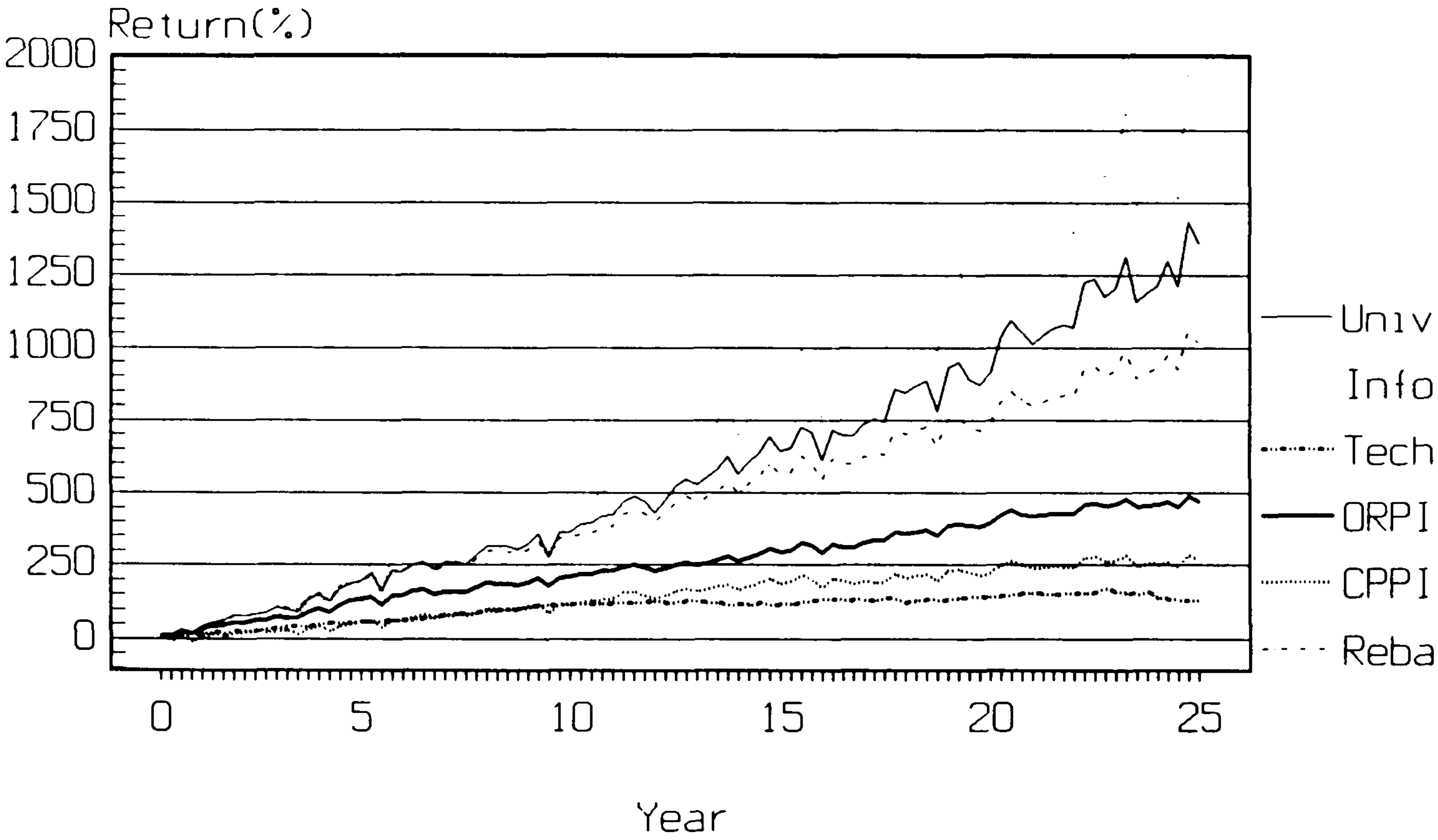


Figure 3A
Performance of Investors
(No Cashflow Stop Orders)

