A CRITIQUE ON EFFICIENT MARKET HYPOTHESIS (EMH): EMPIRICAL EVIDENCE OF RETURN ANOMALIES IN 12 U.S. INDUSTRY PORTFOLIOS

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Cheng Hsun George Lee
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Supervisory Committee:

____

Dr. Andrey Pavlov
Senior Supervisor
Associate Professor of Business Administration

____

Dr. Kian-Guan Lim
Supervisor
Professor of Business Administration

Date Approved: July 31, 2006

ABSTRACT

This paper focuses on two major arguments – the momentum effect and market-learns hypothesis – concerning the validity of the Efficient Market Hypothesis are summarized. Six empirical experiments with 12 U.S. Industry Portfolio are conducted. They not only provide the evidence against some of the EMH assumptions, but also aim to address the formation of return anomalies. Of them, three are designed to assess the validity of EMH with different approaches (White Noise, Effectiveness, Forecastibility) that capture the essence of recent findings from the finance literature and the remaining two are to propose a TSSM that permits an alternative approach to assess presence of return anomalies by enabling investment shift between two markets. An extension of this research may beneficially contribute to the discourse of market efficiency hypothesis, to the rethinking of effectiveness and sophistication of active fund management, and, if possible, to the understanding of the formation of return anomalies on the industry-to-industry basis.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

Since Fama (1969) first introduced the Efficient Market Hypothesis, it has been widely accepted by many financial economists and it has gained a general recognition in the securities markets (Malkiel, 2003). The EMH by definition requires that market prices fully and rapidly reflect the available information and that market investors make rational decisions. As long as these two conditions hold, the market is efficient even with presence of anomalies. Fama (1998) recognizes the existence of market anomalies, and he argues that apparent anomalies are random, unpredictable results,[1] and thus their existence imposes no conflict with the EMH. Although, the EMH is a simple concept to be utilized by investors and finance analysts, whether it is an authentic explanation for the convoluted market behaviors remains a lasting controversy in the finance literature. Despite Fama (1998) claims that there is no long-term persistency in these anomalies that tend to disappear over time, the EMH does not seem a panacea for the market volatility and decisions. Some financial economists firmly believe that return anomalies (maybe measured in a non-linear approach) show undeniable persistency or change signs without pure random over time. In particular, those that stress psychological and behavioural element of stock-price determination and those econometricians argue that stocks are, to some extent, predictable based on past security price patterns as well as some "fundamental" valuation metrics (see Malkiel, 2003).

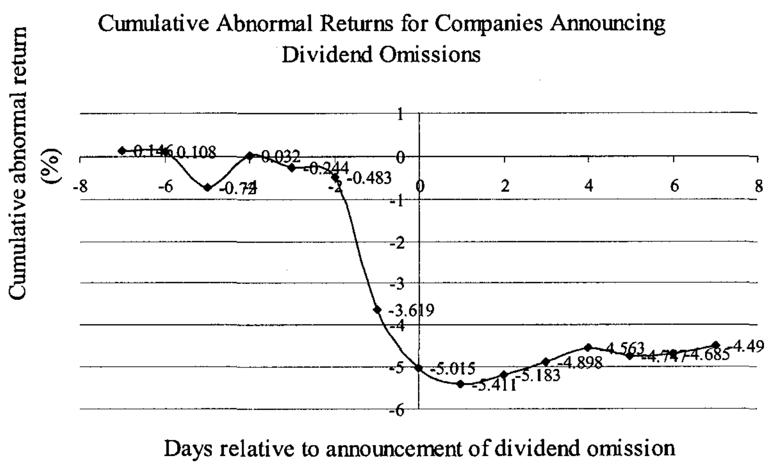
Fama (1969) recognized three forms of market efficiency: (i) weak-form efficiency – prices reflect all information contained in the past parameters, hence technical analysis will not of

[1] Malkiel (2003) implies that in a sense price is dependent on news and news by definition is unpredictable. Thus price change must be unpredictable.

any use to produce excess returns; however fundamental analysis such as researching financial statement may work, (ii) semistrong-form efficiency – prices reflect all publicly available information present in the market (thus such efficiency testing requires evidence of consistent bias of upward or downward after initial price changes), and (iii) strong-form efficiency – prices reflect all relevant information present in the market, including insider information, so that even an investor, with insider information, can not earn excess returns. The EMH is strongly based on the assumption of semi-strong form efficiency in which price would reflect all available information in the market, including historical price and volume information, published accounting statements, information found in annual reports or press, etc. The implication is that no technical analysis can be useful in predicting the future returns and therefore systematically outperform the market – after adjusted for the risk – given the assumption that the price instantaneously reflect the publicly available information, and that the analysis is done on Annual Report including the notes to Financial Statement and the company's essential information. Since a strong belief in EMH would induce employers to put those chartists or analysts out of job, in a sense that analysts could not provide any insight for his/her company, thus is no doubt that the notion of EMH is not popular in the financial industry (Lim, 2006). Furthermore, Harvey (2006) defines EMH as "states that all relevant information is fully and immediately reflected in a security's market price, thereby assuming that an investor will obtain an equilibrium rate of return. In other words, an investor should not expect to earn an abnormal return (above the market return) through either technical analysis or fundamental analysis." But financial analysts and even economists sometimes inquire, for example, that if markets were efficient, how should we trace the drift in long-term market returns? If the EMH always holds, what incentives would investors have for participating in the market, when they have no hope to beat the market in the risk-neutral world? An academic-oriented question would be *"could ex-ante abnormal return be positive on the risk-adjusted basis?"*

Since the EMH implies a stock price react to news immediately, an advocator of semistrong-form efficiency can relax the assumption that the private information ought to be reflected in the prices in a timely fashion, and he can accept the possibility of information leakage before public announcement – however, insider information would still not enable one to trade arbitrage. Note that we are not interested in testing for strong-form efficiency in this study. Some economists such as Szewczyk, S.H., Tsetsekos, G.P., and Santout, Z.m (1997) argue that it is difficult to hold strong-form efficiency valid because of the problem of information leaking (as shown in Figure 1), which could undermine the assumption of the strong-form efficiency that asserts insider information does not lead to abnormal profit making. Grossman-Stiglitz Paradox states that markets cannot be strong-form informationally efficient, since agents who collect costly information have to be compensated with trading profits. Moreover, Wong (2002) documents relative efficiency/"honest" systems within various markets among Hong-Kong and People's Republic of China, and detects the signaling of non-public information leaking.

Figure 1 Cumulative Abnormal Returns of Companies Announcing Dividend Omissions



The purpose of the study in this paper is to provide an objective assessment on, and account for series of testing results calling into question, the validity of EMH. Specifically we examine the semi-strong form of market efficiency with 12 US Industry Portfolio and to see, in a structural perspective, the nature of fund management that mandates part of its business missions to identify and work with return anomalies if they really exist and are extractable. What lies at the heart of the issue of EMH is the return anomalies. Apparent anomalies are empirical results that seem to be inconsistent with the maintained theory of the EMH. They indicate either market inefficiency (potential for arbitrage) as opposed to the Efficient Market Hypothesis, or inadequacies in the underlying asset pricing models, as Schwert (2003, pg. 940) once stressed. Similarly, Marlkiel (2003) makes such claims[2] against EMH's validity. Some recent empirical studies[3] show that return anomalies cannot occur by chance and indeed could be attributable to factors other than Fama's bad-model problems, imposing a great challenge to the validity of the EMH. Researchers like Campbell and Yogo (2003) in econometric field not only claim observing[4] a trend in long-term market returns, but also show the evidence of the predictive power of some market variables such as size and price-earnings multiple[5], price-to-book-value[6] ratio and dividend yield of the stock market as a whole as well as the characteristics of past stock returns that could be a predictor of future returns. On the other hand, economists in the field of behavioral finance also observe the psychological element of stock-price determination that can undermine some aspects of the EMH. As an attempt to explain existence and disappearance of anomalous patterns in the efficiency discourse, Schwert (2003) implies: just as decision-making is aided by more information, so too is the market that will become more efficient when investors

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[2] However he found no long-term persistent return anomalies in the market, which is consistent with Fama (1998)'s conclusion.
[3] See for example Schwert (2003), Campbell and Yogo (2003), and Ang and Bekaert (2004).
[4] Psychologists and statisticians generally assume that people desire to see patterns, even when there is hardly any – or simply an optical illusion.
[5] Note that size and dividend-pricing ratio has been incorporated into the Fama and French's Three Factor model, so it is consistent with the Efficient Market Hypothesis. Malkiel (2003), however, found little additional influence can be attributed to P/E multiples.
[6] While one with low price-earnings multiple is often called value stocks, one with high price-to-book-value ratio is often called growth stocks.

learn from published research results and when information bias is reduced in the market. These two issues will be further discussed in section III and analyzed with testing in section IV.

The remainder of this study is organized as follows: Section II briefly reviews Fama's (1998) methodology and assumptions. In section III we present the analysis of strengths and weaknesses found in Fama's work, along with some of the most important controversial issues that either underlie Fama's (1992, 1998) work or were raised by financial analysts. In Section IV an empirical testing is conducted with GLS and GARCH techniques on 12 industry portfolios and the weak form and semi-strong form efficiency of the U.S. domestic market is examined with three empirical approaches (White Noise, Effectiveness, Forecastibility). The paper concludes with Section V, in which the summary and conclusions are presented.

2 THE RETURN METRICS OF FINANCIAL MARKETS: A REVIEW ON FAMA'S (1998) STUDY

The paper, *Market efficiency, long-term returns, and behavioral finance,* provides an overview of the justifications of the Efficient Market Hypothesis: why the hypothesis has survived the challenge from the literature and what makes it valid over time. Fama (1998) draws together recent findings from finance literature on the EMH with a wide ranging survey that takes the reader close to the frontier of current research. An overview of opposing hypothesis and discussions are analyzed and possible strengths and weaknesses of his hypothesis are outlined. Since Fama (1998) found no dominant phenomenon (of consistent over-reaction or under-reaction) and due to the untestable nature of the joint-hypothesis that underlies the EMH, he argues that the opposing arguments are not promising or convincing.

To start with, Fama (1998) recognizes a growing literature that challenges the underlying assumptions of the EMH. Some (see for example Black (1986)) argue that instead prices incorporate rapidly and accurately to information, prices are actually slowly adjusted because of many market noises and biases[7]. This proposition could tie with another controversial issue: whether the real world is a perfectly competitive market or not. And if the answer is an emphatic no, the slow pricing adjustment hypothesis would definitely provide ground for argument in favour of market inefficiency. After all, due to the impact of market noises on information dissemination, it is quite reasonable to argue that pricing stickiness by Keynesian's theory would result in price over-reaction to information. However based on his research, Fama (1998) argues that (pricing) over-reaction is as frequent as under-reaction in the specified time window; therefore the apparent anomalies would then be legitimately treated as chance occurrence. To further rationalize the occurrence of apparent anomalies, he argues that although some of the market-return patterns are associated with higher future average returns, they could even out in the long run. Hence he concludes that any presence of anomalies presence is consistent with the EMH.

Fama (1998) found that long-term return anomalies are present in most academic studies and he noticed that apparent anomalies are remarkably sensitive to the methodology. For instance, they tend to disappear when value weight measurement is used. Therefore, pricing persistency in stock market or so called the momentum effect stressed by Jegadeesh and Titman (1993) should not exist once an appropriate methodology is implemented[8] . The value-weight approach suggests the possibility of bad-model problem, which seems to mostly concentrate on small capitalization firms and high equity ratios such as that Price-to-Earning and Price-to-Book-

[7] On the contrary, Sunder (1975) found in event studies that security prices adjust rapidly into new information.
[8] See also Banz (1981).

value[9]. Fama (1998) argues, however, that it is quite difficult to correct the bad-model problem because it is necessary to test it jointly with other efficient market models that also seem to have predictive problems with long-term market returns. That is to say, the bad-model problem will eventually come down to finding a better, if not perfect, proxy for the market variable which would be a difficult task for financial economists and researchers. Also there raises an issue concerning the Joint-Hypothesis testing that Grauer[10] (2006) argues that "market efficiency implicitly underlies tests of asset pricing models, but asset pricing models are the benchmark by which markets are judged to be efficient." One would really wonder if both approaches can be verified at the same time." Due to difficulty of methodology, the EMH can hardly be tested and therefore, can not be proven untenable with ease. "The empirical evidence for predictability in common stock returns remains ambiguous, even after many years of research." (Ferson et all, 2005, pg. 3)

Regarding the burgeoning behavioral approaches such as the Barberis, Shleifer, and Vishny (BSV, 1996) and Daniel, Hirshleifer, and Subramanyam (DHS, 1997) models, Fama (1998) points out that there certainly lie ambiguities in classifying anomalies with these two methods and such behavioral approaches to the market reactions are not a complete survey yet and thus do not constitute a valid challenge to the EMH. For example, the DHS model has found fault for predicting that the long-term negative post- event returns of IPOs are preceded by positive returns for a few months following the event (Fama, 1998, pg. 291). In concluding CAPM results, the BSV approach is consistent with the EMH that states long-term abnormal return is a chance result. Hence, the EMH still stands firm – since it was first introduced in 1969.

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[9] See Brav and Gompers, 1997; Brav, Geczy and Gompers, 2000
[10] More information can be found at his Economic course website: http://www.sfu.ca/economics/061co/econ817.html

After long consideration and analysis of several studies on market return anomalies, Fama (1998) concludes that return anomalies seem to be chance results and presence of these anomalies is rather a methodological illusion due to bad-model problems, which is not testable. Fama (1998) also believes that the behavioral models mentioned above are not capable of explaining the market as effectively as the EMH would. Lastly, he suggests to adjust with heteroskedasticity techniques for a trending in the long-term abnormal returns and to use value-weight measure to abate the bad-model problems that originate from small stocks and those with high book-to-market-equity (BE/ME) ratio. After all, he reaffirms his consistent contention: market efficiency survives the challenge from the literature on long-term return anomalies. (Fama, 1998, pg. 283)

2.1 ANALYSIS OF STRENGTHS AND WEAKNESSES AND EXPLAINATIONS OF RISK FACTORS

Fama (1998) examines the extent and nature of the Efficient Market Hypothesis among other different voices. Fama (1969, 1992) not only reaffirms the conclusions from his previous work, but also examines the opposing arguments to the EMH while providing insight into the return anomalies. The merits of his theme work are quite remarkable – however some shortcomings such as inability to explain risk factors in the Efficient Market Hypothesis make his conclusions of market efficiency less promising. Furthermore, market speculators sometimes have a puzzle that if no one can beat the market (as Fama (1998) contends), why would anyone want to undertake risky investment when they can obtain the same rate of risk-adjusted returns in the risk-free investment such as a Treasury Bill? In the following I present two strengths and two weaknesses in Fama's (1998) contention.

2.2 TWO STRENGTHS

2.2.1 First, rationalization of return anomalies

The first strength of his contention is the rationalization of return anomalies. Apparent anomalies are of a puzzle to many financial economists and practitioners: why there is no arbitrage opportunity[11] given the inefficient market? Note that in the finance theory an arbitrage is defined as a trading strategy that generate a completely risk-less profit, and that must be non-negative cash flows for all times. Presence of anomalies, most of the time, is treated by researchers as the evidence against the EMH, which assumes that there is no arbitrage opportunity in the efficient market (e.g. Shleifer (2000) and Barberis and Thaler (2003)). In another words, investors simply think that in the inefficient market, there shall be market anomalies or arbitrage opportunity. However, Fama (1998) stresses that anomalies are rather chance, rational results (implying pricing regularity), while admitting its existence in his model[12]. By looking back to statistical data and results historically and by assessing it with different risk-adjusted[13] methods, Fama (1998) found that apparent anomalies tend to become marginal or disappear: "viewed one-by-one, most long-term return anomalies can reasonably be attributed to chance" (Fama, 1998, pg. 284). Momentum[14] are extremely small and are not likely to permit investors to realize excess returns, said Malkiel (2003, pg. 62) also found difficult to exploit the existing anomalies and believes that financial markets are efficient because they don't allow investors to earn above-average risk adjusted returns or *ex-ante* positive expected return after accounting for bid-ask spreads, brokerage fees, transaction cost, etc. Similarly, Roll (1994)

[11] See for example the talk between Shiller and Roll (Malkiel, 2003, pg. 72)

[12] In response to this seemingly paradox that anomalies cannot be exploited, Malkiel (2003, pg. 62) states, because of the large transaction costs involved in attempting to exploit whatever momentum exists.

[13] By that I mean the anomalies in this case are not induced by or associated with risk. The bottom line is that there is no above-the-average return without above-the-average risk.

[14] It is recognized as one of the cause candidates for return anomalies.

argues that it is every difficult to realize real profit even in the extreme case of market inefficiency: see Malkiel (2003) on the arbitrage opportunity during the Internet bubble. There was an old joke that an economist sees a companion bending down to reach a $100 bill on the street would say, "Don't bother – if it were a genuine $100 bill, someone would have already picked it up" (Lo, 1997). In a sense market return anomalies are recognized as rational outcomes of the market operation and are subject to change with economics fundamentals. Moreover, Fama (1998) points out that finance literature on the long-term market returns fails to identify overreaction or under-reaction as the dominant phenomenon (Fama, 1998, pg. 284) as the EMH allows that when faced with new information investors may over-react or under-react temporarily. As the only consequence to the efficiency discourse, return anomalies can only occur by chance: the expected value of abnormal returns is zero, but chance generates deviations from zero in both directions (Fama, 1998, pg. 284). By rationalizing the formation of abnormal returns, Fama (1998) associates the phenomenon of anomalies with random walk and further upholds the EMH.

The statement that in inefficient markets there must exist arbitrage opportunity that many investors do believe seems illogical. Derived from the EMH, it is quite logical to suppose that in efficient market, pricing regularity is ensured. So logically speaking, if there were irregularity in the pricing had market become inefficient for certain. Also, it is out of the question to suppose that if there is irregularity in the pricing, then there exits market anomalies or arbitrage opportunity. Note that there is no proof for a causal relationship between inefficient market and arbitrage opportunity. So if there is no clear relationship between market inefficiency and arbitrage opportunity, it is therefore incorrect to assume that inefficient market causes a definite arbitrage opportunity. That is to say, one is not guaranteed to be able to exploit arbitrage opportunity in the inefficient market. As a matter of fact, Malkiel (2003) found that there were no profitable and predictable arbitrage opportunities available during the Internet bubble. This counter-argument may seem undoubtful when not all fund managers were found to outperform the market on the average and consistently (Malkiel, 2003; Treynor, 1965; Sharpe, 1966; Jense, 1968).

2.2.2 Second, lack of long term predictability and joint hypothesis issue

The second strength of his contention is the attribution of lack of predictability of long-term market returns to methodology or the bad-model problems. The idea is that with more refinements on the asset-pricing model less the miscalculation or mispredicatability of long-term returns will result. The three factor model had been a good example of model refinement. He argues that once the correct methodology is used, there should not be any return anomalies or long-term abnormal return. Another way he suggests finding a solution to methodology or bad-model problem is like to tread a thorny path: if there is no better model, the EMH will stand valid no matter how. Following the standard scientific rule, however, market efficiency can only be replaced by a better specific benchmark model of price formation (Fama, 1998, pg. 284). This further raises the level of difficulty to test the EMH for validity, because one must find all alternative effective models before being able to overturn Fama's (1998) efficient market hypothesis. Since then, there have been some suggestions on the model improvement or enhancement – and some of these issues will be addressed in Section 4.3. For example, Malkiel (2005) wonders if some of patterns based on fundamental valuation measures of individual stocks would better a proxy for composing risk measures. Some also try to model the implied volatility derived from the Black-Schole model, utilizing the past volatility and errors in refining the current three factor model and analyzing high-dimensional asset returns.

2.3 TWO WEAKNESSES

Although, the EMH is a powerful concept that is generally accepted by vast financial analysts, economists and finance practitioners since 1969, Fama's (1998) justifications for it are subject to scrutiny for two reasons found in this study.

2.3.1 The EMH is not compatible with momentum effect.

Since 1992 he has associated the EMH with the *random walk* concept which allows for crashes and bubbles as long as irrational behaviors is not predictable or exploitable in a long period of time Although Fama (1998) claims that there is no way to predict the long-term abnormal returns, some research results have evidenced persistency in the market returns in either short-window or long-window and others observe them change signs with some random over time[15] – so called momentum effect by Jagadeesh and Titman (1993) or new fact in finance by Cochrane (1999). Some of these anomalous bahaviors, shown by the momentum effect and captured as new fact in finance are indeed inconsistent with any rational asset pricing model including Fama's (1998) EMH. For example, Brenna and Xia (2001) suggest that there are some evidence of anomalies against the EMH, and that might be induced by investing strategy that put weights both the CAPM and new refinements over the investment horizon. The mere fact that return anomalies sometimes disappear or switch signs with time is no evidence that the markets are fully rational (Shiller, 2003, pg. 102). Indeed a further investigation with non-linear methodology should be taken as it is done in section 4.1 in this study.

With respect to short-term abnormal returns, Banz (1981) and Reinganum (1981) evidenced that small firms on NYSE have higher averages than is predicted by the CAPM from 1936-75 (Schwert, 2003, pg. 942). For considerable periods, serial correlations are not zero in the

[15] See for example Malkiel (2003), Shiller (2003), Campbell and Yogo (2003), Ang and Bekaert (2004).

short run, and that the existence of "too many" successive moves in the same direction enables them to reject the hypothesis that stock prices behave like random walks (Lo and MacKinlay, 1999). Furthermore, it is worth noting that Jagadeesh and Titman (1993) also found abnormal returns that are predictable with short-term past returns, which Fama and French (1992)'s three factor model can not explain. In particular, Jagadeesh and Titman (1993) find these returns to be strongly positive for short-term winners:[16] they group all NYSE stock returns from January 1963 to December 1989 into deciles and discover the best prior six-month stock return decile outperformed the worst prior six-month return decile by 10 percent on an annual basis, and once again Jagadeesh and Titman (1993, 2001) show the momentum effect remains large in the post 1989 period (see Chu, 2004).[17] They conclude that these effects are by nature behavioural bias[18] of investors: they tend to invest in past winners and expect them to be high performer into the near future. In addition, the fact that the momentum effect that seems to exist – even after the portfolios are well diversified so that no one should really be concerned about small size and BE/ME effects as an enhancement to the current asset pricing modeling – shows that there are some part of system complication not well explained by existing asset pricing model. Fama and French (1996) also notice the failure of three factor model "to capture the continuation of short-term returns" (pg. 81). A worse situation is that the interception or alpha from the three factor model is also larger than that in the CAPM (see section 4.2). Malkiel (2003) also recognizes the momentum effect: there does seem to be some momentum in short-run stock prices (pg. 61). So one wonders if prices fully and rapidly reflect all available information in the market and abnormal returns are chance results, why would predictable momentum pattern takes place in

[16] Interestingly Fama (1998) also find that stocks with high returns over the past year tend to have high returns over the following three to six months. He is puzzled with momentum effects.
[17] See for example Schwert (2003, pg. 949)
[18] Some evidence supports that people try to predict by seeking the closest match to past patterns, without attention to the observed probability. (Shiller, 2003, pg. 94) Similarly Schwert (2003, pg. 955) mentions that investors tend to sell stocks that have risen rapidly in the recent weeks."

short-window? If the prices were to react to news without delay, why would positive correlation of securities prices (price stickiness) have been consistently observed?