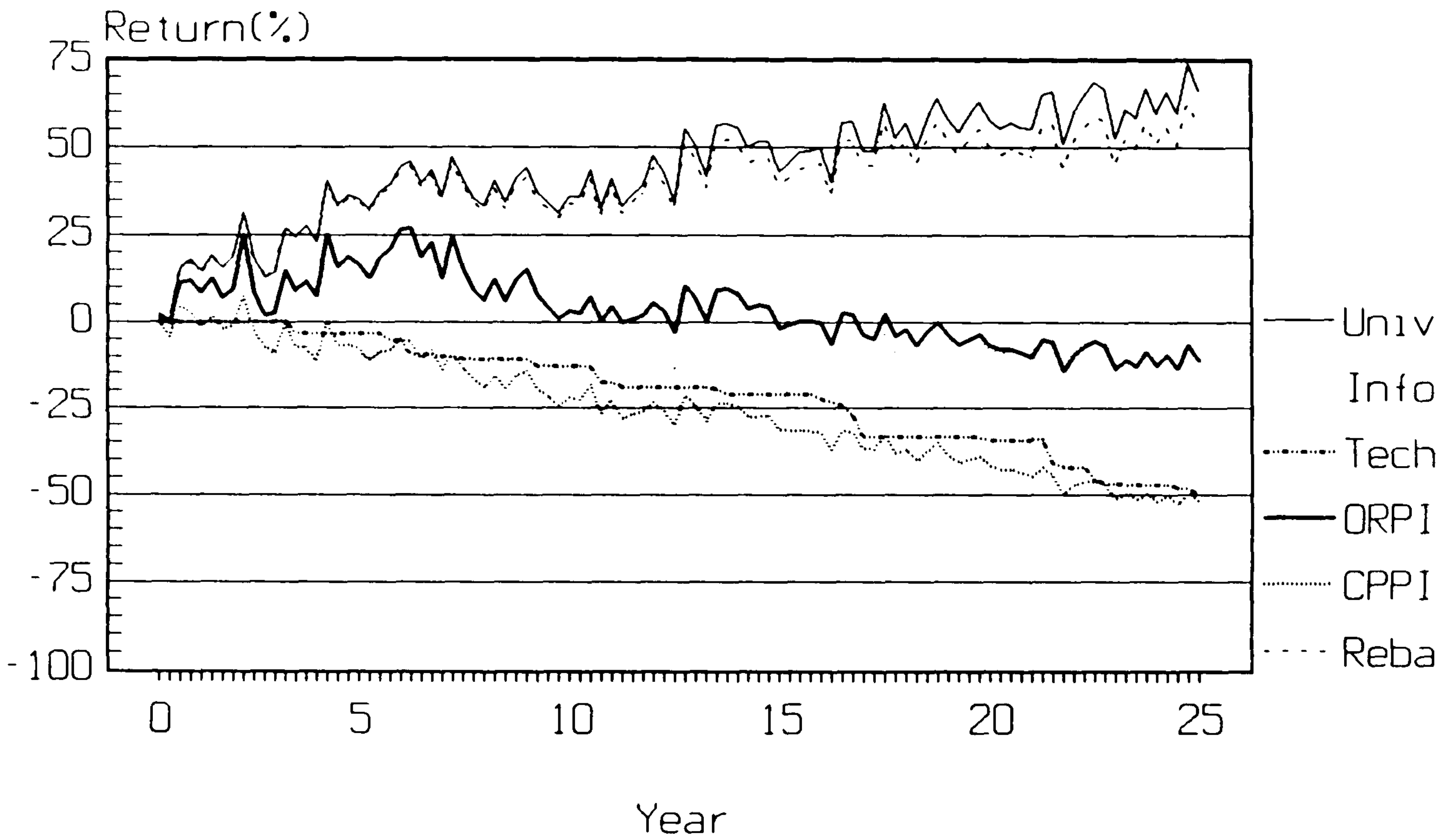


Figure 3B
Performance of Investors
(With Cashflow Stop Orders)