More recent works by Lo and MacKinlay (1999) and Lo, Mamaysky and Wang (2000) have shown that a serial correlation in successive price changes enables them to abandon the concept of random walk. They further find that some stock signals used by technical analysts may actually have some modest predictive power. DeBondt and Thaler (1985) form "winner" and "loser" portfolios, each consist of 35 stock returns, and they find that the loser portfolio on the average beats the winner portfolio by 8% per annum[19] and they also notice a slow drift upward in the cumulative abnormal returns (CARs) of loser stocks (Schwert, 2003, pg. 959). Moreover, financial economists have been pondering the technical causes of the momentum effect. For examples, Lee and Swaminathan (2000) discover that past trading volume could influence both the magnitude and the persistency of future price momentum, and therefore suspect that they might relate the illiquidity[20] to the momentum effect[21]. Both Jegadeesh and Titman (2001) and Schwert (1989) confirm that persistent excess volatility in the stock market in different time windows serve as counter-intuitive to the EMH. Consistently, Shiller (1981), after studying the volatility measure in the stock market, argues that a random walk model does not seem to be promising, and suggests the EMH be subject to modification – this can be further upheld in our testing results with Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process that shows past volatility and error terms do matter (see Bollerslev (1986)). In addition, Campbell and Yogo (2003) have shown that there is indeed evidence for predictability,

[19] Note that neither Fama and French (1988a) nor Zarowin (1989) find it significant in the 1926-1940 period.

[20] However, Liu and Zhang (2005) find the value spread (a common use to capture the liquidity effect) is a weak predictor of stock returns and is subject to sign change for the time window in consideration. They suggest the B/E spread is a more powerful predictor – and that is used in the Fama and French's model. See also Schwert (2003, pg. 947): Fama and French are not able to explain the short-term momentum effects found by Jegadeesh and Titman (1993) using their three-factor model.

[21] In particular, they find that among winners, low volume stocks show greater persistency of price momentum, and among losers, high volume stocks show greater persistency of price momentum.

but conclude that it is more challenging to detect than previous studies may have suggested. Boldly Malkiel (2005) suggests the key factor for rejecting the EMH is whether serial correlation has a consistent pattern over time, given the fact practitioners would exploit the true predictable pattern, to some extent, that patterns are no longer leading to profitability. After all, it is clear that the EMH fails to take the predictable momentum effect into consideration[22] when asserting non-predictability of long-term market returns and therefore makes their contention of no predictability rather weak.

2.3.2 Market becomes more efficient through learning research results.

If the market is at the efficient level, why would there be room for improvement? Many predictable patterns with different asset-pricing models seem to disappear after they are published in the finance literature, stressed by Schwert (2003) who also points out possible explanations for disappearing return anomalies: "[Practitioners] implement strategies to take advantage of anomalous behavior can cause the anomalies to disappear as research findings cause the market to become more efficient" (pg. 968). This viewpoint or market-learns hypothesis is consistent with Malkiel (2003) who argues disappearance of abnormal returns (such as January effect) is attributable to self-destruction instead of bad-model problems that Fama (1998) once addressed: many of these patterns, even if they did exist, could self-destruct in the future, as many of them have already done (pg. 72). From another viewpoint, Boudoukh, Richardson, and Whitelaw (1994), Grinblatt, Titman, and Wermer (1995), and Hong, Lim, and Stein (2000) also argue that momentum can be induced by inadequate information diffusion or under-reaction by the market participants. If so, are those under-reaction and over-reaction abatable once market friction or noises (such as no tax, no transaction cost, no bid-ask spread, no difference in the borrowing and

[22] See also Schwert (2003, pg. 947): Fama and French are not able to explain the short-term momentum effects found by Jegadeesh and Titman (1993) using their three-factor model.

lending rate, and no margin requirement) are mitigated? If research results help market become efficient or improve allocating efficiency, there certainly exists room for improvement and that implies that market is in the state of inefficiency, and that seems to contradict the EMH. Once again market inefficiency logically could only result from pricing irregularity or irrational decisions, leading to arbitrage opportunities.

Shleifer and Vishny (1997) suggest that preference of money managers can cause persistent irregularity in the pricing, which is consistent with Pontiff (1996) who asserts that agency problem associated with money professionals' choice of certain portfolios might contribute to irregularity in the pricing. One might argue that an investor when drawing conclusions from too little data would misprice the underlying asset and therefore cause the bubble in the security price. Furthermore, Grossman and Stiglitz (1980) have implied that imbalanced noise could be present in forming a rational expectation so that the informed agent can possibly trade without revealing his private information and make a profit on information collected. This implies that an investor may benefit, but not irrationally beyond the risk premium undertaken, at the expense of the market which is not as well informed – though all market participants can be rational and utility-maximizing agents (see Rubinsetin, 2001). Consistently, List[23] (2003) argues that experienced agents eliminates market anomalies while unsophisticated parties require judicial attention in asset allocation as the latter suffer important losses and their presence considerably influences the distribution of incomes (pg. 68). This might show that experience and preparedness matter in the financial trading. Dirac (1964) claims that "the person who acts in accordance with limited knowledge will on the average do worse than the person who buys and sells at random" (see Lim, 2006, pg. 2). Furthermore, these findings might shed some light on whether there is a bias in information processing and how does it entail a potential

[23] He approves that "in a competitive market presence of sophisticated consumers yields equilibria consistent with a market that contains only experienced consumers" (pg. 69).

weakness in the EMH concerned by Fama (1998). In fact, the EMH is based on the assumption of semi-strong efficiency: price reflects all available market information, implying that firm traders cannot profit from the fooling investors consistently. So any sound evidence showing the disconnection of price and available market information might put cast a serious doubt on the validity of the EMH. Hence Fama (1998) stresses that [Any alternative model] must specify biases in information processing that cause the same investors to under-react to some types of events and over-react to others (pg. 284). In fact Malkiel (2005) recognizes the program and states: at least ex-post, there seem to be several instances where market prices failed to reflect available information. Similarly, behavioralists claim that investors sometimes exhibit *conservatism*, meaning investors are too slow in adjusting their beliefs to new information, for example, slow responsiveness in security price changes to earnings surprises. Hence Roll (1994) has suggested that market information would require subtle interpretation and scrutiny. If this were true, informed investors would be allowed to make short run excess profit, but they would inevitably alter the prices and thereby convey (maybe publicly available) information to uninformed investors who now would have become informed. That is to say, by and large, *ex post* every market participant will acquire the additional information, and consequently no participant particularly has an information edge over others. It follows that then short run abnormal returns would be possible, even the market in the long run is eventually efficient. Other than these psychological factors, Zhang (2005) attributes the nature of return anomalies to specific risks, "some anomalies are empirical relations of future stock returns with firm characteristics, corporate policies, and events – relations not predicted by current rational asset pricing theories" (pg. 38).

3 DATA SET, METHODOLOGY, AND EMPIRICAL TESTING

I use the data set extracted from Kenneth R. French's Data Library[24] to test for the momentum effect, the explanatory power or R^2 over time, January effect, and any sign of persistency with modified time-series Black Jensen and Schole's (1972) approach that dispenses the data set into an array of portfolios varying in size, BE/ME ratio, and other variables that are specified (such as the FITs). The data contains 240 monthly returns on the equal-weighted indices covering the period from August 1977 to July 1997. Twenty years of panel study is considered a justifiable length for time-series analysis and we believe the explanatory power of any possible model combination can hardly be sustainable at any longer periods after around 1993 or the 190 period on the scale (as shown in Figure 13). An extension of monthly data set covering October 1995 to September 2005 is also examined for the model's explanatory power and forecastibility. The returns are given, where dividend are believed part of total value. To test to second period with the estimated parameters obtained in the first period, this sample ranging from August 1977 to July 1997 is divided into 2 periods of 15 and 5 years, and each period is analyzed separately. We believe the estimated parameters are more accurate with more data included. The data partition is motivated by rendering an in-sample testing and verifying out-of-the-sample forecasting within the last four-year time window from August 1993 to July 1997.

A series of testing conducted in the following is to examine semi-strong form of market efficiency – check if the expected rates of risk-adjusted returns are the same cross-sectional. The null hypothesis is that the market is efficient; therefore rejection of the null hypothesis indicates

[24] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

market inefficiency, but does not necessarily indicate any real arbitrage opportunity[25]. In addition, for a strategy of investing stocks of small size firms or buying firms in late December and selling in early January may not work, because the market is already informed of this type of return anomalies and would exploit them. If there is an obvious pattern in the stock price movement, the profit would be competed away.

First, to test the Efficiency Market Hypothesis we assess non-linear transformation of the IPs' regression residuals with the CAPM model and detect for the magnitude and frequency of positive autocorrelation, an experiment similar to that by Akgiray (1989) to see whether returns are purely random and EMH can hold. Second, we test the effectiveness of different models such as CAPM, Three Factor model (FF), Five Factor model (FFF) and Six Factor model (SFF) and verify with the statistical significance of variables such as Small-minus-Big (SMB)[26], High-minus-Low (HML) and FITs in order to learn whether CAPM can be replaced with ease by other models. Third, we construct a modified 3 factor model that include the FITs and a Fama and French' factor to forecast the future returns, and examine how would the explanatory power of the modified model peak and fall over time in a span of 20 years. This part of testing also aims to examine Fama (1998)'s updated contention that predictability is impossible even though market is less efficiency. Lastly, to further test for market efficiency in the U.S. financial market context, we formulate a portfolio strategy that allows an investor to switch between two markets of US Treasury securities market and the S&P 500 stock index in periods of August 1977 to July 1997. To keep up with the updated data, we then analyze a time series of monthly data for the interest rate on 3-month US government Treasury bills from October 1985 through September 2005. The strategy assumes that little, if any, transaction cost, and that when the US Treasury securities

[25] The considerable economic, but small statistical dependency might not permit investors to realize excess returns.
[26] Fama (1997) states: "SMB is the difference between the returns on portfolios of small and big stocks (below or above the NYSE median), and HML is the difference between the returns on portfolios of high- and low- BE/ME stocks (above and below the .7 and .3 fractiles of BE/ME."

market is declining, he/she would be able to switch to the stock index market. We use the CIR VR interest model to estimate the future 1 month interest rate as well as the GARCH process for CAPM and the 3 Factor Model for forecasting the future stock index returns. The return distribution of 12 Industry Portfolio (IPs) and more details of further methodology in the time span of in-sample observations of 15 years are as follows:

Figure 2 Boxplot of Returns of 12 Industry Portfolio

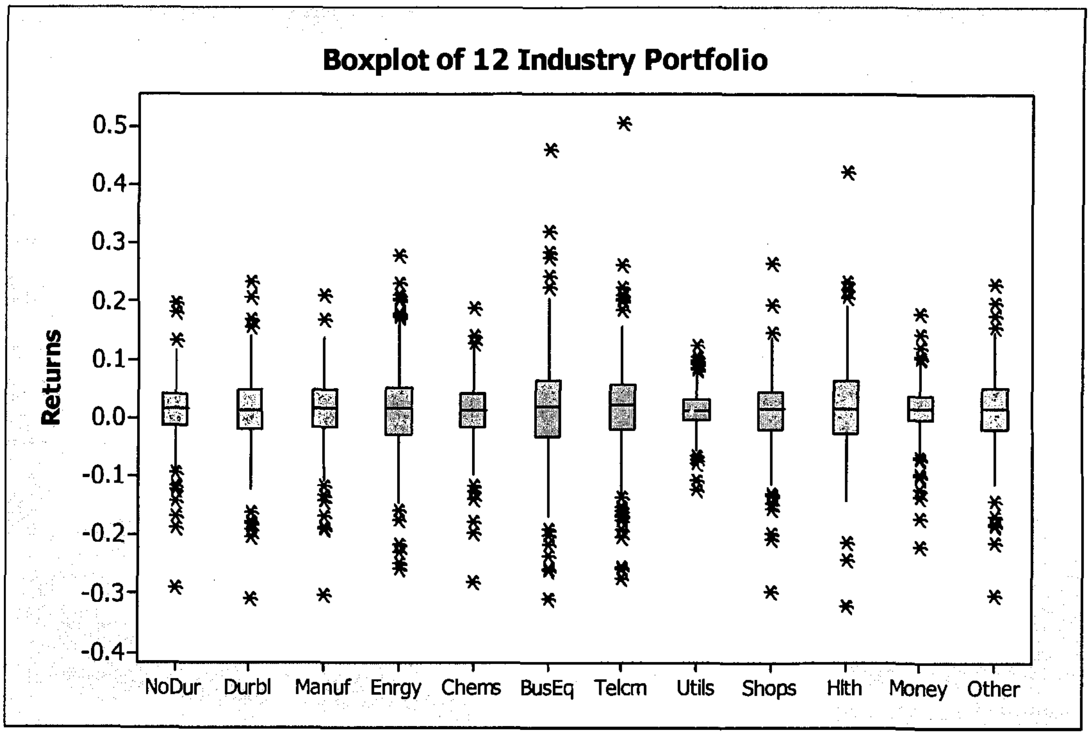
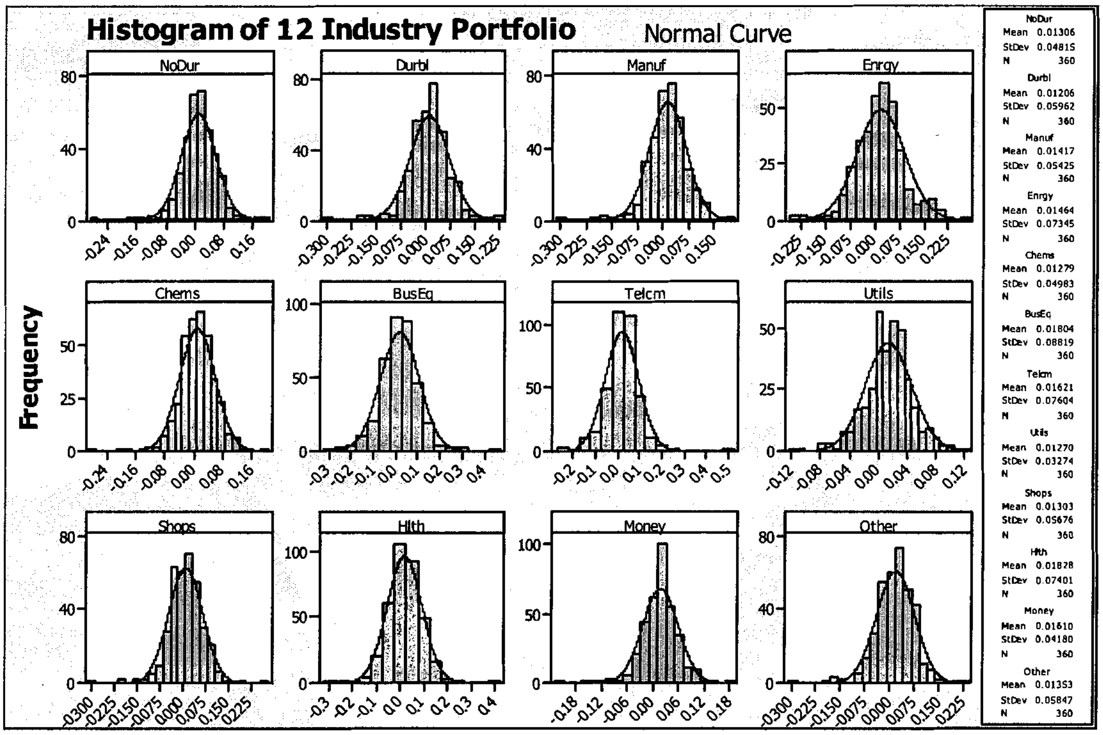


Figure 3 Histogram and Normal Curve of Returns of 12 Industry Portfolio



Following Fama (1998)'s suggestion of adjustment on methodology, General Least Square (GLS) technique is used to correct for some forms of non-spherical disturbances such as heteroskedasticity and serial correlation across sections – embedded in past stock price – and use the three factor model (and later includes 'the fit') to abate the bad-model problems that have been first refined with small capitalization variable and the BE/ME variable, etc. The return distributions of these independent variables are shown below:

Figure 4 Boxplot of Returns of Excess Market Return, SMB, HML, MOMEN, and RF.

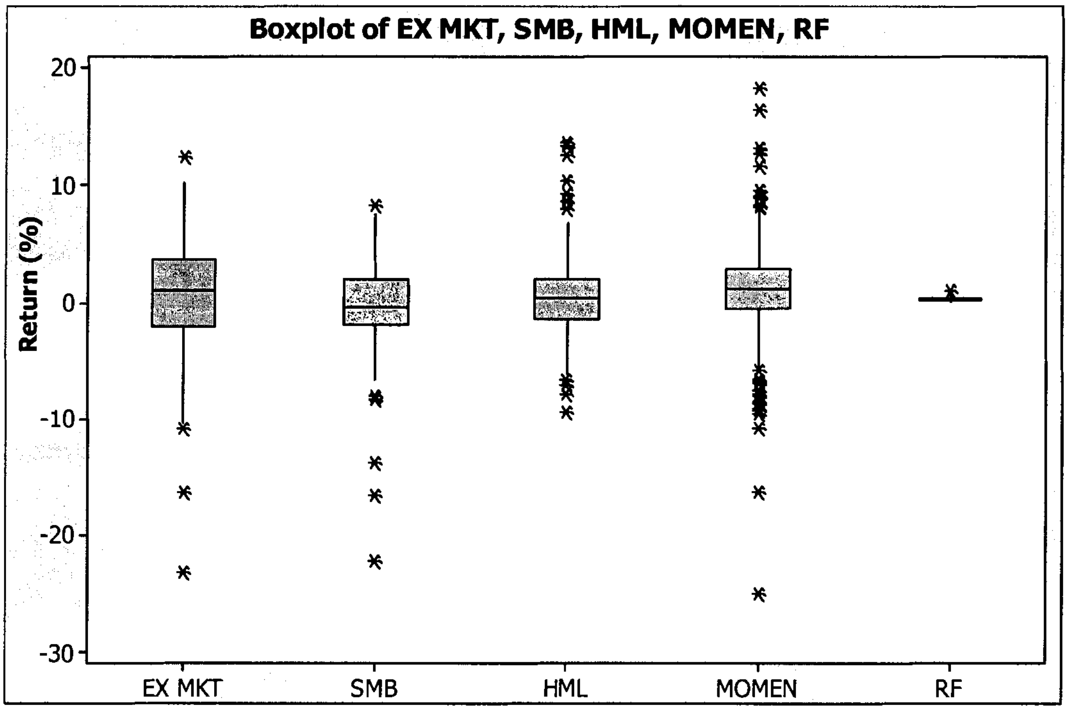
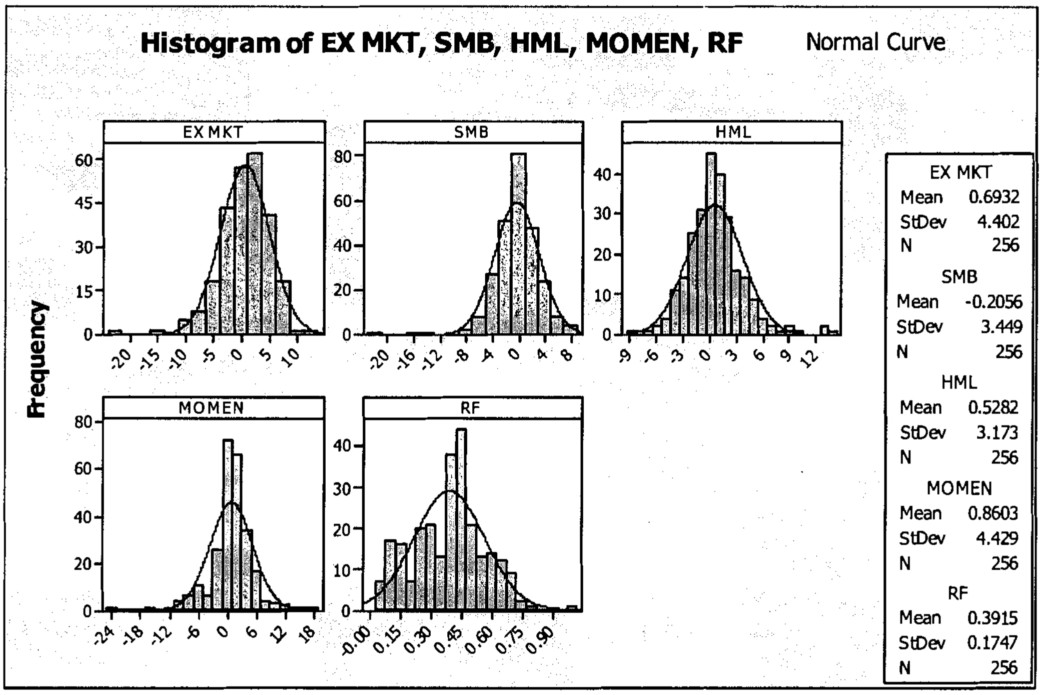


Figure 5 Histogram and Normal Curve of Returns of Ex Market, SMB, HML, MOMEN, and RF



4 RESULTS AND DISCUSSION

It is found that (i) the momentum effect and January effect exhibit statistically, though not economically, significant when both tested separately within the first 15-year investment horizon, but become less significant in the last 4-year horizon. Also once a conditional variable, the FIT[27], composed with modified 3 Factor model is inserted, the former two become less statistically significant at 5% level for the F-test, (ii) the explanatory power of the modified Black, Jensen and Scholes (BJS)'s model peaks and falls over time with some long-term in-sample evidence, but if we extend the time from current 15 year horizon to include another 4 years, it still results a sound out-of-sample evidence, though at much lower R-squares and the t-statistics, and (iii) consistent with Malkiel (2005) and Zhang (2005), we also find there are some evidence of predictability in a stock model even we do not assume market efficiency – such predictability depends on the correlation of the identified variable implicitly causing the abnormal returns (or return anomalies) to the underlying asset or investment.

4.1 Empirical Testing I White Noises for CAPM and FF

This section includes a comprehensive analysis of the distributional and time-series properties of portfolio residuals in the 12 industry portfolio denotes as IP_i for periods from August 1977 to Oct 2005: 340 periods. The purpose is to determine whether the regression residual of portfolio price movements can be adequately represented by linear white-noise processes and to identify an appropriate model if the residuals are not random – the experiment is done similar to Akgiray (1989). The assumption is that even though the original data exhibit randomness, the residual after fitting Y_{t+s} and Y_t should result in random residuals. If R_{t+s} and R_t are statistically independent, then the process is called "strictly white noise" or purely

[27] Ferson and Harvey (1992) provide an informative discussion of the FIT, reflecting the changes in the fundamental value in the economy.

random. If the regression residual process R_t is "strictly white noise", the autocorrelation value, with any form of transformation to the return residuals, should be close to zero and for any and all lags. That is to say, there is no way we can infer from the current value R_{t+s} to what next value R_t will be. Further, the process $\{|R_t|\}$ and $\{R_t^2\}$ should also be strictly white noise as well. Otherwise, Akgiray (1989) argues this is a conclusive rejection of the hypothesis that residual series are strict white-noise processes and therefore serves as statistical evidence against semistrong-form efficiency.

In order to investigate the reasons for lack of independence, the sample autocorrelation functions are analyzed. The estimated autocorrelations plot for the residual series $\{R_t\}$, $\{|R_t|\}$, and $\{R_t^2\}$ for the whole 340 periods from August 1977 to October 2005 are shown in figure 7-12. For notation, $\{R_t\}$, $\{|R_t|\}$, and $\{R_t^2\}$ are denoted as *Autocorrelation function* (ACF), *Absolute Autocorrelation function* (AACF), and *Squared Autocorrelation function* (SACF), respectively. Some of the IP_i residual series display high degree of first lag (lag 1) autocorrelation while some display apparently insignificant autocorrelations beyond the second lag.

The sample autocorrelation function is defined as $\overline{\rho_k} = \dfrac{\sum_{t=1}^{T-k}(y_t - \overline{y})(y_{t+k} - \overline{y})}{\sum_{t=1}^{T}(y_t - \overline{y})^2}$

where $y_t = \varepsilon_t$, representing the white noise process. If the return residual is found to follow white noise process then it can not be random walk. Random walk Hypothesis, as one of the EMH's major assumptions, implies returns residuals are serially uncorrelated so that $\overline{\rho_k}$ should be zero theoretically. In addition, we define the standard error of the estimated partial autocorrelation $\overline{\rho_{kk}}$ as $\overline{\sigma}[\overline{\rho_{kk}}] \cong \frac{1}{\sqrt{T}}$.