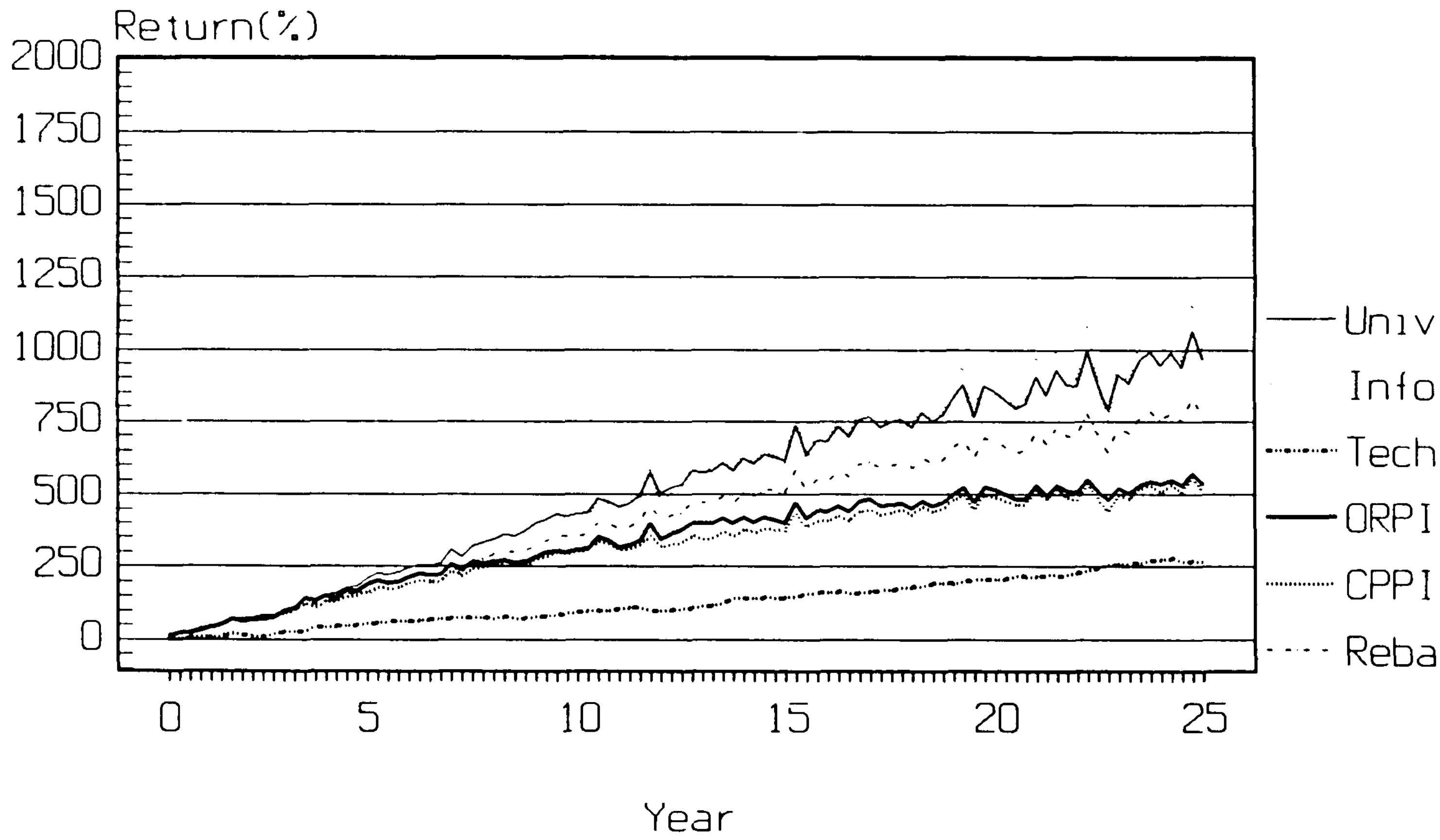


Figure 4A
Performance of Test Investors
(No Cashflow Small wealth)

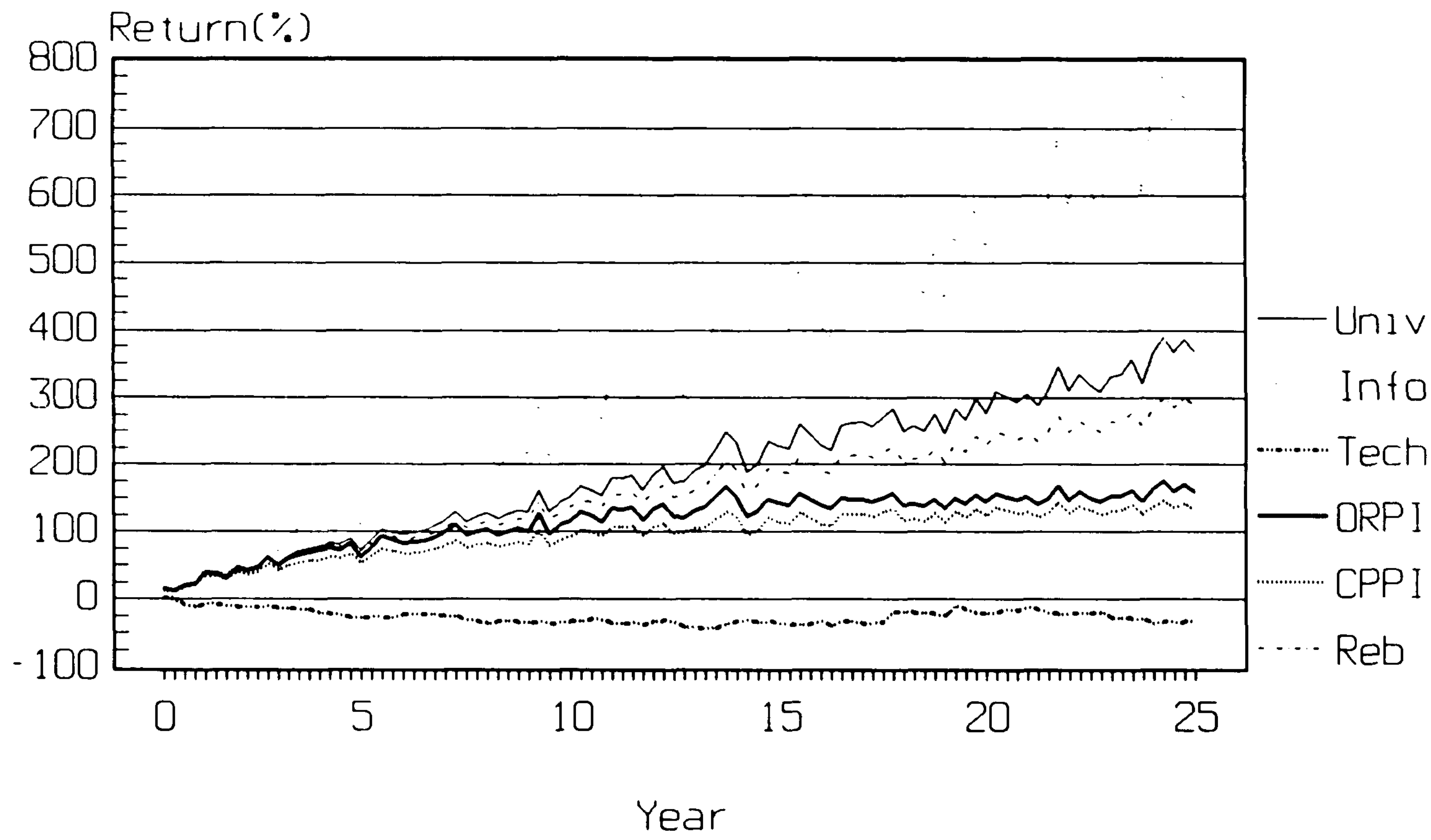