Like Akgiray (1989), using $1/\sqrt{T}$ (0.054233 in this case) as the standard error of these estimates, some of the residuals in this study are greater than $7/\sqrt{T}$ (0.379628). Note that ninety-five percent confidence bands ($\pm 2/\sqrt{T}$) are plotted on the 6 panels of 12 Industry Portfolio (See Hamilton, 1994, pg. 112, for band construction) on the assumption that the model is AR(1). According to Akgiray (1989), even though the $1/\sqrt{T}$ value may be an understatement of the standard error (due to the non-normality of returns), seven times this value is a sufficiently large confident bound. Similarly, the autocorrelations in the absolute and square residual series are always much higher than those in the residual series, and some of them are consistently significantly positive up to 30 lags (see Figure 7-12, for example). This is consistent with Fama and French (1998) who find mean reverse effect at a 3 to 5 year horizon, which is about 36 month and 60-month observations (See Figure 6). In addition, Box (1994) notes that the use of $1/\sqrt{T}$ as standard error for residuals of IPs might underestimate the statistical significance at low lags but could be satisfactorily at longer lags. Nevertheless, Akgiray (1989) states that since it is not always the case that the autocorrelation between absolute residuals is generally higher than that in square residual, this finding may not agree with those reported in the classic work of Fama (1965) who argues that price changes should reflect the same magnitude in the residuals. Moreover, it is shown in the autocorrelation plot that the distribution of the next absolute or square residuals depends not only on the current residual but also on several previous residuals. In the other word, a pattern exhibits a strong positive autocorrelation over long lags for both the squared and absolute ACFs, and is decreasing linearly and continuously until it becomes negatively auto-correlated – exhibiting a clear marked correlation pattern in majority of the IPs. This gives a conclusive statistically rejection of the hypothesis that residual series are strictly white-noise processes. Note that Akgiray (1989) suggests of using GARCH to model the nonlinear process such as conditional heteroskedasticity residual to account for time-varying patter in returns, as is the case for the squared residual series displaying a significant pattern of autocorrelation over long lags in this study. However the trend eventually enters the negative zone after passing a certain lag – this is of some evidence against the *Random Walk Hypothesis*, in which there exists no mean-reversion effect. Both the variable, Momentum, and the return residuals of 12 IPs exhibit a marked pattern of positive autocorrelation up to a certain lag, which is sufficient enough to prove the violation of random walk that lies at the core of the problem with the EMH.

Figure 6 Autocorrelation Plot of ACF, AACF, SACF of Momentum

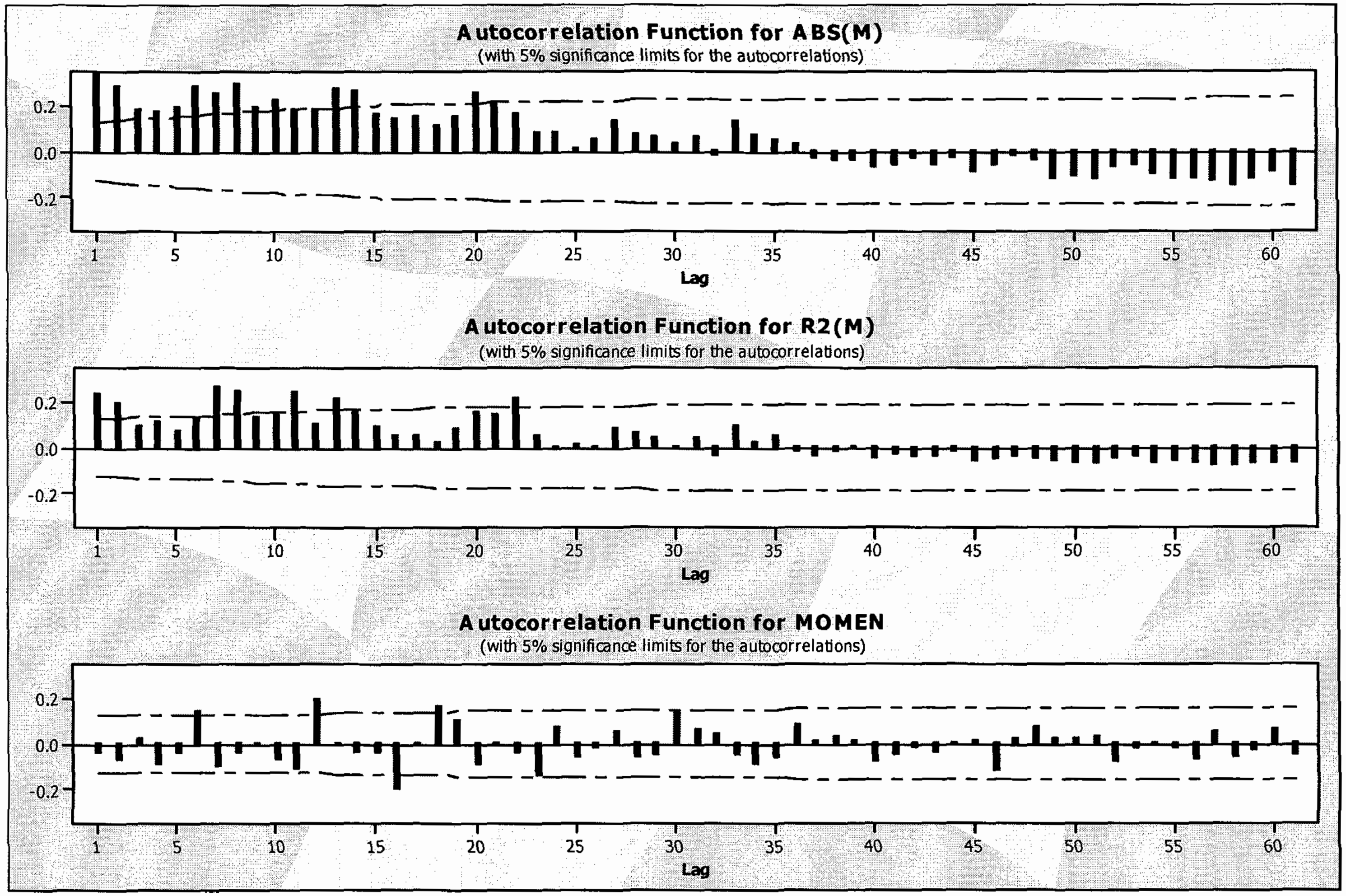


Figure 7 Autocorrelation Plot of IP1 and IP2

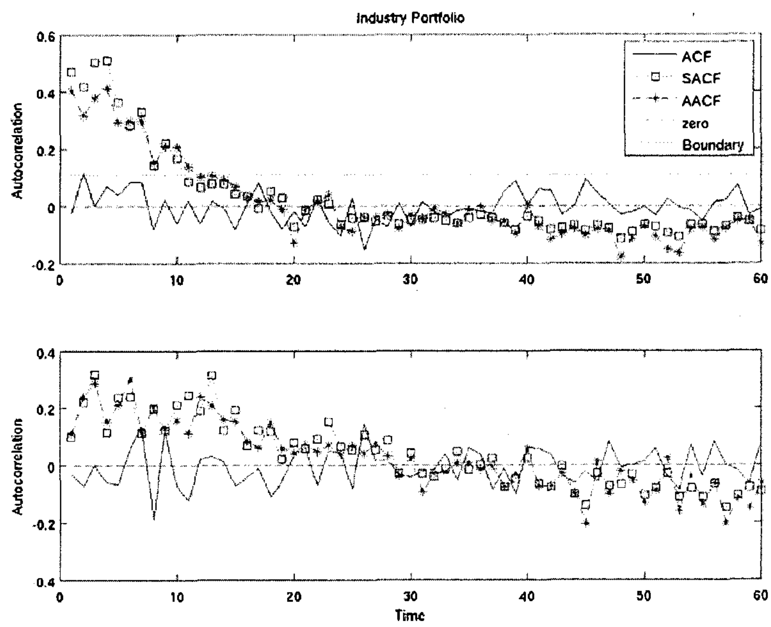


Figure 8 Autocorrelation Plot of IP3 and IP4

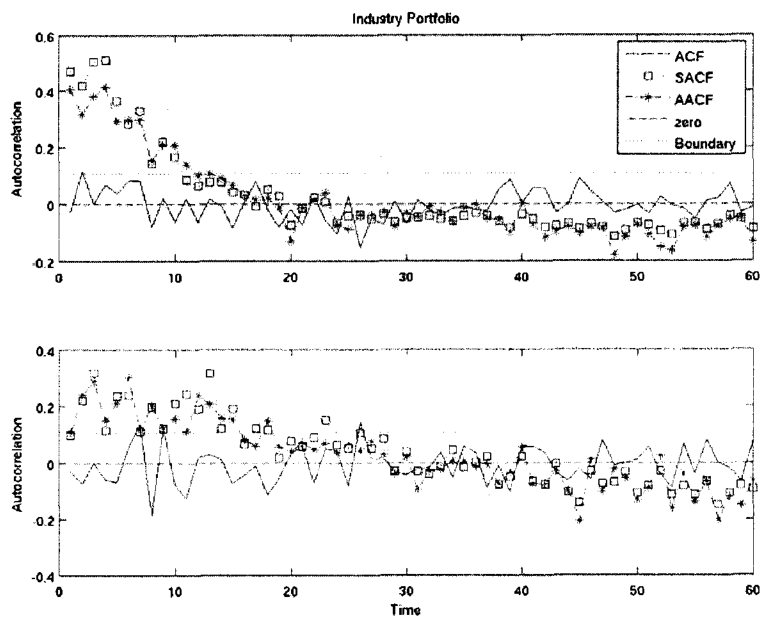


Figure 9 Autocorrelation Plot of IP5 and IP6

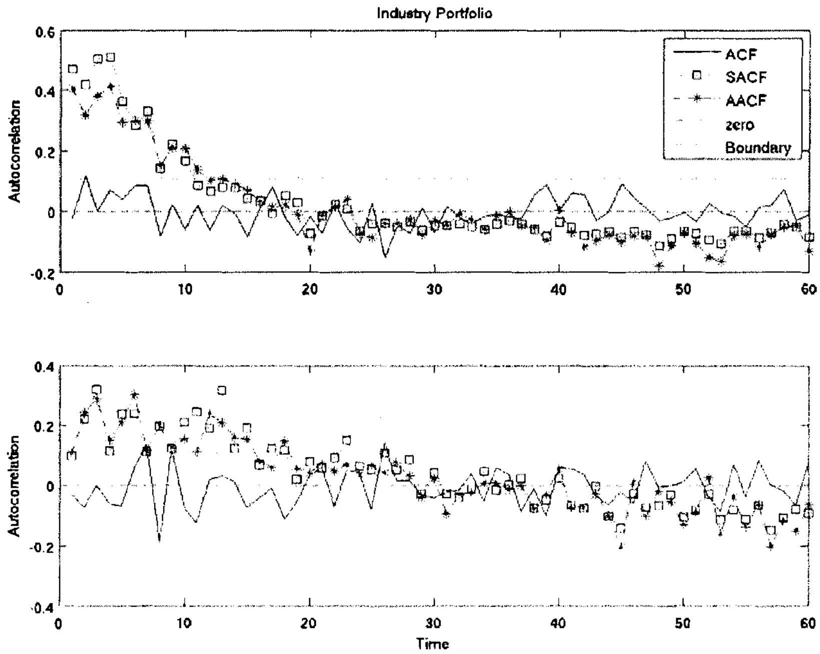


Figure 10 Autocorrelation Plot of IP7 and IP8

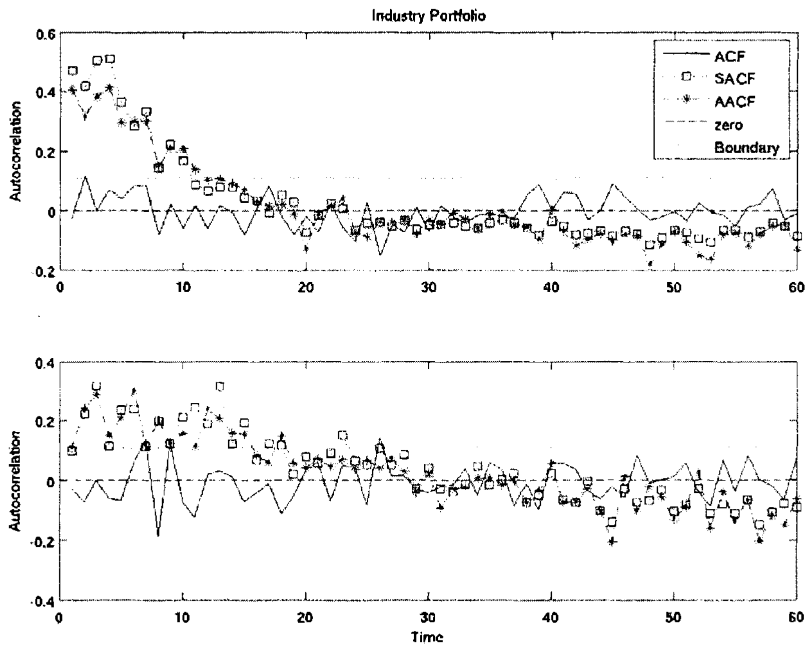


Figure 11 Autocorrelation Plot of IP9 and IP10

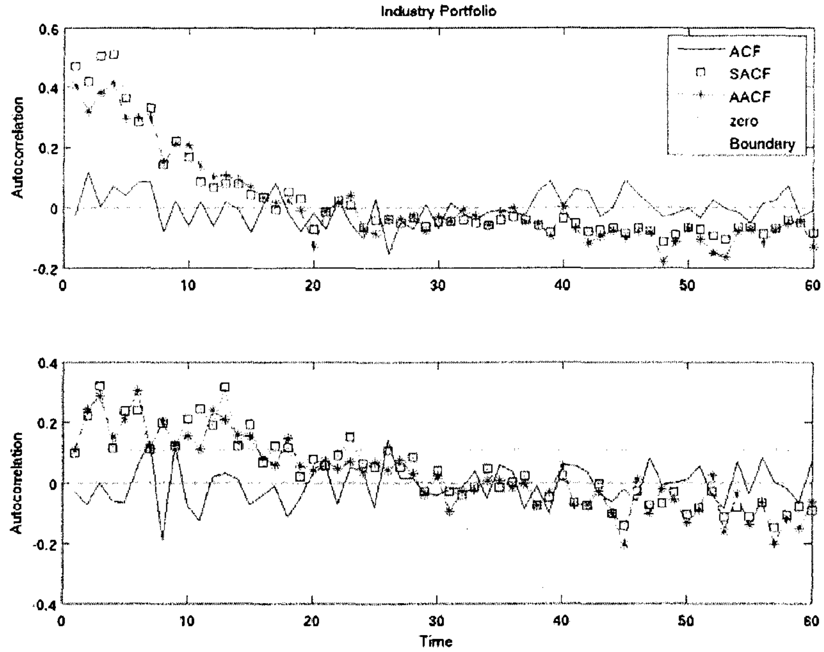
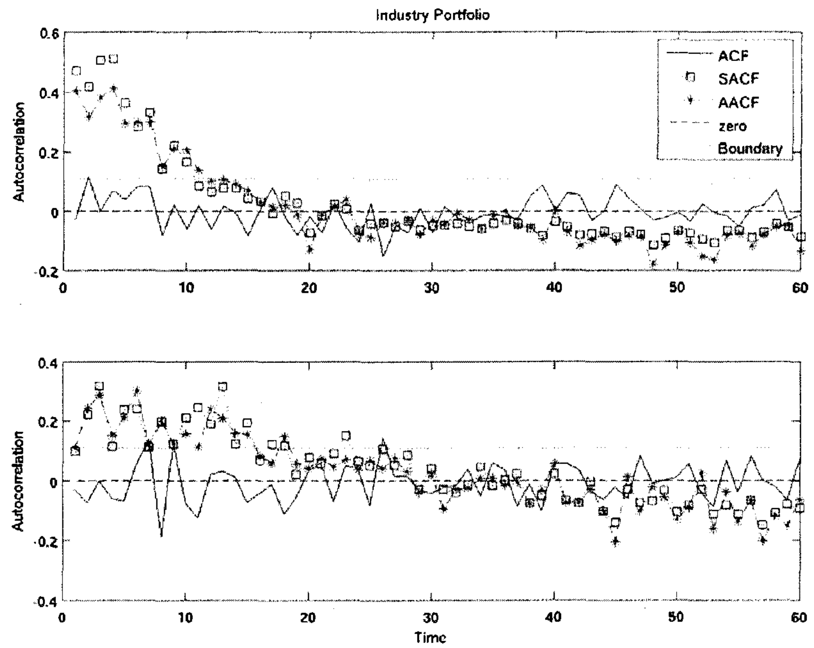


Figure 12 Autocorrelation Plot of IP11 and IP12



4.2 Empirical Testing II Effectiveness of Various Models

Before accounting for heteroscedastic time-series models, we intend to examine the effectiveness of each measure of most recognized asset-pricing models such as the Capital Asset Pricing Model (CAPM) of Sharpe & Lintner and the Fama French's Three Factor Model (FF) as well as the Five Factor Model (FFF) and Six Factor Model (SFF). While Five Factor Model includes the identified return anomalies candidate such as January effect and the Momentum effect, the SFF include an identified variable, a proxy for the "FIT". Note we have three candidates for the FITs: FIT1, FIT 2 and the combination of the two for SFF (FIT1&2). To compare the models, we use the dataset from the Ken and French Library providing for 12 Industry Portfolios, the three factors, and the momentum (Refer to Figure 2-5) over time periods including observations from August 1977 to July 1997. The objective is to examine the frequency of significant absolute alphas and the corrected R^2 for model effectiveness. Note that 12 industry portfolio, IP_i, contains NoDur, Durbl, Manuf, Enrgy, Chems, BusEq, Telcm, Utils, Shops, Hlth, Money, and Other (correspondingly, the monthly returns for Consumer NonDurables, Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Telephone and Television Transmission, Utilities, Wholesale and Retail, Healthcare, Finance, and Other industry portfolios of security). For example, IP_2 refers to Consumer Durables. Note the explanatory power of HML seems to be more lasting than is SMB as shown in Table 1 through 6, and we confirm that the combination of FIT1 and FIT2 are significant in each subset of 20 years of time-series data.

CAPM: $r_{a,t} = \alpha_a + \beta_a MKT_t + \varepsilon_{a,t}$

Fama and French Three Factor Model: $r_{a,t} = \alpha_a + \beta_{a,1} MKT_t + \beta_{a,2} SMB_t + \beta_{a,3} HML_t + \varepsilon_{a,t}$

Five Factor Model:

$$r_{a,t} = \alpha_a + \beta_{a,1} MKT_t + \beta_{a,2} SMB_t + \beta_{a,3} HML_t + \beta_{a,4} MO_t + \beta_{a,5} JAN_t + \varepsilon_{a,t}$$

Six Factor Model:

$$r_{a,t} = \alpha_a + \beta_{a,1} MKT_t + \beta_{a,2} SMB_t + \beta_{a,3} HML_t + \beta_{a,4} MO_t + \beta_{a,5} JAN_t + \beta_{a,6} FIT_{n,t} + \varepsilon_{a,t}.$$

where $r_{a,t} = r_i - r_f$ and $\varepsilon_{a,t} \sim N(0,\sigma)$. We define F-test as $F_{q,N-k} = \frac{\left(R_{ur}^2 - R_r^2\right)/q}{\left(1 - R_{ur}^2\right)/(n-k)}$ where

R_{ur}^2 is the R-square for unrestricted model, q for number of restrictions and k for total independent variables (including the alpha).

Table 1 20 Years of Significant Variables in Various Models

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	4	12	10	7	8	1	9
SFF(FIT2)	2	12	10	7	7	3	6
SFF(FIT1)	2	12	10	7	7	2	3
FFF	2	12	10	7	8	2	
FF	3	12	10	7			
CAPM	1	12					

Table 2 First 5 years of Significant Variables in Various Model

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	3	9	2	4	2	1	6
SFF(FIT2)	0	12	4	4	7	2	2
SFF(FIT1)	0	12	5	3	6	0	2
FFF	0	12	6	4	6	2	
FF	0	12	4	5			
CAPM	0	12					

Table 3 Second 5 years of Significant Variables in Various Model

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	3	11	5	7	1	0	5
SFF(FIT2)	0	12	5	7	10	1	1
SFF(FIT1)	0	12	5	7	7	0	1
FFF	0	12	5	7	9	0	
FF	1	12	5	6			
CAPM	1	12					

Table 4 Third 5 years of Significant Variables in Various Model

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	2	11	5	5	2	1	6
SFF(FIT2)	1	12	8	4	1	1	2
SFF(FIT1)	1	12	7	5	2	1	2
FFF	1	12	6	5	2	1	
FF	2	12	8	6			
CAPM	1	12					

Table 5 Last 5 years of Significant Variables in Various Model

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	3	11	3	6	4	0	3
SFF(FIT2)	1	12	5	7	4	0	0
SFF(FIT1)	0	12	5	6	3	0	0
FFF	1	12	5	7	4	0	
FF	2	12	5	7			
CAPM	0	12					

Table 6 20 Years of Significant Variables in Various Models of 240 Periods from October 1985 to September 2005

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	2	12	6	10	6	2	8
SFF(FIT2)	0	12	5	10	6	3	3
SFF(FIT1)	0	12	5	10	4	4	1
FFF	0	12	5	10	5	4	
FF	2	12	5	10			
CAPM	0	12					

In light of the t-statistics of the absolute alphas, the CAPM seems to be effective in reflecting variations in market movement than that of the FF over 20 years of analysis, because at 5% significant level there is only one extreme IP_i (out of twelve) compared with three for FF, two for FFF and two for SFF for both candidate FIT1 and FIT2. Because CAPM scores less significant in the alpha reading, it implies that much more of the variations in the dependent variable can be explained by the variations in the independent variables than if it were the case for other models such as FF, FF, FFF and SFF. Having said that, the R^2 provides counter evidences showing all of FF, FFF and SFF outperform the CAPM on the average (see Table 7-

13). The F-test also shows that F-values in majority of each measure are higher than 3.7 (at 5% significant level). The F-test as a proof of increased explanatory power of the CAPM model due to adding new and significant variables such as SMB and HML, MOMENTUM and JAN, and FITs[28]– the add-on components to the FF, FFF, SFF models, respectively. Note that for the combination of FIT1 and FIT2 at t = T (meaning present-to-present), the F-tests of SFF_FF scores 11.002 comparative with 15.865 of the FF_CAPM reading, suggesting that adding the FIT1&2 is two-third as much significant to FF as FF to CAPM in terms of explanatory power in synchronous time (Table 16). This suggests that FIT1&2 is a significant fact in explaining the IPs. Since CAPM is can be regarded as a subset of FF, the robust F-test results and a bit higher R^2 of other models such as FF, FFF, and SFF allow us to conclude the new variable, FIT1&2, matter.

Table 7 CAPM: MKTRF

α	β1	α - tstat	β1-tstat	C R^2	R^2	DW
0.0041	0.8984	2.8389	27.1830	0.7554	0.7564	1.6623
-0.0018	1.0229	-0.8688	21.2330	0.6531	0.6545	1.6136
-0.0009	1.0981	-0.9176	48.3460	0.9072	0.9076	1.9989
0.0010	0.8457	0.3991	14.1860	0.4559	0.4582	1.6649
0.0005	1.0309	0.4358	37.3070	0.8534	0.8540	1.9853
-0.0015	1.1850	-0.7378	24.7970	0.7198	0.7210	1.9811
0.0021	0.7116	1.1670	17.6020	0.5637	0.5656	1.7835
0.0010	0.5302	0.5602	13.3070	0.4242	0.4266	1.9381
0.0001	1.0941	0.0714	29.7430	0.7871	0.7880	1.6503
0.0027	0.9728	1.4765	23.5830	0.6991	0.7003	1.7675
0.0024	1.0012	1.6233	29.1080	0.7798	0.7807	1.6667
-0.0009	1.1665	-0.8910	50.3360	0.9138	0.9141	1.8062
		1	12			

[28] FIT candidates are FIT1, FIT2, and combination of the two.