Figure 4B
Performance of Test Investors
(With Cashflow Small wealth)

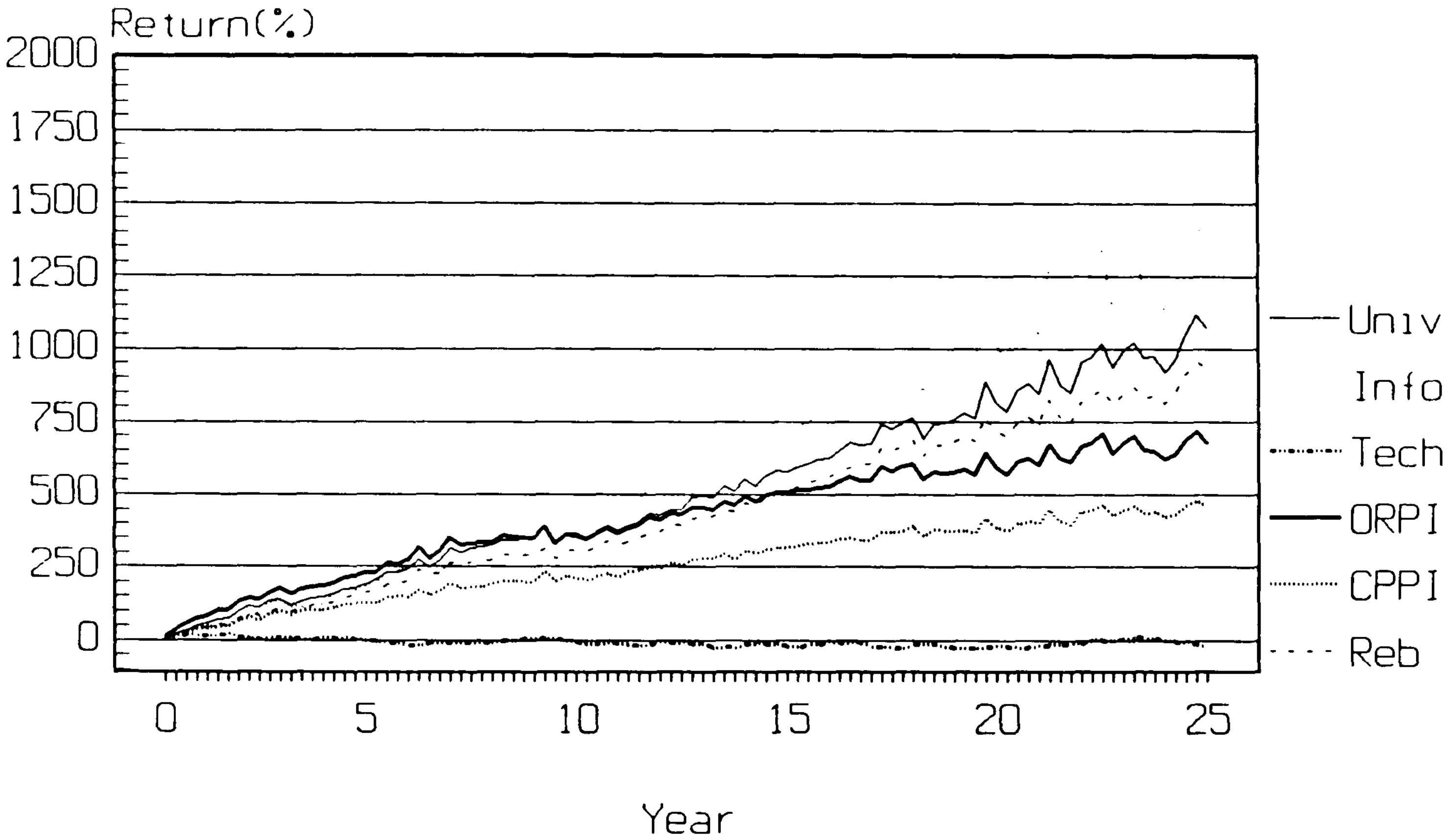
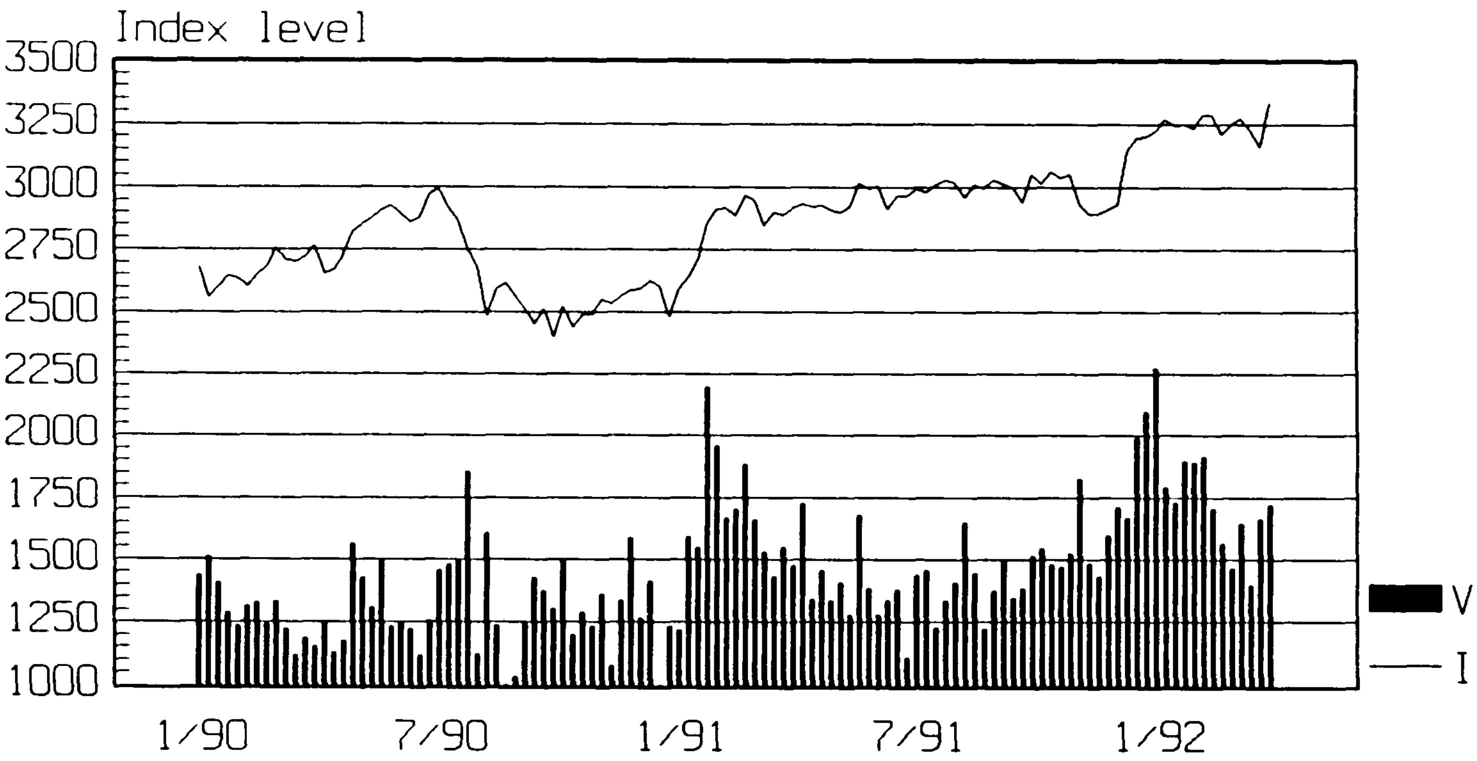


Figure 5
Dow Jones Index NYSE Volume
Weekly Index and Trading Volume