Table 8 Fama and French's 3 Factor Model: MKTRF, SMB, HML

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0043	0.9025	-0.0790	-0.0260	2.8783	23.4810	-1.3307	-0.3998	0.7552	0.7582	1.6673
-0.0047	1.1351	0.2462	0.5119	-2.3090	21.7740	3.0593	5.8024	0.6994	0.7031	1.8004
-0.0009	1.0703	0.1643	-0.0126	-0.9405	41.8880	4.1646	-0.2915	0.9131	0.9142	2.0058
-0.0001	0.9580	-0.2702	0.2497	-0.0521	14.1480	-2.5850	2.1789	0.4807	0.4872	1.6216
0.0004	1.0567	-0.0976	0.0393	0.2995	33.0990	-1.9799	0.7269	0.8552	0.8570	2.0056
0.0012	0.9914	0.2293	-0.5513	0.6451	19.8420	2.9721	-6.5192	0.7734	0.7762	1.8424
0.0009	0.8110	-0.2019	0.2403	0.5146	17.9450	-2.8929	3.1419	0.5966	0.6016	1.7858
-0.0009	0.6904	-0.3186	0.3904	-0.5772	16.7990	-5.0205	5.6124	0.5468	0.5525	1.9386
0.0004	1.0245	0.3216	-0.0770	0.2265	25.3320	5.1502	-1.1245	0.8096	0.8120	1.6767
0.0053	0.8639	-0.2059	-0.4800	3.1094	19.6050	-3.0264	-6.4371	0.7459	0.7491	1.8462
0.0002	1.1043	0.1063	0.4094	0.1593	29.9480	1.8675	6.5602	0.8127	0.8151	1.8196
-0.0010	1.1303	0.2355	-0.0053	-1.0258	45.0110	6.0737	-0.1250	0.9251	0.9260	1.8814
Number of Significant Variables				3	12	10	7			

Table 9 Fama and French's 3 Factor Model: MKTRF, SMB, HML

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0043	0.9025	-0.0790	-0.0260	2.8783	23.4810	-1.3307	-0.3998	0.7552	0.7582	1.6673
-0.0047	1.1351	0.2462	0.5119	-2.3090	21.7740	3.0593	5.8024	0.6994	0.7031	1.8004
-0.0009	1.0703	0.1643	-0.0126	-0.9405	41.8880	4.1646	-0.2915	0.9131	0.9142	2.0058
-0.0001	0.9580	-0.2702	0.2497	-0.0521	14.1480	-2.5850	2.1789	0.4807	0.4872	1.6216
0.0004	1.0567	-0.0976	0.0393	0.2995	33.0990	-1.9799	0.7269	0.8552	0.8570	2.0056
0.0012	0.9914	0.2293	-0.5513	0.6451	19.8420	2.9721	-6.5192	0.7734	0.7762	1.8424

0.0009	0.8110	-0.2019	0.2403	0.5146	17.9450	-2.8929	3.1419	0.5966	0.6016	1.7858
-0.0009	0.6904	-0.3186	0.3904	-0.5772	16.7990	-5.0205	5.6124	0.5468	0.5525	1.9386
0.0004	1.0245	0.3216	-0.0770	0.2265	25.3320	5.1502	-1.1245	0.8096	0.8120	1.6767
0.0053	0.8639	-0.2059	-0.4800	3.1094	19.6050	-3.0264	-6.4371	0.7459	0.7491	1.8462
0.0002	1.1043	0.1063	0.4094	0.1593	29.9480	1.8675	6.5602	0.8127	0.8151	1.8196
-0.0010	1.1303	0.2355	-0.0053	-1.0258	45.0110	6.0737	-0.1250	0.9251	0.9260	1.8814
Number of Significant Variables				**3**	**12**	**10**	**7**			

Table 10 FFF: MKTRF, SMB, HML, MO, JAN

α	β1	β2	β3	β4	β5	α - tstat	β1-tstat	β2-tstat	β3-tstat	β4-tstat	β5-tstat	C R^2	R^2	DW
0.005	0.916	-0.067	0.005	-0.008	-0.011	3.159	23.275	-1.124	0.068	-0.175	-1.969	0.757	0.762	1.649
-0.003	1.151	0.231	0.455	-0.190	0.005	-1.550	21.858	2.904	5.057	-3.013	0.647	0.710	0.716	1.816
0.000	1.082	0.162	-0.027	-0.083	-0.001	-0.108	41.611	4.119	-0.610	-2.681	-0.397	0.915	0.917	2.013
-0.002	0.942	-0.255	0.306	0.186	-0.005	-0.522	13.646	-2.445	2.596	2.250	-0.507	0.489	0.500	1.623
0.002	1.082	-0.097	0.026	-0.151	-0.007	1.648	33.964	-2.020	0.482	-3.963	-1.575	0.864	0.866	2.051
0.001	0.980	0.194	-0.656	-0.146	0.023	0.528	19.852	2.604	-7.776	-2.478	3.450	0.791	0.795	1.784
0.001	0.817	-0.204	0.232	-0.043	-0.001	0.695	17.518	-2.891	2.914	-0.780	-0.074	0.594	0.603	1.793
-0.002	0.682	-0.309	0.425	0.109	-0.003	-0.986	16.255	-4.881	5.932	2.182	-0.559	0.554	0.563	1.956
0.002	1.056	0.328	-0.073	-0.146	-0.012	1.445	25.894	5.331	-1.054	-2.990	-2.135	0.817	0.821	1.717
0.005	0.864	-0.213	-0.502	-0.043	0.004	2.953	19.033	-3.108	-6.483	-0.789	0.670	0.745	0.751	1.840
0.002	1.128	0.107	0.398	-0.139	-0.007	1.229	30.267	1.898	6.251	-3.120	-1.271	0.819	0.823	1.823
-0.001	1.127	0.231	-0.019	-0.012	0.004	-1.068	43.594	5.906	-0.428	-0.390	1.003	0.925	0.926	1.884
Number of Significant Variables						**2**	**12**	**10**	**7**	**8**	**2**			

Table 11 SFF: MKTRF, SMB, HML, MO, JAN, FIT1

α	β1	β2	β3	β4	β5	β6	α – tstat	β1-t stat	β2-tstat	β3-tstat	β4-tstat	β5-tstat	β6-tstat	C R^2	R^2	DW
0.01	0.88	-0.07	-0.03	0.00	-0.01	0.00	3.26	20.33	-1.16	-0.46	0.09	-1.68	-1.84	0.76	0.77	1.66
0.00	1.16	0.23	0.47	-0.19	0.00	0.00	-1.57	19.92	2.91	4.98	-3.05	0.56	0.51	0.71	0.72	1.82
0.00	1.10	0.16	-0.01	-0.09	0.00	0.00	-0.17	38.24	4.15	-0.19	-2.86	-0.60	1.40	0.92	0.92	2.02
0.00	1.04	-0.25	0.41	0.15	-0.01	0.00	-0.68	13.89	-2.43	3.43	1.83	-0.97	3.12	0.51	0.52	1.68
0.00	1.10	-0.10	0.04	-0.16	-0.01	0.00	1.61	31.00	-2.00	0.70	-4.04	-1.68	0.84	0.86	0.87	2.05
0.00	1.02	0.20	-0.61	-0.16	0.02	0.00	0.45	18.73	2.65	-6.99	-2.71	3.17	1.71	0.79	0.80	1.78
0.00	0.79	-0.21	0.20	-0.03	0.00	0.00	0.76	15.27	-2.92	2.42	-0.59	0.12	-1.32	0.60	0.61	1.81
0.00	0.59	-0.31	0.33	0.14	0.00	0.00	-0.81	13.31	-5.18	4.60	2.91	0.11	-4.62	0.59	0.60	2.13
0.00	1.04	0.33	-0.09	-0.14	-0.01	0.00	1.48	23.04	5.31	-1.22	-2.85	-2.00	-0.73	0.82	0.82	1.72
0.01	0.84	-0.21	-0.53	-0.03	0.01	0.00	3.00	16.73	-3.13	-6.52	-0.63	0.82	-1.07	0.75	0.75	1.86
0.00	1.08	0.10	0.34	-0.12	0.00	0.00	1.39	26.50	1.87	5.23	-2.72	-0.83	-2.99	0.83	0.83	1.89
0.00	1.14	0.23	-0.01	-0.02	0.00	0.00	-1.11	39.72	5.92	-0.15	-0.51	0.86	0.90	0.92	0.93	1.88
Number of Significant Variables							2	12	10	7	7	2	3			

Table 12 SFF: MKTRF, SMB, HML, MO, JAN, FIT2

α	β1	β2	β3	β4	β5	β6	α - tstat	β1-tstat	β2-tstat	β3-tstat	β4-tstat	β5-tstat	β6-tstat	C R^2	R^2	DW
0.0	0.9	-0.1	0.0	0.0	0.0	0.0	3.4	23.1	-1.2	0.2	0.1	-2.2	-2.5	0.8	0.8	1.7
0.0	1.1	0.2	0.5	-0.2	0.0	0.0	-1.4	21.6	2.9	5.2	-2.8	0.4	-2.2	0.7	0.7	1.8
0.0	1.1	0.2	0.0	-0.1	0.0	0.0	-0.1	41.2	4.1	-0.6	-2.6	-0.5	-0.6	0.9	0.9	2.0
0.0	1.0	-0.2	0.3	0.1	0.0	0.0	-0.9	15.2	-2.6	2.5	1.8	0.0	6.0	0.6	0.6	1.9
0.0	1.1	-0.1	0.0	-0.2	0.0	0.0	1.6	33.7	-2.0	0.5	-4.0	-1.5	0.4	0.9	0.9	2.0
0.0	1.0	0.2	-0.6	-0.1	0.0	0.0	0.7	19.6	2.6	-7.7	-2.3	3.3	-2.0	0.8	0.8	1.8
0.0	0.8	-0.2	0.2	0.0	0.0	0.0	0.8	17.3	-2.9	3.1	-0.6	-0.3	-2.3	0.6	0.6	1.8
0.0	0.7	-0.3	0.4	0.1	0.0	0.0	-0.9	16.0	-4.9	6.0	2.3	-0.7	-1.2	0.6	0.6	2.0
0.0	1.0	0.3	-0.1	-0.1	0.0	0.0	1.6	25.7	5.4	-0.9	-2.8	-2.4	-2.6	0.8	0.8	1.7

α	β1	β2	β3	β4	β5	β6	α - tstat	β1-tstat	β2-tstat	β3-tstat	β4-tstat	β5-tstat	β6-tstat	C R^2	R^2	DW
0.0	0.9	-0.2	-0.5	0.0	0.0	0.0	3.0	18.8	-3.1	-6.4	-0.7	0.6	-0.5	0.7	0.8	1.8
0.0	1.1	0.1	0.4	-0.1	0.0	0.0	1.4	30.0	1.9	6.4	-2.9	-1.5	-2.0	0.8	0.8	1.9
0.0	1.1	0.2	0.0	0.0	0.0	0.0	-1.0	43.2	5.9	-0.4	-0.4	1.0	-0.2	0.9	0.9	1.9
Number of Significant Variables							**2**	**12**	**10**	**7**	**7**	**3**	**6**			

Table 13 SFF: MKTRF, SMB, HML, MO, JAN, FIT1&2

α	β1	β2	β3	β4	β5	β6	α - tstat	β1-tstat	β2-tstat	β3-tstat	β4-tstat	β5-tstat	β6-tstat	C R^2	R^2	DW
0.0	0.0	0.0	0.0	0.0	0.0	0.0	-30.5	4.4	-0.2	0.3	-0.5	-0.1	142.3	1.0	1.0	0.3
0.0	1.3	0.2	0.5	-0.2	0.0	0.0	-0.9	13.4	2.8	5.1	-3.0	0.5	-1.3	0.7	0.7	1.8
0.0	1.1	0.2	0.0	-0.1	0.0	0.0	0.4	24.4	4.0	-0.6	-2.7	-0.6	-1.2	0.9	0.9	2.0
0.0	1.6	-0.3	0.3	0.2	0.0	0.0	2.5	14.8	-3.3	2.9	2.4	-1.5	-7.6	0.6	0.6	1.7
0.0	1.0	-0.1	0.0	-0.2	0.0	0.0	1.0	18.0	-1.9	0.5	-4.0	-1.4	1.3	0.9	0.9	2.1
0.0	1.3	0.2	-0.7	-0.1	0.0	0.0	2.3	15.2	2.4	-8.1	-2.6	3.0	-4.4	0.8	0.8	1.8
0.0	0.5	-0.2	0.2	0.0	0.0	0.0	-1.0	6.7	-2.7	3.0	-0.8	0.5	4.1	0.6	0.6	1.8
0.0	0.6	-0.3	0.4	0.1	0.0	0.0	-1.8	7.4	-4.8	6.0	2.2	-0.3	2.1	0.6	0.6	2.0
0.0	0.6	0.4	-0.1	-0.1	0.0	0.0	-2.0	9.4	6.8	-1.2	-3.4	-1.3	8.8	0.9	0.9	1.8
0.0	0.4	-0.2	-0.5	0.0	0.0	0.0	-0.2	5.4	-2.9	-7.3	-0.8	1.8	8.1	0.8	0.8	2.0
0.0	1.0	0.1	0.4	-0.1	0.0	0.0	0.0	14.9	2.1	6.3	-3.1	-0.9	2.8	0.8	0.8	1.8
0.0	1.3	0.2	0.0	0.0	0.0	0.0	0.4	27.7	5.8	-0.4	-0.4	0.6	-3.3	0.9	0.9	1.9
Number of Significant Variables							**4**	**12**	**10**	**7**	**8**	**1**	**9**			

Table 14 Overal 20 Years of F-tests (with the FIT1) at t = T for Model Explanatory (present-to-present)

FFF_FF	FF_CAPM	FFF_CAPM	SFF_FFF	SFF_FF	SFF_CAPM
1.9527	0.9069	1.4335	3.3210	1.7729	1.8322
5.2541	19.3320	12.6410	0.2549	2.5644	10.1320
3.5962	9.0860	6.4411	1.9389	2.2073	5.5649
2.9508	6.6810	4.8711	9.3316	3.7085	5.9863
8.2497	2.4878	5.4452	0.6963	3.9993	4.4902
10.8620	29.1210	21.2080	2.8869	5.6087	17.6910
0.3063	10.6770	5.4602	1.7218	0.5815	4.7288
2.8392	33.1800	18.2680	19.5740	6.1576	20.1610
5.8055	15.0630	10.7410	0.5337	2.8808	8.6826
0.6490	22.9400	11.7600	1.1395	0.6046	9.6432
5.1366	21.9400	13.9230	8.5845	4.5056	13.2970
0.6681	18.9690	9.7917	0.8045	0.5307	7.9884
4.0225	***15.8650***	***10.1650***	***4.2323***	***2.9268***	***9.1831***

Table 15 Overal 20 Years F-tests (with the FIT2) at t = T for Model Explanatory (present-to-present)

FFF_FF	FF_CAPM	FFF_CAPM	SFF_FFF	SFF_FF	SFF_CAPM
1.9527	0.9069	1.4335	6.3195	2.5102	2.4729
5.2541	19.3320	12.6410	4.5795	3.5991	11.2060
3.5962	9.0860	6.4411	0.3574	1.8237	5.2103
2.9508	6.6810	4.8711	31.2900	9.0631	11.7110
8.2497	2.4878	5.4452	0.1435	3.8702	4.3689
10.8620	29.1210	21.2080	4.0148	5.8667	18.0070
0.3063	10.6770	5.4602	5.1217	1.4292	5.4946
2.8392	33.1800	18.2680	1.5351	1.7547	14.9580
5.8055	15.0630	10.7410	6.4534	4.2908	10.1270
0.6490	22.9400	11.7600	0.2481	0.3830	9.4278
5.1366	21.9400	13.9230	3.8028	3.3605	12.0480
0.6681	18.9690	9.7917	0.0500	0.3431	7.8116
4.0225	***15.8650***	***10.1650***	***5.3263***	***3.1912***	***9.4036***

Table 16 Overal 20 Years F-tests (with the FIT1&2) at t = T for Model Explanatory (present-to-present)

FFF_FF	FF_CAPM	FFF_CAPM	SFF_FFF	SFF_FF	SFF_CAPM
1.9527	0.9069	1.4335	230.3500	57.5980	4147.9000
5.2541	19.3320	12.6410	1.7591	2.9243	10.5010
3.5962	9.0860	6.4411	1.5254	2.1070	5.4717
2.9508	6.6810	4.8711	45.8150	12.6050	16.2360
8.2497	2.4878	5.4452	1.5987	4.2100	4.6894
10.8620	29.1210	21.2080	17.9440	9.0531	22.1920
0.3063	10.6770	5.4602	15.9190	4.1215	8.0857
2.8392	33.1800	18.2680	4.3776	2.4485	15.7230
5.8055	15.0630	10.7410	58.2390	16.6250	26.9370
0.6490	22.9400	11.7600	51.1890	13.0480	25.1260
5.1366	21.9400	13.9230	7.8010	4.3180	13.0890
0.6681	18.9690	9.7917	10.6020	2.9661	10.3930
4.0225	***15.8650***	***10.1650***	***37.2600***	***11.0020***	***358.8600***

4.3 Empirical Testing III Forecastibility of Various Models

It illustrates in Figure 13 that the predictive ability of the FF, FFF, SFF models using variables such as SMB, HML, MOM, JAN, and FITs – along with the excess market returns (the rate of return on S&P 500 minus the risk-free interest rate) – drop considerably when the model is applied over an extended time period of 5 years (1993:09-1997:07). This phenomenon may be due to the exploitation of arbitrage opportunities seen to exist by informed investors, especially after the publication of research results. The article of Fama was published in 1992 – to simulate the time period covered by it, the growth of each of 12 Industry Portfolio was regressed onto monthly data for the period 1977:08-1992:08. The overall long-term predictive ability of various factor models was then checked using data for 1993:09-1997:08 of 4 year period. It is demonstrated that the explanatory power of the SFF remains robust in-sample around Time = 100 with approximately 10 ~ 100 frequencies for time-varying R-square above 0.05 and even out-sample around Time = 200 with roughly 10 ~ 20 frequencies, varying from model to model.

Figure 13 Forecastibility R^2 Plot of Various Models

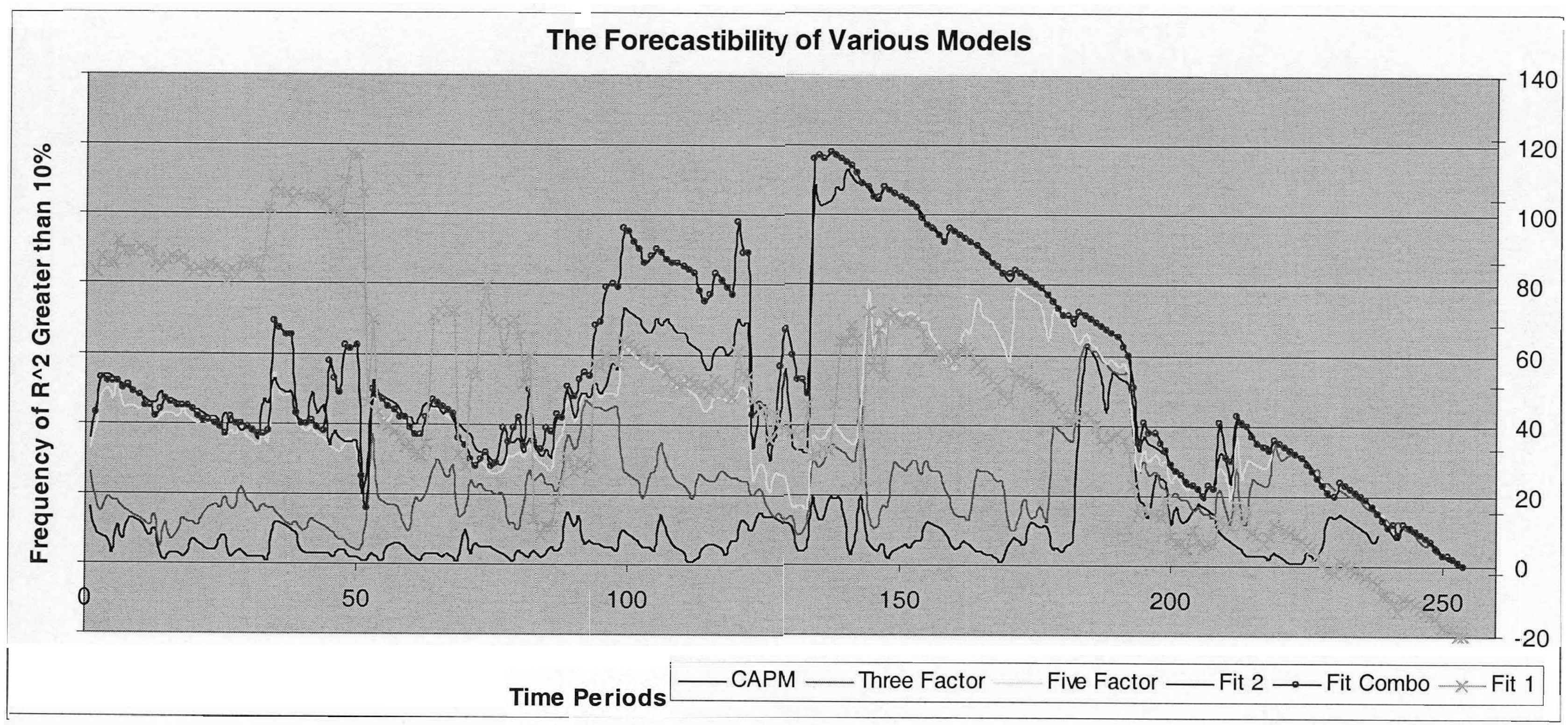


Table 17 Likely Chance of Forecastibility of Various Model

CAPM				
Single Loop			**Multiple Loop**	
13/239	5.10%		2,298/64,770	3.55%

FFF				
Single Loop			**Multiple Loop**	
30/239	11.76%		10,343/64,770	16.10%

FF				
Single Loop			**Multiple Loop**	
23/239	9.02%		5,573/64,770	8.60%

SF1				
Single Loop			**Multiple Loop**	
161/239	45.49%		18,983/64,770	29.31%

SF2				
Single Loop			**Multiple Loop**	
33/239	12.94%		12,872/64,770	19.87%

SF1&2				
Single Loop			**Multiple Loop**	
13/239	5.4%		2,298/64,770	3.55%

Note that the above forecastibility results of various models show that each of the FIT1 and FIT2 has high explanatory power. That is to say, with the same argument for say 5% forecastibility of the model is more likely valid for the SFF model with FIT1 and FIT2 than for other models. It also shows in that FIT1 and FIT2 (Table 17) are significant – and so is the SMB (Table 19). Further, unlike the Chen (2003) who finds no empirical evidence of the forecastibility of the FF factors (see Petkova, 2005), we find that of these two factors, one is significant while another is not. In addition, FF factors are collectively not significant over CAPM in the F-tests at $t = T+1$ (meaning one-time-ahead-to-present in asynchronous time; Table 21-23). Similarly, Rosenberg, Reid, and Landstein (1985) and Stambaugh (2002) also find Fama and French's two factors, market capitalization and book-to-equity value, statistically significant.