I Index V Volume

Figure 6
Performance of Investors (1/90-4/92)
(30-min Data No Cashflow Ex-post test)

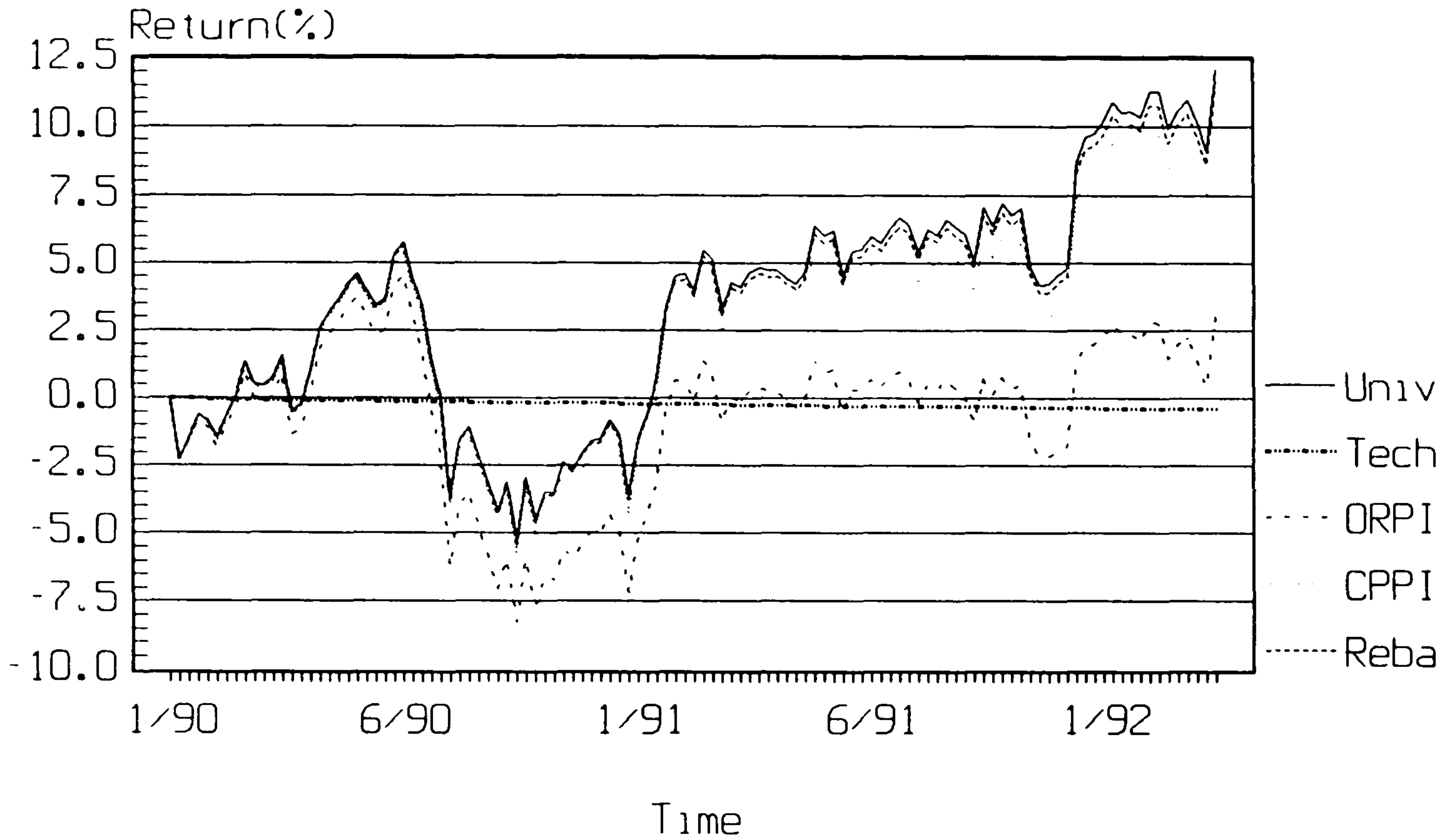
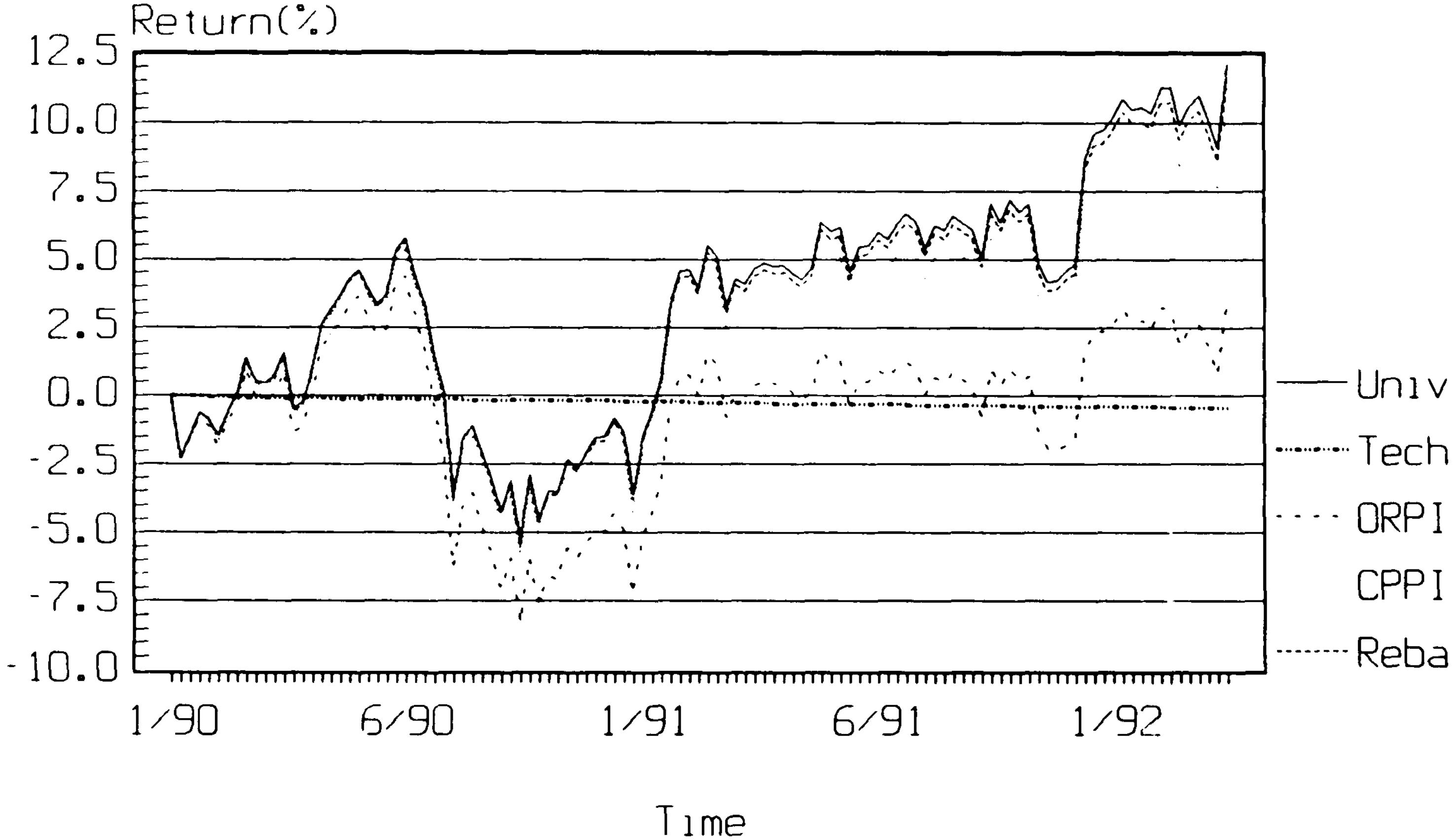


Figure 7
Performance of Investors (1/90-4/92)
(30 min Data No Cashflow Ex-ante test)



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