Table 18 The Explanatory Power of SMB and HML

History length or investment objective		$\tilde{\alpha}_A$ for σ_{α_N} of			$\lvert\hat{\alpha}_A - \tilde{\alpha}_A\rvert$ for σ_{α_N} of		
	$\hat{\alpha}_A$	0	2%	∞	0	2%	∞
Panel A. $r_{A,t} = \alpha_A + \beta_A \mathrm{MKT}_t + \varepsilon_{A,t}$							
13–23 months	−4.81	−2.07	−1.87	−1.34	3.27	3.29	3.33
24–35 months	−2.85	−1.64	−1.53	−1.17	2.53	2.47	2.72
36–59 months	−2.87	−1.61	−1.35	−1.13	2.44	2.24	2.10
60–119 months	−1.49	−0.97	−0.91	−0.56	1.35	1.29	1.42
120–239 months	−0.84	−0.09	−0.08	0.03	1.29	1.04	0.96
240 months and greater	−0.53	−0.17	−0.26	−0.14	0.70	0.53	0.17
Small company growth	−8.45	−1.59	−0.97	−0.05	7.20	7.66	8.30
Other aggressive growth	−5.41	−0.97	−0.74	−1.06	4.80	4.65	4.58
Growth	−2.17	−0.97	−1.01	−1.17	1.64	1.48	1.52
Income	−0.39	−1.84	−1.40	−0.45	1.27	1.07	0.83
Growth and income	−0.51	−0.97	−0.87	−0.59	0.93	0.89	1.02
Maximum capital gains	−2.29	−1.47	−1.53	−1.95	2.16	1.75	1.34
Sector funds	−1.06	−3.96	−2.70	0.09	4.95	3.48	2.95
All funds	−2.13	−1.25	−1.07	−0.74	2.05	1.87	1.90
Panel B. $r_{A,t} = \alpha_A + b_{A,1}\mathrm{MKT}_t + b_{A,2}\mathrm{SMB}_t + b_{A,3}\mathrm{HML}_t + \eta_{A,t}$							
13–23 months	−1.68	−2.07	−1.96	−1.43	1.66	1.55	1.59
24–35 months	−1.63	−1.64	−1.52	−1.38	1.40	1.25	1.01
36–59 months	−1.29	−1.61	−1.46	−1.14	1.05	0.95	0.78
60–119 months	−0.92	−0.97	−0.94	−0.66	0.76	0.57	0.39
120–239 months	0.07	−0.09	−0.06	0.08	0.64	0.42	0.24
240 months and greater	0.12	−0.17	−0.13	0.17	0.76	0.50	0.05
Small company growth	−0.41	−1.59	−1.16	−0.08	1.45	1.15	0.92
Other aggressive growth	−0.37	−0.97	−0.45	0.08	1.76	1.34	0.96
Growth	−0.88	−0.97	−0.86	−0.72	0.90	0.78	0.59
Income	−2.03	−1.84	−1.90	−1.74	0.74	0.61	0.47
Growth and income	−1.19	−0.97	−1.00	−1.11	0.79	0.68	0.44
Maximum capital gains	−0.28	−1.47	−1.32	−0.34	1.40	1.03	0.45
Sector funds	−1.84	−3.96	−3.51	−2.48	3.18	2.44	1.35
All funds	−1.07	−1.25	−1.14	−0.86	1.09	0.91	0.65

**Taken from Pastor and Stambaugh (2002).*

Table 19 Number of Significant Variables in Various Models

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	4	2	**3**	0	0	0	1
SFF(FIT2)	9	1	**3**	0	0	0	5
SFF(FIT1)	10	3	**3**	2	0	0	11
FFF	8	1	**3**	0	0	0	0
FF	10	1	**3**	1	0	0	0
CAPM	10	1	0	0	0	0	0

Table 20 Number of Significant Variables in Various Models of 240 periods from October 1985 to September 2005

	Alpha	MKTRF	SMB	HML	MO	JAN	FIT
SFF(FIT1&2)	5	1	0	0	**1**	0	0
SFF(FIT2)	6	1	0	0	**1**	0	**9**
SFF(FIT1)	4	1	0	0	**2**	0	**3**
FFF	4	1	0	0	**1**	0	0
FF	6	1	0	0	0	0	0
CAPM	6	1	0	0	0	0	0

Table 21 Overal 15 Years of F-tests (with the FIT1) at t = T+1 for Model Forecastibility (one-time-ahead-to-present)

FFF_FF	FF_CAPM	FFF_CAPM	SFF_FFF	SFF_FF	SFF_CAPM
0.6899	1.5709	1.1283	10.3970	2.9255	3.1173
0.1496	4.0664	2.0934	17.6670	4.4855	5.6277
0.0373	0.7511	0.3911	17.4180	4.3717	4.1018
0.0444	2.2374	1.1318	8.0657	2.0377	2.6049
0.0429	0.7973	0.4168	15.3490	3.8572	3.6417
0.2902	0.6772	0.4817	17.3320	4.4664	4.1595
0.4283	0.7450	0.5848	3.2326	1.0176	1.1280
0.8842	1.1285	1.0058	9.1820	2.7152	2.7458
0.5256	1.1895	0.8552	12.9820	3.4915	3.4710
0.4444	3.1762	1.8028	8.8629	2.4278	3.3355
0.0393	0.4440	0.2399	7.7738	1.9624	1.8061
0.0849	2.2190	1.1433	17.6210	4.4442	4.7977
0.3051	***1.5835***	***0.9396***	***12.1570***	***3.1836***	***3.3781***

Table 22 Overal 15 Years of F-tests (with the FIT2) at t = T+1 for Model Forecastibility (one-time-ahead-to-present)

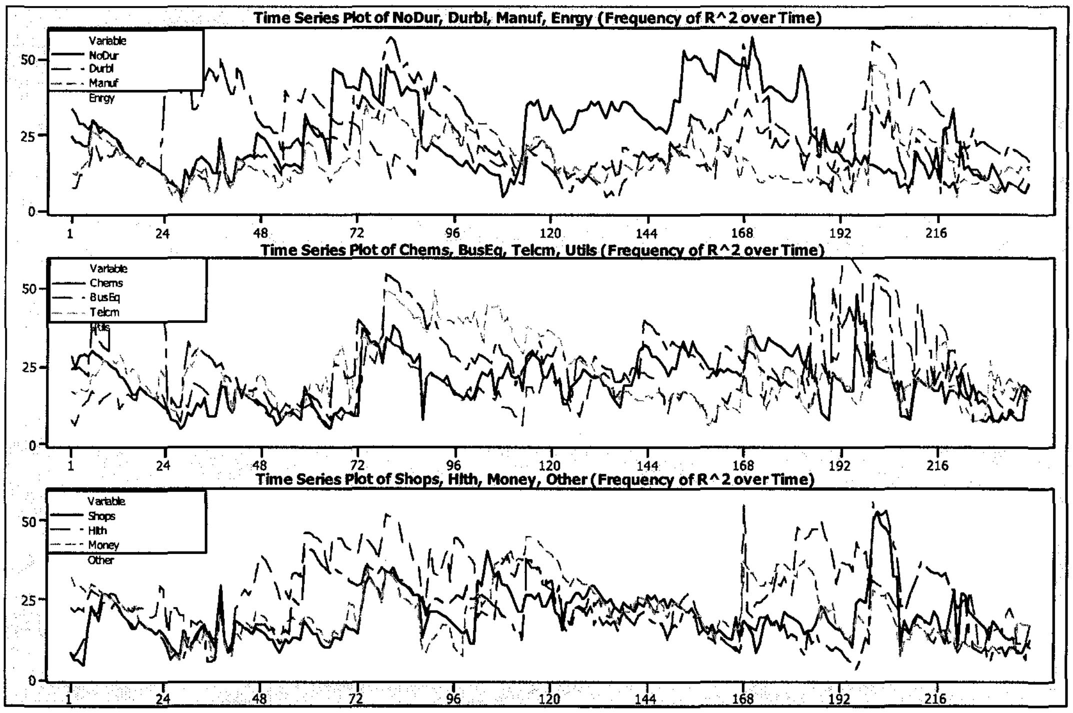
FFF_FF	FF_CAPM	FFF_CAPM	SFF_FFF	SFF_FF	SFF_CAPM
0.6899	1.5709	1.1283	4.6957	1.5085	1.8758
0.1496	4.0664	2.0934	3.9709	1.0658	2.5044
0.0373	0.7511	0.3911	3.2337	0.8267	0.9718
0.0444	2.2374	1.1318	17.1140	4.2989	4.6671
0.0429	0.7973	0.4168	1.4837	0.3921	0.6328
0.2902	0.6772	0.4817	2.0502	0.6554	0.8008
0.4283	0.7450	0.5848	2.6522	0.8731	1.0078
0.8842	1.1285	1.0058	1.7059	0.8602	1.1508
0.5256	1.1895	0.8552	4.9157	1.4840	1.7002
0.4444	3.1762	1.8028	2.9877	0.9645	2.0601
0.0393	0.4440	0.2399	6.0923	1.5421	1.4474
0.0849	2.2190	1.1433	3.0628	0.8074	1.5436
0.3051	***1.5835***	***0.9396***	***4.4970***	***1.2732***	***1.6969***

Table 23 Overal 15 Years of F-tests (with the FIT1&2) at t = T+1 for Model Forecastibility (one-time-ahead-to-present)

FFF_FF	FF_CAPM	FFF_CAPM	SFF_FFF	SFF_FF	SFF_CAPM
0.6899	1.5709	1.1283	4.3786	1.4297	1.8085
0.1496	4.0664	2.0934	0.2521	0.1373	1.7198
0.0373	0.7511	0.3911	0.2674	0.0854	0.3655
0.0444	2.2374	1.1318	0.2946	0.0957	0.9617
0.0429	0.7973	0.4168	2.1501	0.5587	0.7692
0.2902	0.6772	0.4817	0.3930	0.2421	0.4631
0.4283	0.7450	0.5848	1.7870	0.6576	0.8296
0.8842	1.1285	1.0058	2.2243	0.9888	1.2581
0.5256	1.1895	0.8552	2.1410	0.7934	1.1197
0.4444	3.1762	1.8028	0.7125	0.3979	1.5834
0.0393	0.4440	0.2399	1.4372	0.3788	0.4815
0.0849	2.2190	1.1433	0.5524	0.1803	1.0237
0.3051	***1.5835***	***0.9396***	***1.3825***	***0.4955***	***1.0320***

Hence we would reasonably construct the modified 3 Factor model with SMB, FIT1 and FIT2 for period from August 1977 to July 1997. The forecast ability of such model is demonstrated in Table 26 and 27. Another important finding is that MO or the momentum effect matters in the new period from October 1985 to September 2005.

Figure 14 Time Series of Frequency of R^2 of 12 Industry Portfolio



Over the extended period, data examination using a single loop shows that corrected $R^2 \geq$ 5% with the modified 3 factor model is 223/255, or 85.49% of the time for Consumer Durable portfolio. Moreover, the data distribution tends to be cyclical over the given time horizon, being more accurate in periods 81-125 (1984:04-1987:12). Conversely, the theory – that up to 5% of portfolio growth is explainable using the modified 3 factor model is valid for most of the time (especially for Consumer Durable portfolio) – may not be applicable to other portfolios. Another robust result is that data examination using a multiple loop shows that corrected $R^2 \geq 5\%$ with the same model can be 26,604/64,770, or 41.07% of the time for Consumer Durable portfolio. The results for all other industry portfolios are as follow:

Table 24 The Single Loop and Multiple Loop Results of New Factors: SMB, FIT1 and FIT2

New Factors (SMB, FIT1, FIT2)			
Single Loop Result		Multiple Loop Result	
41 / 255	16.08%	18,941 / 62,770	29.24%
223 / 255	85.49%	26,604 / 64,770	41.07%
149 / 255	58.43%	23,995 / 64,770	37.05%
161 / 255	63.14%	24,936 / 64,770	38.50%
85 / 255	33.33%	18,901 / 64,770	29.18%
172 / 255	67.45%	25,530 / 64,770	39.42%
0 / 255	0.00%	4,147 / 64,770	6.40%
27 / 255	10.59%	2,485 / 64,770	3.84%
157 / 255	61.57%	23,088 / 64,770	35.65%
36 / 255	14.12%	8,867 / 64,770	13.69%
89 / 255	34.90%	17,322 / 64,770	26.74%
186 / 255	72.94%	25,758 / 64,770	39.77%

In addition, we temporarily construct the Benchmark model with SMB, the 3 modified Factor (FF) model with SMB, FIT1, and FIT2, and the Five Factors (FFF) Model with SMB, FIT1, FIT2, MO and JAN. Despite we find that imposition of MO and JAN do not matter in the model's forecastibility in the specified time window from August 1977 to July 1997 as they score low F-test scores and the average of the scores, we show that restrictions on FIT1 and FIT2 are significant at 5% level with respect to the unrestricted model consists of SMB, FIT1 and FIT2 (as shown in Table 35)! Furthermore, it can be shown that the variation in the independent variable can be explained by the variation in the combination of FIT1 and FIT2 for as high as 12.09% (of corrected R^2) for IP2. The next step is to design a trading strategy that the modified FF model can follow and allow investors to make absolute or above-the-average positive returns.

Table 25 Comparison of Various Models

FFF_FF	FF_Benchmark	FFF_Benchmark
0.3169	6.0963	3.1889
0.0349	13.0540	6.4913
0.0363	9.6143	4.7860
0.0316	13.4250	6.6732
0.0014	6.1650	3.0571
0.8686	8.7413	4.8001
0.7114	1.7397	1.2235
1.4869	1.8209	1.6577
0.1743	9.2514	4.6804
1.5194	3.2196	2.3766
0.0783	7.1428	3.5827
0.1577	10.1660	5.1257
0.4515	***7.5364***	***3.9703***

Table 26 Number of Significant Variables in Various Models

	Alpha	SMB	FIT1	FIT2	MO	JAN
FFF	9	3	10	4	0	0
FF	**9**	**3**	**10**	**5**	0	0
CAPM	10	3	0	0	0	0

Table 27 Significance of Various Variables of New 3 Factor Model

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0106	0.1418	-0.0026	-0.0008	3.7418	1.2533	-2.6348	-2.1543	0.0460	0.0579	2.0291
0.0056	0.3648	-0.0053	-0.0009	1.7027	2.7618	-4.5897	-2.0093	0.1209	0.1319	2.0141
0.0072	0.1372	-0.0043	-0.0007	2.3282	1.1070	-3.9339	-1.7345	0.0709	0.0825	2.0981
0.0063	0.3048	-0.0031	0.0020	1.9142	2.3240	-2.7386	4.5326	0.1069	0.1181	2.0531
0.0079	0.1090	-0.0035	-0.0004	2.5811	0.8910	-3.3011	-1.0276	0.0424	0.0544	2.1511
0.0071	0.1706	-0.0051	-0.0006	1.8891	1.1335	-3.9178	-1.2594	0.0645	0.0762	2.0235
0.0074	0.0803	-0.0011	-0.0005	2.8066	0.7636	-1.2451	-1.3238	0.0054	0.0179	2.1019
0.0052	-0.0519	-0.0013	-0.0002	2.2892	-0.5763	-1.7150	-0.7486	0.0035	0.0160	2.2155
0.0081	0.1969	-0.0040	-0.0010	2.4374	1.4877	-3.5030	-2.3148	0.0729	0.0845	1.9773
0.0096	0.1108	-0.0022	-0.0006	2.9624	0.8591	-1.9756	-1.4899	0.0187	0.0310	1.9986
0.0099	0.1128	-0.0029	-0.0010	3.1996	0.9131	-2.6918	-2.5128	0.0506	0.0625	1.8934
0.0076	0.2777	-0.0046	-0.0007	2.3214	2.1375	-4.0844	-1.7002	0.0890	0.1004	1.9989
Number of Significant Variables				**9**	**3**	**10**	**5**			

Table 28 Number of Significant Variables in Various Models of 240 Periods from October 1985 to September 2005

	Alpha	SMB	FIT1	FIT2	MO	JAN
FFF	**5**	**0**	**3**	**9**	**2**	0
FF	9	0	2	9	0	0
CAPM	8	0	0	0	0	0

Table 29 Significance of Various Variables of New 3 Factor Model (exchange SMB with MO) of 240 Periods from October 1985 to September 2005

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0096	-0.1531	-0.0020	-0.1001	3.2679	-2.3960	-1.7418	-3.0003	0.0602	0.0720	1.9974
0.0059	-0.0057	-0.0035	-0.1548	1.4804	-0.0651	-2.2896	-3.4005	0.0583	0.0702	1.9048
0.0074	-0.1034	-0.0025	-0.0791	2.2818	-1.4561	-2.0268	-2.1350	0.0326	0.0448	2.0223
0.0073	-0.0485	-0.0016	0.1607	2.2499	-0.6888	-1.3049	4.3699	0.0676	0.0793	2.1651
0.0090	-0.1451	-0.0022	-0.0901	2.8438	-2.1132	-1.7932	-2.5143	0.0453	0.0573	2.1041
0.0062	0.1790	-0.0012	-0.0691	1.2022	1.5874	-0.6082	-1.1739	0.0059	0.0184	1.9894
0.0045	0.1023	-0.0017	-0.0611	1.2840	1.3496	-1.2557	-1.5446	0.0133	0.0257	1.9528
0.0068	-0.0744	-0.0005	-0.0372	2.5378	-1.2761	-0.5287	-1.2238	0.0021	0.0146	1.9845
0.0076	-0.0421	-0.0034	-0.1306	2.2554	-0.5717	-2.6557	-3.4001	0.0663	0.0781	1.9807
0.0098	-0.0851	-0.0018	-0.1008	3.0492	-1.2124	-1.4667	-2.7531	0.0350	0.0471	2.0678
0.0089	0.0362	-0.0024	-0.1335	2.6735	0.5018	-1.8632	-3.5475	0.0561	0.0680	2.0318
0.0071	-0.0477	-0.0023	-0.1093	2.0935	-0.6469	-1.7932	-2.8380	0.0374	0.0495	1.9738
				9	2	3	9			

4.4 Empirical Testing IV The Optimal Interest Rate Model for TSSM

In Section V and VI, we aim to develop a two-phase portfolio strategy called Two-Stage Switching Model (TSSM) for changing market detection from forecasted returns, which allows for an investment to switch between the Treasury securities market and the general market index. The general market is represented by the S&P500 in this case since we are using 12 US Industry Portfolios. This strategy does not aim to provide a trading rule that could beat the buy-and-hold strategy on stock returns, but rather to model the possibly transacting activity in a simple, close economy where the bond market and stock market are present. The way of evaluation would be based on the cumulative compounded returns and the Sharpe ratios. First, we evaluate Chan, Karolyi, Longstaff and Sanders (CKLS, 1992) models of interest rates:

$$r_{t+1} - r_t = \alpha + \mathrm{B}_1 r_1 + \varepsilon_{t+1} \qquad (1)$$

$$E[\varepsilon_{t+1}] = 0, E[\varepsilon_{t+1}^2] = v_{t+1} = \sigma^2 r_t^{2\gamma} \qquad (2)$$

We would use Merton's Model as Eq. (1) as the restricted model with the conditions in Eq. (2) while all other models have restrictions on Γ.

Description of Interest Rate Models

GMM defines $E(X_i - \overline{X}) = 0$ so $\overline{X} = \frac{1}{N}\sum X_i = \overline{\overline{X}}$ where $\overline{\overline{X}}$ is the sample mean. Secondly it defines $E[X_{ji}\varepsilon_i] = EX_{ji}[Y_i - \overline{B_j}X_{ji}] = 0$, so that $\left(\frac{1}{N}\right)\sum X_{ji}\overline{\varepsilon_{ji}} = \frac{1}{N}\sum X_{ji}(Y_i - \overline{B_j}X_{ji}) = 0$. Also $E\left[\frac{\partial \ln f(\bullet)}{\partial B_i}\right] = 0$. GMM estimates weights the errors by their estimated variances.

$\varepsilon_{t+1} = r_{t+1} - r_t - \mathrm{B}_1 r_t$; $E\begin{bmatrix} \varepsilon_{t+1} \\ \varepsilon_{t+1} r_t \\ \varepsilon_{t+1}^2 - \sigma^2 r_t^{2\gamma} \\ (\varepsilon_{t+1}^2 - \sigma^2 r_t^{2\gamma}) r_t \end{bmatrix} = 0$; restricting γ to zero would yield a linear regression model.

Merton's Model : $dr = \alpha dt + \sigma dZ$

Vasicek's Model : $dr = (\alpha + \mathrm{B}r)dt + \sigma dZ$

CIR's Model : $dr = (\alpha + \mathrm{B}r)dt + \sigma r^{1/2} dZ$

Brennan-Schwartz Model : $dr = (\alpha + \mathrm{B}r)dt + \sigma r dZ$

Information Matrix: I(B) = - E $\begin{bmatrix} \frac{\partial^2 \ln L}{\partial B_1^2} & \frac{\partial^2 \ln L}{\partial B_1 \partial B_2} & \cdots \\ \frac{\partial^2 \ln L}{\partial B_1 \partial B_2} & \frac{\partial^2 \ln L}{\partial B_2^2} & \cdots \\ \cdots & \cdots & \cdots \\ & & \end{bmatrix}$ since $E\left[\frac{\partial \ln L}{\partial B_1}\right] = 0$;

$E\left[-\frac{\partial^2 \ln L}{\partial \sigma_a \partial B_1}\right] = 0$ for moderate or large samples. The inversion of Information Matrix can be used to calculate the t-statistics.

Testing Results:

Table 30 Parameters of Full Model of Interest Rate

Parameter	Coeff	Std Err	Null	t-stat	p-val
alpha	0.020322	0.014724	0	1.38	0.1675
beta	-0.281382	0.24135	0	-1.17	0.2437
sigma^2	7.436281	10.41641	0	0.71	0.4753
gamma	1.997358	0.294875	0.5	5.08	0

Table 31 Characteristics of Full Model of Interest Rate

Long-run mean, theta	=	7.22%
Speed of adj, kappa	=	0.2814
Volatility parm, sigma	=	2.727
Cond. Vol. parm, gamma	=	1.9974
Average Cond Volatility	=	0.48%
R^2 (yld change)	=	0.0117
R^2 (sqrd yld chg)	=	0.1858

Table 32 Estimation Results of Various Interest Rate Models

	alpha	beta	Sigma^2	gamma
Full	0.0203	-0.2814	7.4363	1.9974
	(0.0147)	(0.2413)	(10.4164)	(0.2949)
Merton	0.0009	0	0.0001	0
	(0.0035)		(0.0001)	
Vasicek	0.0092	-0.1345	0.0001	0
	(0.0133)	(0.2267)	(0.0001)	
CIR SR	0.007	-0.1037	0.0015	0.5
	(0.0132)	(0.2259)	(0.0015)	
Dothan	0	0	0.0267	1
			(0.0198)	
GBM	0	0.0201	0.0261	1
		(0.0595)	(0.0201)	
Brennan-Schwarz	0.0059	-0.0858	0.0266	1
	(0.0135)	(0.2290)	(0.0206)	
CIR VR	0	0	0.4665	1.5
			(0.2090)	
CEV	0	0.0413	9.9192	2.0979
		(0.0613)	(15.0598)	(0.3206)

Table 33 Comparison and the P-values of Various Models

Model	J_T	p-value	df	R^2_1	R^2_2
Full	0		0	0.0117	0.1858
Merton (0)	4.4946	0.1057	2	0	0
Vasicek (0)	4.6318	0.0314	1	0.0027	0
CIR SR (0.5)	5.8855	0.0153	1	0.0016	0.0005
Dothan (1)	6.5225	0.0888	3	0	0.0046
GBM (1)	6.5780	0.0373	2	0.0001	0.0044
Brennan-Schwarz (1)	6.7567	0.0093	1	0.0011	0.0046
CIR VR (1.5)	**4.2314**	**0.2375**	**3**	**0**	**0.0324**
CEV (2.0979)	1.6818	0.1947	1	0.0003	0.1536

Table 34 Tests Results of Restrictions on the Full Model

Unrestricted Model	Merton	Vasicek	CIR	B-S	CIR VR (G15)	G175	G2
Restricted Model	0	0	0.5	1	1.5	1.75	2
Alpha	-0.0001	0.0202	0.0094	0.0076	0.0030	0.0031	0.0036
Beta		-0.2805	-0.1317	-0.1113	-0.0237	-0.0269	-0.0375
Volatility	0.0221	0.0220	0.0662	0.2118	0.7483	1.4762	3.0131
	0	2.7773	121.66	211.42	254.18	252.35	234.31

From the above analytical output, we can conclude that many restrictions are *not* valid. In other words, Models with Γ from 0 to 2 have significantly improved the estimation compared to Merton's model. It shows that Model with Γ of 1.5 or CIR VR performs the best estimation, with a p-value of 0.2357 which most resembles the full model. Hence we would use CIR VR to forecast the *ex ante* future 1 month return on our portfolios of security for period from August 1977 to July 1997[29]. Also it is shown that CIR VR has highest likelihood ratio of 254.1805. Note the full model of the interest rate model is $r_{t+1} - r_t = 0.0203 - 0.2814 r_1 + \varepsilon_{t+1}$ with $E[\varepsilon_{t+1}] = 0, E[\varepsilon_{t+1}^2] = v_{t+1} = 7.4363 r_t^{2(1.9974)} = 7.4363 r_t^{3.9948}$

4.5 Empirical Testing V Implementation of Two-Stage Switching Model

To account for conditional heteroskedasticity residual for better modeling the non-linear process, we would use the alternative model, developed by Bollerslev (1986) under the name Generalized Autoregressive Conditional Heteroscedasticity (GARCH). This model not only allows the first and second moments of $\{R_t\}$ to be dependent on its past values and variances, but

[29] Same interest rate model applies to the new period from October 1985 to September 2005.

also attribute price movement to rational expectations of investors and irrational component of behavioral finance (Lim, 2006). This dependency between R_{t+s} and R_t is formulated as a linear function for nonlinear approximation, yielding easy statistical estimation and economic implications.

Similar to Akgiray (1989), the empirical evidence presented so far indicates that residual series of monthly industry portfolio residuals with CAPM exhibit significant levels of dependence: the probability distribution of R_{t+s} is not independent on R_t for several values of s. The conditional heteroscedastic processes with GARCH not only allow for autocorrelation between the first and second moments of residual distributions over time but also consequently fit to data very satisfactorily. For example, some of the GARCH terms exhibit significant t-statistics. Hence we can infer that the GARCH models provide improved forecast of volatility as Akgiray (1989) suggests.

The use of GLS technique considers to weight observations in inverse proportion to the variances of the associated errors, abating the heteroscedasticity and serial correlation that tend to give illusory results such as R-square. For likelihood ratio test, we first define $L(B_{ur})$ when restrictions do no apply, and $L(B_r)$ represent the maximum value when the restrictions do apply.

Let $\lambda = \dfrac{L(B_r)}{L(B_{ur})}; 0 \leq \lambda \leq 1$. Set $\begin{cases} H_0 : B = 0; \textit{then } \lambda = 1 \textit{ when restrictions do not apply} \\ H_0 : B \neq 0; \textit{then } \lambda = 0 \textit{ when restrictions do apply} \end{cases}$.

Given the decision rule, we would be able to reject the hypothesis when λ is small for large sample size. The critical value can be sought with $-2[L(B_R) - L(B_{UR})] \sim \chi^2_m$ where m represents the number of restrictions. To implement the likelihood ratio test, we use the Maximum Likelihood Estimation (MLE) to estimate the population mean and variance by minimizing the $\sum(X_i-\mu)^2$ in the log-likelihood function: $\ln L = -\frac{N}{2}\ln\sigma^2 - \frac{N}{2}\ln(2\pi) - \left(\frac{1}{2\sigma^2}\right)\sum(X_i-u)^2$. Note that MLE is a consistent but biased estimator of the variance: $\overline{\sigma}^2 = \frac{\sum(X_i-\mu)^2}{N}$.

Within the class of such models, GARCH (1,1) processes show the best fit and forecast accuracy, though not significantly better than GARCH-in-Mean (1,1). GARCH-in-Mean and GARCH exhibit a likelihood ratio test of 870.8286 and 870.8289, respectively in the case of FF as well as of 845.8052 and 561.4864 in the case of CAPM. As well both t-statistics of a1 in GARCH and GARCH-in-Mean are significant and so are the *sigma* in the MLE and a2 in the GARCH-in-Mean, justifying the hypothesis that CAPM and FF can be enhanced by adding the past volatility – either of constant or not. In particular, the GARCH-in-Mean not only demonstrates the past variance matters, but also results in a much lower alpha score. Many of a2 are significant for both CAPM and FF, though conditional variance (σ^2) is insignificant. Further, empirical evidence about slight reduction of the number of significant size effect and small capitalization can also be verified with the insertion of the GARCH terms, and the improved parameter estimates would justify the importance and the impact of the past value variance that would enhance the CAPM and FF models. In light of this, the GARCH model may be used to further understand the relationship between volatility and expected returns[30] in the nonlinear-modeling context and the volatility trading on the basis of imperfect information. The Durbin-Watson Test also shows that nonzero (or positive) serial correlation is present in the OLS estimation for CAPM and FF.

[30] The fundamental valuation theories, in finance, such as the capital asset pricing models, are based on some hypothesized risk-return relationship.

Table 35 OLS Estimation Results for CAPM

α	β1	α - tstat	β1-tstat	C R^2	R^2	DW
0.0110	0.0174	**3.0268**	0.2254	-0.0053	0.0003	1.8525
0.0035	0.1568	**0.7909**	1.6864	0.0102	0.0157	1.8585
0.0052	0.0667	**1.2449**	0.7631	-0.0023	0.0033	1.9821
0.0066	0.0159	**1.4827**	0.1699	-0.0055	0.0002	2.0080
0.0067	-0.0046	**1.6947**	-0.0551	-0.0056	0.0000	1.9739
0.0019	0.1063	**0.4154**	1.0746	0.0009	0.0064	1.8970
0.0075	-0.0597	**2.3042**	-0.8685	-0.0014	0.0042	1.9639
0.0062	-0.1203	**2.2819**	-2.0891	0.0184	0.0239	1.9755
0.0077	0.1015	**1.7685**	1.1081	0.0013	0.0069	1.7830
0.0087	0.0168	**2.2150**	0.2012	-0.0054	0.0002	1.9613
0.0066	0.0848	**1.6959**	1.0244	0.0003	0.0059	1.7340
0.0057	0.1300	**1.3060**	1.4214	0.0057	0.0112	1.9311
		4	1			

Table 36 GLS Estimation Results for CAPM

α	β1	α - tstat	β1-tstat	C R^2	R^2	DW
0.0121	-0.1342	**2.6974**	-1.7630	0.0117	0.0173	1.9553
0.0042	-0.0115	**0.7965**	-0.1253	-0.0056	0.0001	1.9646
0.0055	0.0304	**1.2727**	0.3462	-0.0050	0.0007	1.9895
0.0066	0.0218	**1.4857**	0.2321	-0.0053	0.0003	1.9987
0.0070	-0.0407	**1.6980**	-0.4836	-0.0043	0.0013	1.9853
0.0029	-0.0363	**0.5416**	-0.3684	-0.0049	0.0008	1.9704
0.0075	-0.0768	**2.2245**	-1.1121	0.0013	0.0069	1.9782
0.0062	-0.1292	**2.2306**	-2.2334	0.0219	0.0274	1.9864
0.0093	-0.1449	**1.5994**	-1.6338	0.0093	0.0149	1.9285
0.0092	-0.0300	**2.1922**	-0.3587	-0.0049	0.0007	1.9975
0.0083	-0.1840	**1.4835**	-2.3427	0.0246	0.0301	1.9012
0.0068	-0.0500	**1.3131**	-0.5494	-0.0039	0.0017	1.9629
		4	2			

Table 37 MLE Estimation Results for CAPM

α	β1	Sigma	α - tstat	β1-tstat	Sigma-tstat	C R^2	R^2
0.0177	0.0129	0.0481	**4.9070**	0.1688	18.0010	0.0002	0.0001
0.0102	0.1498	0.0579	**2.3398**	1.6309	17.9910	0.0146	0.0083
0.0118	0.0597	0.0544	**2.8971**	0.6915	17.9910	0.0026	0.0030
0.0133	0.0004	0.0585	**3.0205**	0.0041	17.9980	0.0000	0.0000
0.0133	-0.0001	0.0521	**3.3955**	-0.0015	17.9840	0.0000	0.0000
0.0086	0.0993	0.0617	**1.8649**	1.0143	17.9930	0.0057	0.0030
0.0142	-0.0670	0.0430	**4.4010**	-0.9822	17.9900	0.0053	0.0026
0.0129	-0.1273	0.0360	**4.7725**	-2.2269	17.9930	0.0268	0.0094
0.0144	0.0946	0.0572	**3.3427**	1.0413	17.9920	0.0060	0.0038
0.0154	0.0100	0.0521	**3.9421**	0.1210	18.0000	0.0001	0.0000
0.0133	0.0779	0.0517	**3.4324**	0.9485	17.9930	0.0050	0.0034
0.0123	0.1230	0.0570	**2.8815**	1.3588	17.9920	0.0102	0.0093
			11	1	12		

Table 38 GARCH Estimation Results for CAPM

α	β1	A1	a2	a3	α - tstat	β1-tstat	a1-tstat	a2-tstat	a3-tstat	15y R^2	5y R^2
0.0183	-0.0066	-0.0023	-0.0256	0.0000	**4.9221**	-0.0799	-4.7803	-0.5507	0.0000	0.0000	0.0000
0.0102	0.1498	-0.0033	0.0000	-0.0052	**1.3919**	0.9296	-3.4345	0.0000	-0.0176	0.0146	0.0083
0.0118	0.0596	-0.0027	0.0000	0.0924	**2.7504**	0.6124	-4.2800	0.0000	0.3786	0.0026	0.0030
0.0126	0.0016	-0.0002	-0.0849	0.8544	**3.1864**	0.0168	0-16.068i	-4.8698	40.8220	0.0000	0.0000
0.0133	0.0002	-0.0024	0.0000	0.1157	**3.3125**	0.0018	-4.7355	0.0000	0.5225	0.0000	0.0000
0.0086	0.0994	-0.0036	0.0000	0.0469	**1.7820**	0.8849	-3.4081	0.0000	0.1542	0.0057	0.0030
0.0137	-0.1058	-0.0005	-0.0585	0.6774	**4.1799**	-1.3876	-20.5750	-0.9776	12.2160	0.0133	0.0064
0.0132	-0.1281	-0.0006	-0.1223	0.3907	**4.9973**	-2.0764	-12.5570	-1.1786	3.7527	0.0271	0.0095
0.0151	0.0734	-0.0032	-0.0256	0.0065	**3.2116**	0.7101	-3.9460	-0.3506	0.0230	0.0036	0.0023
0.0158	-0.0023	-0.0027	-0.0193	0.0000	**3.9442**	-0.0257	-4.2542	-0.4073	0.0000	0.0000	0.0000
0.0153	0.0229	-0.0023	-0.1638	0.0000	**4.2980**	0.2592	-22.7820	0-0.94606i	0+4.2986e-09i	0.0004	0.0003
0.0123	0.1230	-0.0032	0.0000	0.0222	**2.7540**	1.2085	-3.9512	0.0000	0.0785	0.0102	0.0093
					10	1	11	1	3		

Table 39 GARCH-in-Mean Estimation Results for CAPM

α	β1	sigma	a1	a2	a3	α - tstat	β1-tstat	a1-tstat	a2-tstat	a3-tstat	sigma-tstat	15y R^2	5y R^2
0.02	0.02	0.05	0.00	0.02	0.06	**0+0.68562i**	0.19	0+0.11625i	-5.10	2.80	0.27	0.00	0.00
0.01	0.15	0.04	0.00	0.00	0.05	**0+0.47418i**	1.63	0+0.14349i	-4.01	0.00	0.20	0.01	0.01
0.01	0.10	0.07	0.00	0.00	0.06	**0+0.79587i**	1.15	0+0.47177i	0+3.2159i	0+0.0033818i	0+0.21944i	0.01	0.01
0.03	0.00	-0.24	0.00	0.43	0.00	**3.07**	0.01	-1.32	-7.43	2.67	-0.03	0.00	0.00
0.01	0.00	0.07	0.00	0.00	0.04	**0+0.20119i**	0.00	0+0.074909i	0+3.2989i	0-0.0066174i	0+0.14746i	0.00	0.00
0.01	0.10	-0.05	0.00	0.00	-0.08	**0+0.42456i**	1.01	0-0.11104i	-3.66	0.00	-0.27	0.01	0.00

α	β1	sigma	a1	a2	a3	α - tstat	β1-tstat	a1-tstat	a2-tstat	a3-tstat	sigma-tstat	15y R^2	5y R^2
0.01	-0.09	0.02	0.00	0.04	0.05	**0.30**	-1.19	0.02	0+4.06 61i	0.66	0+0.29 962i	0.01	0.00
0.01	-0.12	0.07	0.00	0.10	-0.01	**0+0.59 361i**	-2.02	0+0.12965i	0+3.76 86i	0+1.44 22i	0-0.06 9764i	0.02	0.01
0.03	0.04	-0.18	0.00	0.05	0.36	**0+1.75 97i**	0.45	0-0.73379i	-5.42	2.85	3.16	0.00	0.00
0.03	-0.02	-0.28	0.00	0.03	-0.28	**0+0.97 883i**	-0.25	0-0.4705i	0+3.733 i	0+2.85 99i	0-1.806i	0.00	0.00
0.04	-0.01	-0.52	0.00	0.31	-0.06	**1.93**	-0.07	-1.32	0+4.75 35i	1.55	0-0.33 673i	0.00	0.00
0.01	0.12	0.04	0.00	0.00	0.10	**0+0.42 531i**	1.36	0+0.10438i	-4.27	0.00	0.42	0.01	0.01
						1	1	0	6	3	1		

Table 40 OLS Estimation Results for FF

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0114	-0.0428	0.1725	-0.1163	**3.0464**	-0.4647	1.1689	-0.7129	-0.0055	0.0114	1.8198
0.0024	0.1177	0.4517	0.1144	**0.5308**	1.0733	2.5703	0.5890	0.0362	0.0523	1.8629
0.0055	-0.0012	0.2029	-0.1266	**1.3008**	-0.0114	1.2120	-0.6842	-0.0021	0.0147	1.9842
0.0073	-0.1147	0.3999	-0.2386	**1.6150**	-1.0367	2.2547	-1.2167	0.0215	0.0379	1.9356
0.0072	-0.0686	0.1668	-0.1329	**1.7603**	-0.6844	1.0387	-0.7489	-0.0071	0.0098	1.9516
0.0026	0.0200	0.2071	-0.1895	**0.5447**	0.1689	1.0934	-0.9049	0.0016	0.0184	1.9290
0.0080	-0.1134	0.0972	-0.1355	**2.4058**	-1.3774	0.7366	-0.9289	-0.0042	0.0126	1.9109
0.0074	-0.1797	-0.0370	-0.2309	**2.6573**	-2.6230	-0.3371	-1.9019	0.0276	0.0439	1.8980
0.0076	0.0523	0.2317	-0.0446	**1.7084**	0.4772	1.3193	-0.2297	0.0003	0.0171	1.7919
0.0104	-0.1058	0.1163	-0.3685	**2.5917**	-1.0704	0.7343	-2.1043	0.0122	0.0287	1.9973
0.0068	0.0477	0.1309	-0.0582	**1.6786**	0.4800	0.8227	-0.3306	-0.0064	0.0105	1.7238
0.0059	0.0421	0.3148	-0.1347	**1.3412**	0.3873	1.8064	-0.6993	0.0162	0.0327	1.9348
				4	1	2	1			

Table 41 GLS Estimation Results for FF

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0126	-0.2069	0.2046	-0.1449	**2.7274**	-2.3128	1.4115	-0.8695	0.0192	0.0358	1.9455
0.0034	-0.0389	0.4425	0.0338	**0.6458**	-0.3593	2.5350	0.1698	0.0189	0.0355	1.9522
0.0059	-0.0298	0.2055	-0.1394	**1.3467**	-0.2833	1.2233	-0.7426	-0.0035	0.0134	1.9917
0.0078	-0.1676	0.4221	-0.2625	**1.6260**	-1.5101	2.3733	-1.3133	0.0265	0.0429	1.9820
0.0077	-0.1369	0.1831	-0.1494	**1.7685**	-1.3643	1.1376	-0.8244	-0.0014	0.0155	1.9783
0.0032	-0.0588	0.1994	-0.1569	**0.6055**	-0.4984	1.0524	-0.7328	-0.0070	0.0099	1.9783
0.0084	-0.1737	0.1244	-0.1638	**2.2917**	-2.1110	0.9414	-1.0980	0.0098	0.0265	1.9749
0.0080	-0.2513	-0.0099	-0.2897	**2.5596**	-3.6845	-0.0902	-2.3295	0.0603	0.0761	1.9688
0.0092	-0.1594	0.1643	-0.0603	**1.6085**	-1.5150	0.9611	-0.3051	0.0001	0.0169	1.9334
0.0107	-0.1113	0.1208	-0.3858	**2.6564**	-1.1181	0.7609	-2.1850	0.0143	0.0310	1.9996
0.0095	-0.2661	0.0444	-0.2366	**1.6282**	-2.9087	0.2967	-1.3519	0.0299	0.0462	1.8805
0.0068	-0.0783	0.3035	-0.1442	**1.3716**	-0.7237	1.7435	-0.7302	0.0041	0.0209	1.9681
				4	4	2	2			

Table 42 MLE Estimation Result for FF

α	β1	β2	β3	Sigma	α - tstat	β1-tstat	β2-tstat	β3-tstat	Sigma-tstat	C R^2	R^2
0.0181	-0.0510	0.1727	-0.1206	0.0478	**4.9148**	-0.5622	1.1873	-0.7501	**17.9910**	0.0115	0.0308
0.0091	0.1095	0.4519	0.1102	0.0568	**2.0757**	1.0165	2.6174	0.5774	**17.9920**	0.0516	0.0576
0.0122	0.0000	0.1996	-0.1227	0.0541	**2.9164**	0.0000	1.2131	-0.6747	**17.9920**	0.0144	0.0537
0.0140	-0.1229	0.4001	-0.2429	0.0574	**3.1588**	-1.1283	2.2913	-1.2580	**17.9920**	0.0385	0.1300
0.0139	-0.0768	0.1669	-0.1372	0.0519	**3.4729**	-0.7804	1.0580	-0.7870	**17.9910**	0.0102	0.0352
0.0093	0.0117	0.2073	-0.1937	0.0613	**1.9760**	0.1010	1.1123	-0.9400	**17.9920**	0.0180	0.0310
0.0148	-0.1216	0.0973	-0.1399	0.0428	**4.4787**	-1.4986	0.7482	-0.9724	**17.9910**	0.0140	0.0203
0.0141	-0.1880	-0.0369	-0.2352	0.0356	**5.1390**	-2.7795	-0.3400	-1.9628	**17.9920**	0.0475	0.0330
0.0143	0.0441	0.2318	-0.0488	0.0569	**3.2655**	0.4080	1.3395	-0.2553	**17.9920**	0.0164	0.0253
0.0171	-0.1140	0.1164	-0.3728	0.0514	**4.3266**	-1.1700	0.7457	-2.1594	**17.9910**	0.0293	0.0532
0.0135	0.0395	0.1311	-0.0624	0.0516	**3.3913**	0.4031	0.8353	-0.3599	**17.9920**	0.0097	0.0159
0.0126	0.0357	0.3144	-0.1375	0.0564	**2.9059**	0.3332	1.8331	-0.7253	**17.9930**	0.0322	0.0836
					11	1	2	2	**12**		

Table 43 GARCH Estimation Results for FF

α	β1	β2	β3	a1	a2	a3	α – tstat	β1- tstat	β2- tstat	β3- tstat	a1- tstat	a2- tstat	a3- tstat	15y R^2	5y R^2
0.02	-0.06	0.16	-0.12	0.00	0.01	-0.18	**4.83**	-0.60	1.10	-0.76	-5.57	0.25	-0.94	0.01	0.03
0.01	0.11	0.45	0.11	0.00	0.00	0.03	**2.07**	1.01	2.62	0.58	-4.01	-0.01	0.09	0.05	0.06
0.01	0.00	0.20	-0.12	0.00	0.00	0.06	**2.63**	0.00	1.18	-0.67	-4.13	0.00	0.25	0.01	0.05
0.01	-0.04	0.41	-0.21	0.00	0.01	-0.99	**3.32**	-0.39	2.39	-1.12	0+0.02 0357i	0+3.24 43i	0-85 8.11i	0.04	0.13
0.01	-0.08	0.17	-0.14	0.00	0.00	0.06	**3.30**	-0.70	1.04	-0.79	-4.51	0.00	0.25	0.01	0.04
0.01	0.01	0.21	-0.19	0.00	0.00	0.00	**1.82**	0.11	1.08	-0.90	-3.20	0.00	-0.01	0.02	0.03
0.01	-0.19	0.09	-0.20	0.00	0.07	-0.70	**4.10**	-1.97	0.66	-1.43	-29.50	0.83	-8.90	0.03	0.04
0.01	-0.20	-0.03	-0.23	0.00	0.11	-0.43	**5.31**	-2.70	-0.30	-1.95	-14.49	1.08	-4.06	0.05	0.03
0.01	0.04	0.23	-0.05	0.00	0.01	-0.32	**3.12**	0.32	1.30	-0.27	-4.79	0.10	-1.76	0.02	0.02
0.02	-0.13	0.09	-0.38	0.00	-0.03	0.00	**4.22**	-1.23	0.57	-2.20	-4.30	-0.52	0.00	0.03	0.05
0.01	0.03	0.13	-0.07	0.00	0.01	-0.63	**3.30**	0.22	0.80	-0.40	-8.98	0.17	-7.24	0.01	0.02
0.01	0.03	0.32	-0.14	0.00	0.00	0.02	**2.64**	0.26	1.83	-0.73	-4.02	0.00	0.08	0.03	0.08
							11	2	2	1	11	0	3		

Table 44 GARCH-in-Mean Estimation Results for FF

α	β1	β2	β3	sigma	a1	a2	a3	α - tstat	β1-tstat	B2-tstat	β3-tstat	a1-tstat	a2-tstat	a3-tstat	sigma-tstat	15y R^2
0.08	-0.08	0.16	-0.16	-1.39	0.00	-0.01	0.48	0+2.70i	**-0.83**	***1.07***	***-0.96***	0-2.14i	**-15.97**	-0.44	8.50	0.01
0.01	0.11	0.45	0.11	0.03	0.00	0.00	0.07	0.54	**1.02**	***2.62***	***0.58***	0.11	**-4.15**	0.00	0.26	0.05
0.01	0.00	0.20	-0.12	0.03	0.00	0.00	0.09	0+0.58i	**0.00**	***1.21***	***-0.68***	0+0.08i	**-4.52**	0.00	0.39	0.01
0.00	-0.11	0.33	-0.17	0.22	0.00	0.03	-0.92	0.07	**-1.04**	***1.96***	***-0.91***	0.55	**0-4.84i**	0+1.99i	0-46.82i	0.02
0.01	-0.08	0.17	-0.14	0.05	0.00	0.00	0.09	0+0.56i	**-0.78**	***1.06***	***-0.79***	0+0.14i	**-4.80**	0.00	0.40	0.01
0.00	0.00	0.21	-0.20	0.07	0.00	0.00	0.10	0+0.20i	**0.02**	***1.13***	***-0.98***	0+0.20i	**-3.93**	0.00	0.39	0.02
-0.01	-0.20	0.12	-0.18	0.67	0.00	0.04	-0.92	-0.89	**-2.47**	***0.96***	***-1.38***	1.82	**-1.26**	5.32	0-159.27i	0.03
0.02	-0.19	-0.02	-0.23	-0.09	0.00	0.02	-0.78	0.43	**-2.76**	***-0.19***	***-1.97***	-0.08	**-286.65**	2.02	-19.08	0.05
0.01	0.04	0.23	-0.05	0.04	0.00	0.00	0.06	0+0.77i	**0.41**	***1.34***	***-0.25***	0+0.13i	**-4.12**	-0.46	0.24	0.02
0.15	-0.20	0.10	-0.35	-2.73	0.00	-0.01	0.00	0+3.21i	**-1.79**	***0.63***	***-2.00***	0-3.23i	**-12.79**	-1.35	0.00	0.03
0.01	0.04	0.13	-0.07	0.06	0.00	0.00	0.09	0.07	**0.39**	***0.84***	***-0.38***	0.02	**-4.74**	-0.14	0.39	0.01
0.01	0.03	0.31	-0.14	0.00	0.00	0.00	0.03	0+1.00i	**0.32**	***1.84***	***-0.73***	0+0.00i	**-4.06**	0.00	0.11	0.03
								0	**2**	***1***	***2***	0	**10**	2	1	

Then we proceed to develop and construct a strategy that enables us to both reach Pareto efficiency by optimizing the welfare of resource allocation and to outperform the market with conservative approach: the rule is that we maintain our investment in the Treasury securities market unless it makes fewer returns than that that on the S&P500 stock market. We may assume negligible, if not no at all, transaction cost in the competitive market where all available economic and non-economic resources are traded. To formulate a trading model in forecasting returns on IP, the dependent variable, we have selected three independent variables as SMB, FIT1 and FIT2. These variables[31] are defined as follows:

$$Growth\_IP_{t+1} = \frac{IP_{t+1} - IP_t}{IP_t} \qquad SML_t = \frac{SML_t - SML_{t-1}}{SML_{t-1}}$$

$$FIT1_t = \frac{Spot\_FIT1_t - Spot\_FIT1_{t-1}}{Spot\_FIT1_{t-1}}$$

$$FIT2_t = \frac{Spot\_FIT2_t - Spot\_FIT2_{t-1}}{Spot\_FIT2_{t-1}}$$

To test this model, we select 15 years of monthly data, starting from August 1977 to July 1992. The tables below indicate the results for coefficients and t-statistics for each model testing technique: OLS, GLS, MLE, GARCH and GARCH-in-Mean. The results are unbiased and consistent.

[31] Source of data: (1) Ken and French Datalibrary – 12 Industry Portfolio (IP)
(2) St. Louis Fed – FIT1
(3) St. Louis Fed – FIT2

Table 45 OLS Estimation Results for Modified 3 Factor Model (SMB, FIT1, FIT2)

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0115	-0.0035	-0.0851	0.1227	3.2708	-2.9959	-1.9525	0.8959	0.0619	0.0777	2.0552
0.0044	-0.0060	-0.1092	0.4108	1.0816	-4.3911	-2.1627	2.5892	0.1490	0.1633	2.0210
0.0059	-0.0049	-0.0878	0.1616	1.4981	-3.7063	-1.7949	1.0519	0.0851	0.1004	2.1158
0.0051	-0.0034	0.1895	0.3742	1.2124	-2.3788	3.6521	2.2970	0.1055	0.1205	2.0522
0.0070	-0.0045	-0.0587	0.0997	1.8364	-3.4885	-1.2386	0.6703	0.0635	0.0792	2.1778
0.0029	-0.0057	-0.0737	0.1833	0.6376	-3.7424	-1.3235	1.0486	0.0786	0.0941	1.9808
0.0074	-0.0010	-0.0617	0.0453	2.2855	-0.8801	-1.5337	0.3588	0.0027	0.0194	2.1552
0.0060	-0.0014	-0.0312	-0.1057	2.1759	-1.4939	-0.9165	-0.9906	0.0046	0.0213	2.2858
0.0087	-0.0047	-0.1214	0.2003	2.1084	-3.3931	-2.3678	1.2438	0.0891	0.1043	1.9538
0.0091	-0.0027	-0.0684	0.0945	2.3522	-2.0767	-1.4191	0.6244	0.0236	0.0399	2.0812
0.0077	-0.0036	-0.1213	0.1125	2.0471	-2.8160	-2.5916	0.7651	0.0701	0.0856	1.9233
0.0065	-0.0053	-0.0829	0.2942	1.5825	-3.8559	-1.6273	1.8388	0.1014	0.1165	2.0133
				6	**10**	**5**	**1**			

Table 46 GLS Estimation Results for Modified 3 Factor Model (SMB, FIT1, FIT2)

α	β1	β2	β3	α - tstat	β1-tstat	β2-tstat	β3-tstat	C R^2	R^2	DW
0.0116	0.1265	-0.0036	-0.0890	3.3799	0.9257	-3.1009	-2.0602	0.0686	0.0843	2.0021
0.0043	0.4181	-0.0061	-0.1130	1.0821	2.6384	-4.4900	-2.2540	0.1570	0.1712	1.9656
0.0060	0.1988	-0.0050	-0.0955	1.6208	1.3080	-3.8703	-2.0025	0.1002	0.1154	2.0075
0.0051	0.3787	-0.0033	0.1891	1.2491	2.3265	-2.3927	3.6719	0.1070	0.1220	2.0017
0.0071	0.1196	-0.0047	-0.0686	2.0577	0.8208	-3.8247	-1.5094	0.0827	0.0982	2.0151
0.0030	0.1820	-0.0056	-0.0725	0.6608	1.0374	-3.7113	-1.2961	0.0773	0.0929	1.9924
0.0074	0.0271	-0.0012	-0.0732	2.4940	0.2182	-1.1805	-1.8846	0.0130	0.0296	1.9878
0.0061	-0.1320	-0.0018	-0.0425	2.5776	-1.2903	-2.1706	-1.3457	0.0268	0.0432	2.0218
0.0088	0.1869	-0.0046	-0.1176	2.0637	1.1531	-3.2823	-2.2681	0.0818	0.0973	1.9905
0.0093	0.1027	-0.0029	-0.0738	2.4962	0.6826	-2.2234	-1.5569	0.0305	0.0468	1.9990
0.0078	0.0941	-0.0034	-0.1134	1.9582	0.6352	-2.5932	-2.3826	0.0568	0.0727	1.9799
0.0066	0.3030	-0.0053	-0.0843	1.6151	1.8909	-3.8752	-1.6578	0.1044	0.1195	1.9939
				7	**2**	**11**	**6**			

Table 47 MLE Estimation Results for Modified 3 Factor Model (SMB, FIT1, FIT2)

α	β1	β2	β3	Sigma	α - tstat	β1-tstat	β2-tstat	β3-tstat	Sigma-tstat	C R^2	R^2
0.0181	0.1219	-0.0033	-0.0837	0.0464	5.2169	0.9001	-2.8428	-1.9409	17.9900	0.0713	0.1293
0.0110	0.4099	-0.0058	-0.1078	0.0535	2.7519	2.6226	-4.2939	-2.1668	17.9910	0.1575	0.2260
0.0125	0.1609	-0.0047	-0.0864	0.0519	3.2266	1.0620	-3.5924	-1.7911	17.9900	0.0945	0.2890
0.0117	0.3735	-0.0031	0.1909	0.0550	2.8394	2.3254	-2.2551	3.7326	17.9910	0.1186	0.1394
0.0136	0.0989	-0.0043	-0.0572	0.0502	3.6267	0.6745	-3.3665	-1.2265	17.9910	0.0733	0.1708
0.0095	0.1825	-0.0054	-0.0722	0.0590	2.1447	1.0580	-3.6452	-1.3153	17.9910	0.0887	0.1252
0.0140	0.0446	-0.0007	-0.0603	0.0427	4.3855	0.3571	-0.6884	-1.5172	17.9910	0.0169	0.0191
0.0126	-0.1065	-0.0012	-0.0297	0.0362	4.6412	-1.0069	-1.2679	-0.8829	17.9890	0.0174	0.0191
0.0154	0.1997	-0.0045	-0.1200	0.0545	3.7576	1.2544	-3.2741	-2.3678	17.9910	0.0986	0.1643
0.0158	0.0937	-0.0025	-0.0669	0.0512	4.1087	0.6269	-1.9327	-1.4050	17.9900	0.0357	0.0410
0.0144	0.1117	-0.0034	-0.1199	0.0497	3.8491	0.7686	-2.6733	-2.5907	17.9900	0.0800	0.1444
0.0131	0.2934	-0.0051	-0.0815	0.0541	3.2398	1.8578	-3.7454	-1.6205	17.9910	0.1105	0.2562
					12	**2**	**9**	**5**	**12**		

Table 48 GARCH Estimation Results for Modified 3 Factor Model (SMB, FIT1, FIT2)

α	β1	β2	β3	a1	a2	a3	α – tstat	β1- tstat	B2- tstat	β3- tstat	a1- tstat	a2- tstat	a3- tstat	15y R2	5y R2
0.02	0.00	-0.09	0.11	0.00	-0.02	0.00	5.21	-2.80	-1.98	0.78	-5.04	-0.37	0.00	0.07	0.13
0.01	-0.01	-0.11	0.41	0.00	0.00	0.06	3.68	-4.45	-2.17	2.84	-4.78	0 -4.59 57e-007i	0.41	0.16	0.23
0.01	0.00	-0.09	0.16	0.00	0.00	-0.05	3.14	-3.56	-1.75	1.03	-4.53	0.00	-0.19	0.09	0.29
0.01	0.00	0.17	0.31	0.00	-0.08	0.87	3.26	-2.59	3.63	2.00	0 - 6.1 887i	-4.01	43.36	0.10	0.13
0.01	0.00	-0.06	0.10	0.00	0.00	-0.01	3.54	-3.36	-1.21	0.66	-4.64	0.00	-0.03	0.07	0.17
0.01	-0.01	-0.07	0.18	0.00	0.00	-0.01	2.11	-3.64	-1.32	1.02	-3.72	0.00	-0.03	0.09	0.13
0.01	0.00	-0.07	0.01	0.00	-0.03	-0.94	4.07	-0.85	-1.70	0.07	-1.60	-8.88	0 – 102.78i	0.02	0.02
0.01	0.00	-0.05	-0.09	0.00	-0.18	0.00	5.02	-0.95	-1.55	-0.81	-7.04	-1.49	0.00	0.02	0.02
0.02	0.00	-0.12	0.20	0.00	0.00	0.10	3.65	-3.17	-2.34	1.21	-4.45	-0.09	0.39	0.10	0.16

α	β1	β2	β3	a1	a2	a3	α – tstat	β1-tstat	B2-tstat	β3-tstat	a1-tstat	a2-tstat	a3-tstat	15y R2	5y R2
0.02	0.00	-0.07	0.09	0.00	-0.01	0.00	4.10	-1.92	-1.43	0.56	-4.38	-0.30	0.00	0.04	0.04
0.01	0.00	-0.12	0.11	0.00	0.00	0.04	3.74	-2.50	-2.56	0.75	-4.81	0.00	0.15	0.08	0.14
0.01	-0.01	-0.08	0.29	0.00	0.00	-0.05	3.19	-3.73	-1.58	1.84	-4.14	0.00	-0.18	0.11	0.26
							12	**9**	**5**	**2**	**10**	**1**	1		

Table 49 GARCH-in-Mean Estimation Results for Modified 3 Factor Model (SMB, FIT1, FIT2)

α	β1	β2	β3	sigma	a1	a2	a3	α – t stat	β1-tstat	B2-tstat	β3-tstat	a1-tstat	a2-tstat	a3-tstat	sigma-tstat	15y R2	5y R2
0.0	0.00	-0.08	0.12	0.11	0.00	0.01	0.06	0 + 0.53607i	-2.83	-1.97	0.85	0 + 0.20995i	0 + 3.5025i	0 + 0.94619i	0 + 0.25674i	0.07	0.13
0.0	-0.01	-0.12	0.43	0.11	0.00	0.02	0.06	0.81	-4.33	-2.42	2.69	0.66	0 + 3.1225i	0 + 1.3868i	0 + 0.22489i	0.17	0.25
0.0	0.00	-0.09	0.16	0.27	0.00	0.00	0.03	0 - 0.54982i	-3.60	-1.79	1.06	9.34	0 + 3.3241i	0 +4.3083e-006i	0 + 0.13488i	0.09	0.29
0.0	0.00	0.17	0.30	-0.30	0.00	0.21	0.14	2.09	-1.75	3.69	1.83	-1.16	0 + 2.6513i	1.40	0 + 0.53381i	0.09	0.10
0.0	0.00	-0.05	0.09	0.34	0.00	0.00	0.04	0 - 0.6796i	-3.32	-1.05	0.59	0 + 4.2386i	0 + 3.4499i	0 - 0.272i	0 + 0.17293i	0.07	0.16
0.0	-0.01	-0.07	0.18	0.06	0.00	0.00	0.06	0 + 0.19715i	-3.65	-1.32	1.06	0 + 0.13162i	0 + 3.003i	0 +9.4371e-005i	0 + 0.2097i	0.09	0.13
0.0	0.00	-0.07	0.06	0.06	0.00	0.02	0.05	0.27	-0.70	-1.59	0.43	0.06	0 + 3.9483i	0.34	0 + 0.24753i	0.02	0.02
0.0	0.00	-0.05	-0.08	-0.22	0.00	0.27	0.06	2.20	-0.86	-1.65	-0.77	-0.80	-7.48	1.74	0.34	0.02	0.02
0.0	0.00	-0.12	0.20	0.13	0.00	0.00	0.05	0 + 0.47124i	-3.27	-2.37	1.25	0 + 0.396i	0 + 3.1727i	0 +1.1927e-005i	0 + 0.19373i	0.10	0.16
0.0	0.00	-0.07	0.09	0.08	0.00	0.01	0.09	0 + 0.46419i	-1.92	-1.44	0.61	0 + 0.1645i	0 + 3.3109i	0 + 0.90664i	0 + 0.36957i	0.04	0.04
0.0	0.00	-0.12	0.11	0.02	0.00	0.00	0.01	0 + 0.74612i	-2.67	-2.59	0.77	0 + 0.067269i	0 + 3.3652i	0.00	0 + 0.036974i	0.08	0.14
0.0	-0.01	-0.08	0.29	0.02	0.00	0.00	-0.01	0 + 0.42497i	-3.75	-1.62	1.86	0 + 0.043446i	0 + 3.177i	0.00	0 - 0.052142i	0.11	0.26
								2	**8**	**4**	**1**	**1**	**1**	**1**			

Description of Models

Likelihood function:

$$L(X,\mu,\sigma^2)=\left[\frac{1}{2\pi\sigma^2}\right]^{N/2}\exp\left[-\frac{\sum(x_i-\mu)}{2\sigma^2}\right]$$

Likelihood function (monthly observation):

$$L(\mu,\sigma^2)=\left[\frac{1}{2\pi\sigma^2/12}\right]^{N/2}\exp\left[-\frac{\sum(dr-\alpha/12)^2}{2\sigma^2/12}\right]$$

Log-likelihood function:

$$L(\theta\mid p,q)=\sum_{t=r}^{T}\log f(\mu_t,v_t),$$

where $f(\mu_t,v_t)$ is the normal density function, μ_t and v_t are calculated recursively by equations (4) – (6). Numerical maximization of $L(\theta\mid p,q)$ gives the maximum likelihood estimates of the parameters for the GARCH (p, q) model. In the other word, the likelihood function can be maximized for several combinations of p and q, and the maximum values can be compared statistically to obtain the optimal order of the process (Akgiray, 1989). The values of p and q are to be pre-specified and several combinations of p and q are use to maximize the likelihood function: $Ln\,L=-N\,Ln\sigma-N\,Ln(2\pi)^{1/2}-\frac{1}{2\sigma^2}\sum(x_i-\mu)^2$

Akgiray (1989)'s GARCH(p,q) model can be described as follows:

$R_t|\Omega_{t-1}\sim F(\mu_t,v_t)$, (3)

$\mu_t=\varphi_0+\varphi_1R_{t-1}$, (4)

$v_t=\alpha_0+\sum_{i=1}^{p}\alpha_i e_{t-i}^2+\sum_{j=1}^{q}\beta_j v_{t-j}$, (5)

$e_t=R_t-\varphi_0-\varphi_1R_{t-1}$, (6)

where R_t is the one-month stock market return, $F(\mu_t, v_t)$ as Eq. (3) is the conditional distribution of the variable, with conditional mean μ_t as Eq. (4), variance v_t as shown in Eq. (5) and volatility

e_t as Eq. (6). Note that the unconditional mean and variance of a GARCH process are constant, but the conditional mean and variance are time dependent as shown above. It can be rewritten for Eq. (5) as $\sigma_t^2 = \frac{\alpha_0}{1-\lambda_1} + \lambda_i \sum_{j=1}^{\infty} \lambda_1^{j-1} \varepsilon_{t-j}^2$ or $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \ldots + \lambda_q \sigma_{t-q}^2$. This allows today's variance depends on all past volatilities, but with geometrically declining weights. The fact that conditional variances are allowed to depend on past realized variances is particularly consistent with the actual volatility pattern of the stock market where there are both stable and unstable periods.

We then use the interest rate model from Section V to forecast one-month T-Bill total return. We choose the CIR VR interest rate model in this test because this model gives highest explanatory power with respect to full model among others and, more importantly, it gives the most significant test statistics such as the likelihood ratio. We use the Matlab code developed in the previous section, and adjust the input data to be from September 1977 to August 1992.

Table 50 Parameters of CIR Interest Rate Model

Model	α	β	Σ	Gamma	Test Ratio
CIR	0.003	-0.0237	0.7483	1.5	254.1805

With the GARCH process and the interest rate model, we are now able to exam the arbitrage opportunity in the specified time window. As the initial trading strategy to forecast the total return in the following month, we use GARCH process for a portfolio return and the model with Γ of 1.5 for the 1-month T-Bill forecast. With the forecasting model making the decision, we then invest 100% of available fund in either IP or 3-month T-Bill, whichever renders a higher return in the next month. The forecasting performance is assessed in the four-year time window from August 1992 to July 1996. In demonstration, we outperform the market in both the compounded return and Sharpe ratio.

Table 51 Basic Investment Strategy TSSM with 100% Stock or 100% T-Bill

100% Stock or 100% T-Bill	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	158.97%	0.7390
2	168.26%	0.7009
3	**174.14%**	**1.0737**
4	139.06%	0.4115
5	161.87%	0.8136
6	**239.07%**	**1.2643**
7	156.64%	0.6670
8	144.52%	0.5136
9	138.93%	0.3696
10	164.56%	0.6312
11	**205.93%**	**1.2602**
12	177.55%	0.9880

In search for alternative strategies the first idea comes to us is the minimum variance portfolio approach. Unfortunately the testing result shows that the weighting we obtain through these formulas can not improve the existing 100% allocation strategy. In fact, compounded return becomes lower and some of the Sharpe ratios are negative. Although the volatility is at much lower level, overall performance of the minimum portfolio structure looks similar to that of the 3-month T-Bill which has compounded last 4 years of return of 118.17%.

Table 52 Minimum Variance Strategy

Minimum Variance	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	115.19%	-0.4912
2	123.88%	0.3185
3	124.53%	0.6712
4	133.03%	0.8604
5	128.32%	0.7257
6	124.24%	0.2353
7	121.21%	0.3455
8	109.07%	-0.5452
9	127.33%	0.4824
10	123.92%	0.5024
11	124.58%	0.5167
12	122.41%	0.3229

The next step is to maximize the compounded returns and the Sharpe ratio with any possible means. It shows in Figure 15 the leverage of Stock weighing composition having a linear relationship with the resulting compounded return. In the other word an increase in portfolio investment leverage with each of 12 Industry Portfolio is accompanied by a proportionate increase in volatility. Furthermore it also indicates in Figure 16 that there's an optimum weighting (for the average results of all IPs) that boosts the value of Sharpe ratio of current modeling against that of the S&P500.

Figure 15 Compounded Returns Over Leverage

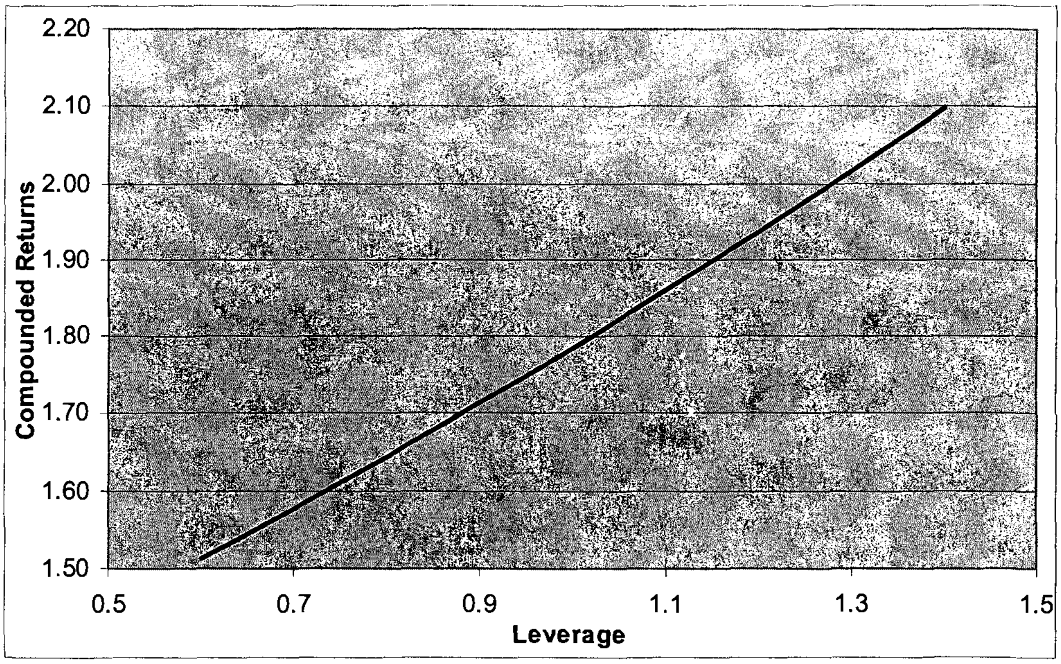
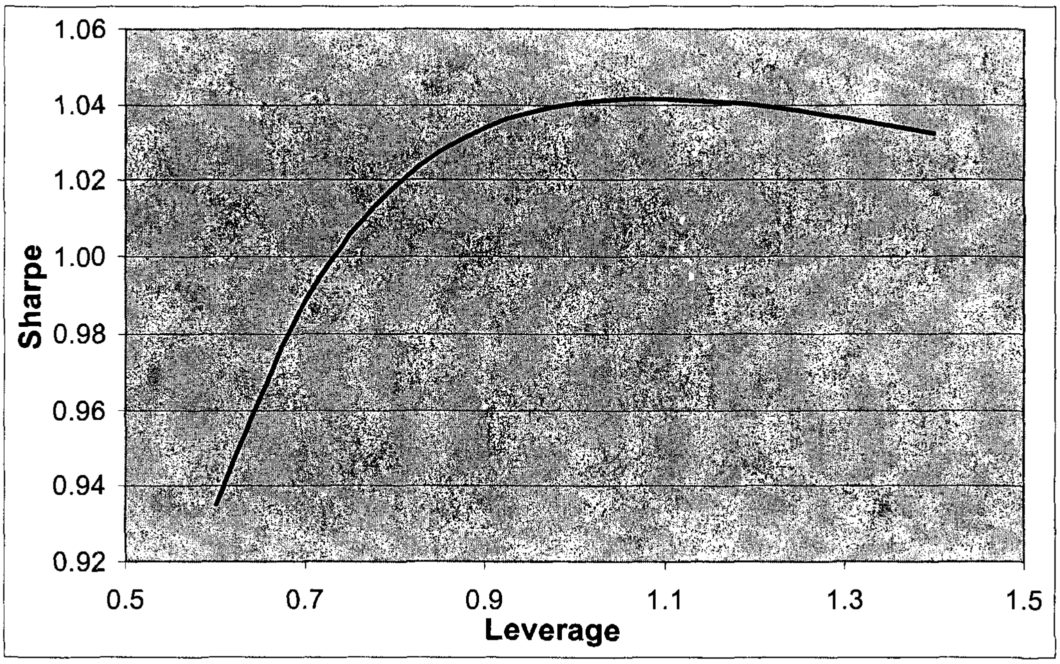


Figure 16 Sharpe Ratio Over Leverage



To improve on the optimality of portfolio performance, our calculation shows that the curve of leverage ratio of investment portfolio peaks at various percentages. That is to say, if our forecasting model recommends investing in IP for next month, we should rebalance the weights in our trading strategy. As a result, the optimality weighting our test renders is to long IP with 80% of available fund and long 3-month T-Bill with the remaining 20%. Our testing result shows that the market return can be outperformed by our strategy 4 times out of 12 if we assume there is no transaction cost involved in the decision-making for investment shift (Figure 17 - 28).

Table 53 Optimal Investment Strategy TSSM with Optimality of Weight Allocation at 80%

Optimality with 80% Allocation	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	149.67%	0.7223
2	159.19%	0.7220
3	**163.34%**	**1.1098**
4	138.38%	0.4775
5	155.06%	0.8646
6	**211.40%**	**1.2844**
7	149.41%	0.6802
8	137.16%	0.4648
9	137.25%	0.4056
10	156.56%	0.6512
11	**187.14%**	**1.2906**
12	**165.49%**	**1.0077**

Although the market can not be totally efficient, there should be a threshold of efficiency below which it becomes extremely difficult to make abnormal profit with technical and fundamental analysis given a transaction cost of trading. Hence, to model the dynamics of financial activity in a close economy, we use of transaction cost as a mechanism means that the return on the Treasury securities market must exceed that on the stock index over some certain percentage to enable the investment shift. If we take into account the transaction cost as a minimum hurdle rate and as the total sunk cost realized for an investment to shift from the T-Bill market to the stock index market, the strategy still outperforms the market 4 times out of 12 in a market less efficient with a transaction cost of 5% is tested; 3 times for a transaction cost of 6%; 2 times for a transaction cost of 7%; and only 1 time for a transaction cost of 7.5%. This suggests that when investing in these 12 U.S. industry portfolios – if we assume these portfolios are market efficient – the maximal rate a fund manager or a management firm can charge its clients would be 7.5% per annum; otherwise there will be no clients willing to invest at all (as the chance of finding the one with '1+' Sharpe Ratio is 1 time out of 12, implying a pure random probability or market efficiency). If these portfolios are presumably efficient, the management fee is about 2% per annum as a typical market rate would be, then there exists some considerable transaction cost. Likely, if these portfolios are presumably efficient, the management fee is about 2% per annum as a typical market rate would be, and there exists some considerable transaction cost, then there are certainly absolute risk-adjusted returns on these clients' investments, which should not exist if the EMH holds. With use of the real data and evaluation benchmarks for 100% allocation of investment shift, we demonstrate that our strategy combined with quantitative methods could outperform the market in 3 portfolios out of 12, given 15 years of parameters and 4 years of forecast. With modified allocation weights and real data ranging from October 1985 to September 2005 in our model, we show in a bear market – when the stock index earns a less return rate than does the treasury bill – the strategy could outperform the market 7 times out of 12, and the transaction cost is quantified at 7.5% per annum. With modified variable, our strategy could beat the S&P500 in 9 portfolios out of 12, having the highest rate of cumulative return at 164.15% over last four years. In the corresponding period, the S&P500 records only 89.27% and the Treasury Bill 109.17%. In particular, the transaction cost, implying the maximum management fee, can be quantified as high as 9% per annum.

Table 54 Improved Investment Strategy TSSM at 80% with 5% Transaction Cost Per Annum

Optimality with Tran. Cost of 5%	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	136.83%	0.4799
2	150.89%	0.6369
3	**152.84%**	**1.0020**
4	130.29%	0.3289
5	145.84%	0.7496
6	**202.46%**	**1.3014**
7	141.98%	0.6165
8	126.73%	0.2491
9	130.54%	0.3022
10	144.82%	0.5029
11	**174.56%**	**1.1912**
12	**160.51%**	**1.1077**

Table 55 Improved Investment Strategy TSSM at 80% with 6% Transaction Cost Per Annum

Optimality with Tran. Cost of 6%	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	131.96%	0.3698
2	148.80%	0.6065
3	149.25%	0.9152
4	121.91%	0.1295
5	141.28%	0.6408
6	**189.76%**	**1.1718**
7	138.58%	0.5401
8	122.69%	0.1479
9	126.55%	0.2199
10	140.85%	0.4405
11	**170.33%**	**1.1212**
12	**157.28%**	**1.0431**

Table 56 Improved Investment Strategy TSSM at 80% with 7% Transaction Cost Per Annum

Optimality with Tran. Cost Of 7%	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	128.34%	0.2846
2	144.72%	0.5388
3	145.17%	0.8103
4	118.56%	0.0398
5	137.41%	0.5456
6	**184.59%**	**1.1069**
7	134.78%	0.4514
8	119.32%	0.0606
9	123.08%	0.1459
10	136.99%	0.3782
11	**165.68%**	**1.0401**
12	152.99%	0.9463

Table 57 Improved Investment Strategy TSSM at 80% with 7.5% Transaction Cost Per Annum

Optimality with Tran. Cost of 7.5%	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	164.51%	0.3809
3 month T-Bill	118.17%	-
1	126.57%	0.2420
2	142.73%	0.5048
3	143.17%	0.7577
4	116.91%	-0.0051
5	135.51%	0.4979
6	**182.06%**	**1.0744**
7	132.92%	0.4069
8	117.67%	0.0169
9	121.37%	0.1088
10	135.09%	0.3470
11	163.41%	0.9994
12	150.88%	0.8977

Table 58 Basic Investment Strategy TSSM with 100% Stock or 100% T-Bill of 240 Periods from October 1985 to September 2005

100% Stock or 100% T-Bill	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	89.27%	-0.029
3 month T-Bill	109.17%	-
1	**122.75%**	**-1.4248**
2	**122.09%**	**-1.0670**
3	**128.91%**	**-1.4375**
4	**132.30%**	**-1.7128**
5	**143.94%**	**-2.9340**
6	51.86%	1.4928
7	76.92%	1.1075
8	100.51%	0.1860
9	**120.77%**	**-1.0843**
10	96.95%	0.7512
11	**120.77%**	**-1.1151**
12	94.78%	0.4599

Table 59 Improved Investment Strategy TSSM at 100% with 7.5% Transaction Cost Per Annum of 240 Periods from October 1985 to September 2005

100% Stock or 100% T-Bill	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	89.27%	-0.029
3 month T-Bill	109.17%	-
1	105.94%	0.1980
2	100.13%	0.2050
3	105.43%	-0.0261
4	108.46%	-0.2077
5	**124.20%**	**-2.0596**
6	42.89%	3.7446
7	63.63%	3.7088
8	101.41%	0.4965
9	102.22%	0.3692
10	91.92%	2.1995
11	105.53%	0.0694
12	80.58%	2.2386

Table 60 Basic Investment Strategy TSSM with 100% Stock or 100% T-Bill (exchange SMB with MO) of 240 Periods from October 1985 to September 2005

100% Stock or 100% T-Bill	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	89.27%	-0.029
3 month T-Bill	109.17%	-
1	**135.06%**	**-2.4845**
2	**113.63%**	**-0.6913**
3	**130.75%**	**-1.6085**
4	**147.37%**	**-2.7994**
5	**164.15%**	**-4.6386**
6	42.68%	2.5852
7	79.80%	1.1704
8	**126.91%**	**-1.5928**
9	**127.04%**	**-1.5351**
10	**117.41%**	**-1.0468**
11	**136.52%**	**-2.1125**
12	96.34%	0.4468

Table 61 Improved Investment Strategy TSSM at 100% with 9% Transaction Cost Per Annum (exchange SMB with MO) of 240 Periods from October 1985 to September 2005

100% Stock or 100% T-Bill	Compounded Return (4-yr)	Sharpe Ratio
S&P 500	89.27%	-0.029
3 month T-Bill	109.17%	-
1	97.18%	1.4151
2	86.93%	1.1701
3	97.98%	0.5854
4	107.80%	-0.1318
5	**113.78%**	**-0.8159**
6	67.07%	1.6289
7	67.39%	2.8670
8	98.10%	0.8987
9	100.88%	0.5421
10	88.26%	2.6452
11	103.79%	0.2504
12	81.67%	2.0627

All three of the optimal, the improved with 5% transaction cost and basic strategies can outperform the market in the specified time window and demonstrate superior compounded return of last 4 years and the Sharpe ratio to that of S&P500 – four times, four times and three times, respectively. Interestingly, it can be demonstrated in Figure 17 – 28 that there exist differences in some specific industry. In the industry to industry analysis, the correlations – among such IP, FIT1, FIT2 and MKTRF – seem to associate why there are systematic differences in some industries. First, we found that there is an obvious correlation between FIT1 and MKTRF as well as the FIT2 and MKTRF as shown in Table 63. Secondly, the magnitude of these correlations increases over time while the sum of two changes in the correlations of FIT1 and MKTRF and FIT2 and MKTRF in two periods of 15 years and following 4 years is -19.80%. We may assume this figure as an acquired rate of correlation from which a higher correlation would make a difference in asset pricing, and therefore results in an extractable profit. Changes in correlations of FIT1 and IPs are shown in Eq. (G), and changes in correlations of FIT2 and IPs are shown in Eq. (H). The total of these two changes in correlation is in Eq. (I), which represents a synergy of drives – nevertheless there in general can be offsetting effect instead of multiplier effect. As well, changes in direct correlations of MKTRF and IPs are shown in Eq. (J). Thirdly, we define $\frac{\partial IPs}{\partial MKTRF} = \left(\frac{\partial IPs}{\partial FIT1} \times \frac{\partial FIT1}{\partial MKTRF}\right) + \left(\frac{\partial IPs}{\partial FIT2} \times \frac{\partial FIT2}{\partial MKTRF}\right)$ in a chain relationship, so that we obtain Eq. (K), and calculate that Eq. (K) $\neq$ Eq. (J), which is directly $\frac{\partial IPs}{\partial MKTRF}$. Given that Eq. (K) $\neq$ Eq. (J), we can infer event K and J are not independent, and therefore claim Eq. (L) needs to be adjusted with the correlation between IPs and MKTRF to render a statistical robust result. In addition, we define Eq. (M) as the sum of changes in correlations of FIT1 and MKTRF, and FIT2 and MKTRF, whereas Eq. (N) is to take into account the dependency of correlations of FIT1 and MKTRF, and FIT2 and MKTRF by subtracting the product of FIT1 and FIT2 from the absolute value of Eq. (M). Finally, it can be shown in Eq. (K) that the absolute value of majority of correlations of IPs and MKTRF exceed the required rate of correlation at -19.10% and they are IP3 (-33.78%), IP6 (-30.05%), IP11 (14.85%), and IP12 (-42.08%). These four industry portfolios are the only ones without offsetting effect (both correlations of FIT1 and IPs and FIT2 and IPs go in the same direction).

Table 62 Correlations of FIT1 and MKTRF, and FIT2 and MKTRF

First 15 Years		**Following 4 Years**	
FIT1	-0.1308	FIT1	-0.2821
FIT2	-0.3135	FIT2	-0.3602
Changes		**Total of Changes**	
FIT1	-0.1513	M	-0.1980
FIT2	-0.0467	N	-0.1910

Table 63 Descriptive Statistics of IPs and its Correlations with FIT1, FIT2 and MKTRF

First 15 years

IP	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
No. obs	180	180	180	180	180	180	180	180	180	180	180	180
AVER	1.601	1.068	1.119	1.417	1.127	0.868	1.433	1.250	1.274	1.286	1.231	1.254
STD	4.690	5.631	5.519	5.846	5.245	6.171	4.282	3.694	5.703	5.224	5.118	5.711
SK	-0.679	-0.463	-0.599	-0.028	-0.420	-0.015	-0.376	0.036	-0.708	-0.355	-0.512	-0.704
KUR	6.050	6.213	6.790	4.847	6.374	4.881	4.037	3.362	6.266	4.219	4.825	6.122
Jarque-Bera	83.588	83.869	118.469	25.613	90.651	26.548	12.290	1.021	95.035	14.931	32.848	87.935
CV @ 5%	reject	reject	reject	reject	reject	reject	reject	can't rej	reject	reject	reject	reject
Autoc(1,1)	0.091	0.158	0.045	-0.001	0.005	0.086	0.000	-0.085	0.172	0.008	0.182	0.124
3rd M	-70.007	-82.718	-100.649	-5.610	-60.577	-3.455	-29.497	1.819	-131.355	-50.645	-68.674	-131.063
4th M	2926	6245	6298	5663	4823	7077	1357	626	6626	3141	3310	6513
A=Correl (FIT1,IP)	-0.174	-0.207	-0.135	0.162	-0.129	-0.177	-0.215	-0.127	-0.187	-0.115	-0.206	-0.126
B=Correl (FIT2,IP)	-0.362	-0.336	-0.272	-0.093	-0.315	-0.153	-0.322	-0.434	-0.339	-0.251	-0.418	-0.284
C=Correl (MKT,IP)	0.886	0.866	0.961	0.706	0.937	0.875	0.752	0.695	0.903	0.843	0.887	0.965

Following 4 Years

IP	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
No. obs	48	48	48	48	48	48	48	48	48	48	48	48
AVER	1.054	1.607	1.387	0.918	1.358	2.057	1.470	0.762	0.855	0.950	1.901	1.286
STD	3.547	4.664	2.944	3.480	3.437	4.118	3.209	3.112	3.735	4.763	3.601	3.419
SK	0.800	0.049	0.170	0.172	0.148	0.089	-0.174	-0.062	0.361	0.400	0.002	0.452
KUR	7.832	2.946	3.595	2.586	3.620	2.221	3.355	2.816	4.125	4.196	3.724	5.085
Jarque-Bera	51.806	0.025	0.941	0.578	0.943	1.278	0.494	0.099	3.570	4.138	1.047	10.334

CV @ 5%	reject	can't rej	can't rej	can't rej	can't rej	can't rej	can't rej	can't rej	can't rej	can't rej	can't rej	reject
Autoc(1,1)	-0.194	0.177	-0.034	-0.066	-0.176	-0.009	-0.028	0.093	-0.226	0.083	0.031	0.051
3rd M	35.686	4.972	4.347	7.241	5.999	6.217	-5.750	-1.867	18.798	43.199	0.109	18.083
4th M	1239	1394	270	379	505	638	356	264	803	2158	626	695
D=Correl (FIT1,IP)	-0.333	-0.219	-0.381	0.298	-0.215	-0.427	-0.025	-0.018	-0.400	-0.324	-0.113	-0.414
E=Correl (FIT2,IP)	-0.179	-0.207	-0.324	-0.285	-0.147	-0.165	-0.449	-0.498	-0.182	-0.108	-0.379	-0.369
F=Correl (MKT,IP)	0.834	0.575	0.908	0.528	0.831	0.782	0.767	0.507	0.812	0.749	0.889	0.894
G=D-A	-0.159	-0.012	-0.246	0.136	-0.086	-0.250	0.190	0.108	-0.213	-0.209	0.094	-0.288
H = E-B	0.183	0.129	-0.052	-0.191	0.168	-0.012	-0.127	-0.064	0.157	0.143	0.039	-0.086
I=SUM(G,H)	0.024	0.117	**-0.298**	-0.055	0.082	**-0.262**	0.063	0.045	-0.055	-0.067	**0.133**	**-0.373**
J = F-C	-0.052	-0.292	-0.053	-0.178	-0.106	-0.093	0.015	-0.187	-0.091	-0.094	0.002	-0.071
K*	0.016	-0.004	0.040	-0.012	0.005	0.038	-0.023	-0.013	0.025	0.025	-0.016	0.048
L**	0.009	0.121	**-0.338**	-0.044	0.077	**-0.301**	0.086	0.058	-0.080	-0.092	**0.149**	**-0.421**

K* = (G*ΔFIT1+H*ΔFIT2) $\neq$ J ; L** = I-(G*ΔFIT1+H*ΔFIT2)

In summary, we discover the systematic differences in the compounded rate of last 4 years and the Sharpe Ratio in some specific industry are associated with correlations of IPs with FIT1, FIT2, and MKTRF and we believe the correlation relationship, if no offsetting effect within, would have a direct impact on the asset pricing and therefore on the profitability or return on investment. With the TSSM strategy, investment returns from 4 out of 12 portfolios (about one-third of the chance) can exceed the market returns in the 4-year period from August 1992 to July 1996, and this suggests that this strategy allows the investment to outperform the market on the risk-adjusted basis, though the significant compounded returns tend to drop over time – an evidence inconsistent with the semi-strong form of the EMH (see Copeland and Mayers, 1982).

Figure 17 Performance Comparison of Interest, SP500 and IP1

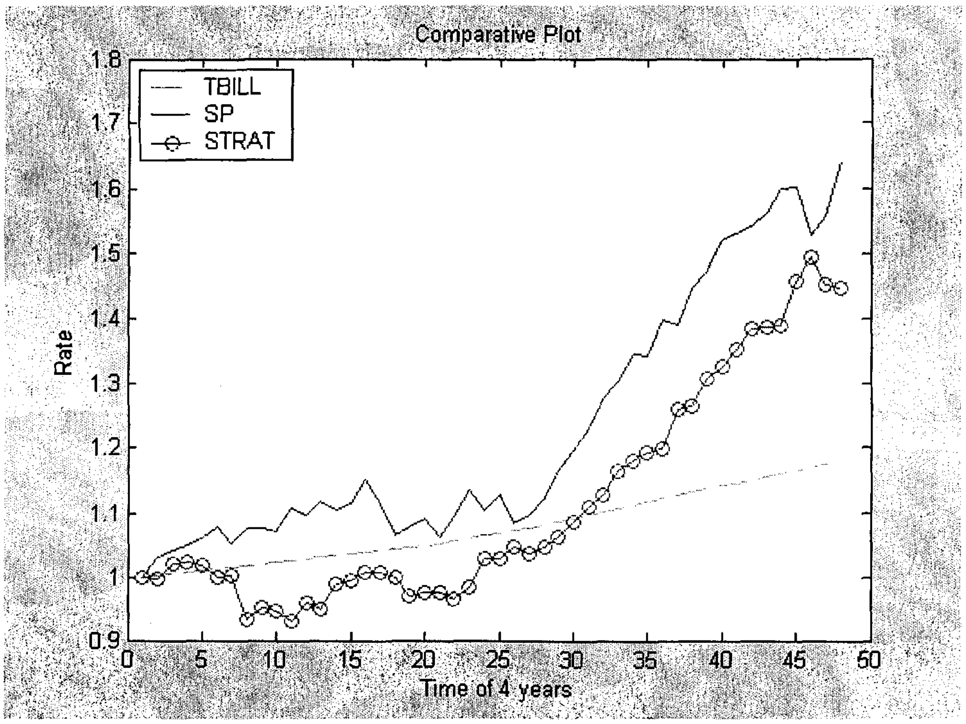


Figure 18 Performance Comparison of Interest, SP500 and IP2

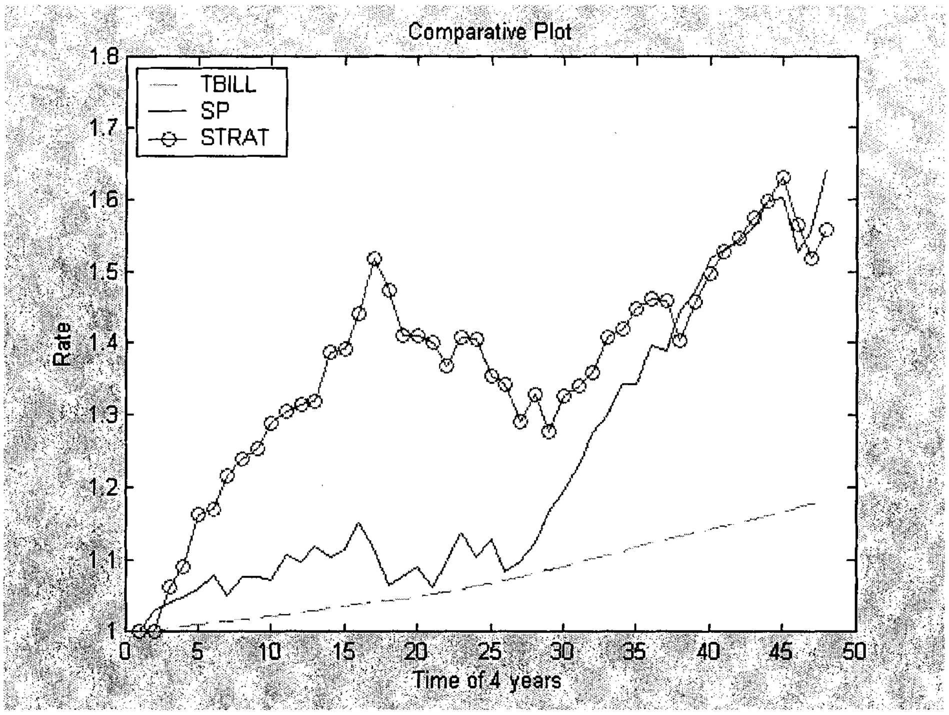


Figure 19 Performance Comparison of Interest, SP500 and IP3

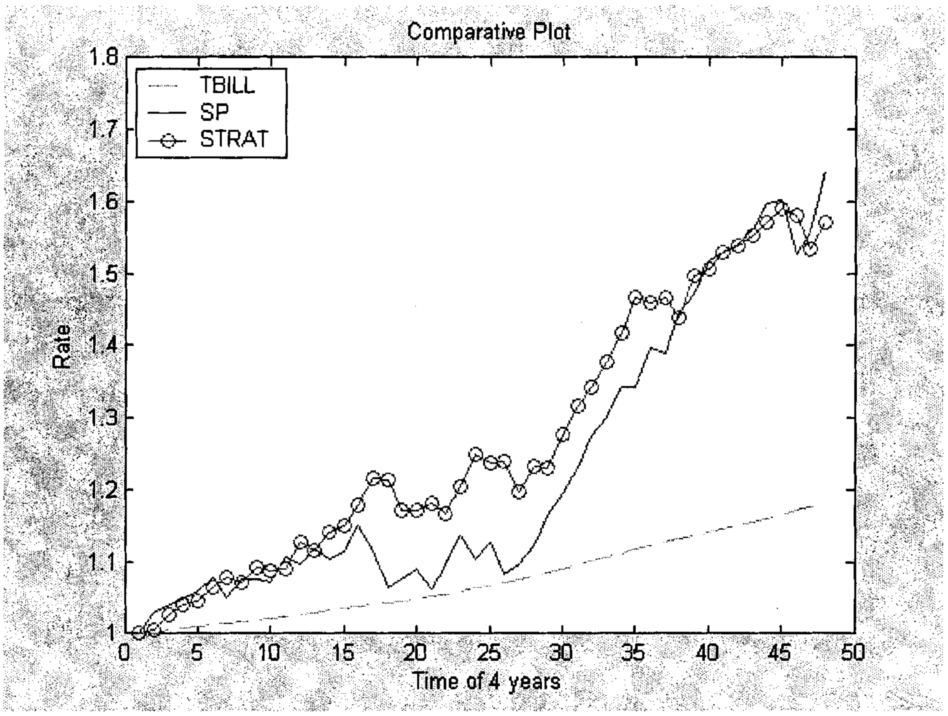


Figure 20 Performance Comparison of Interest, SP500 and IP4

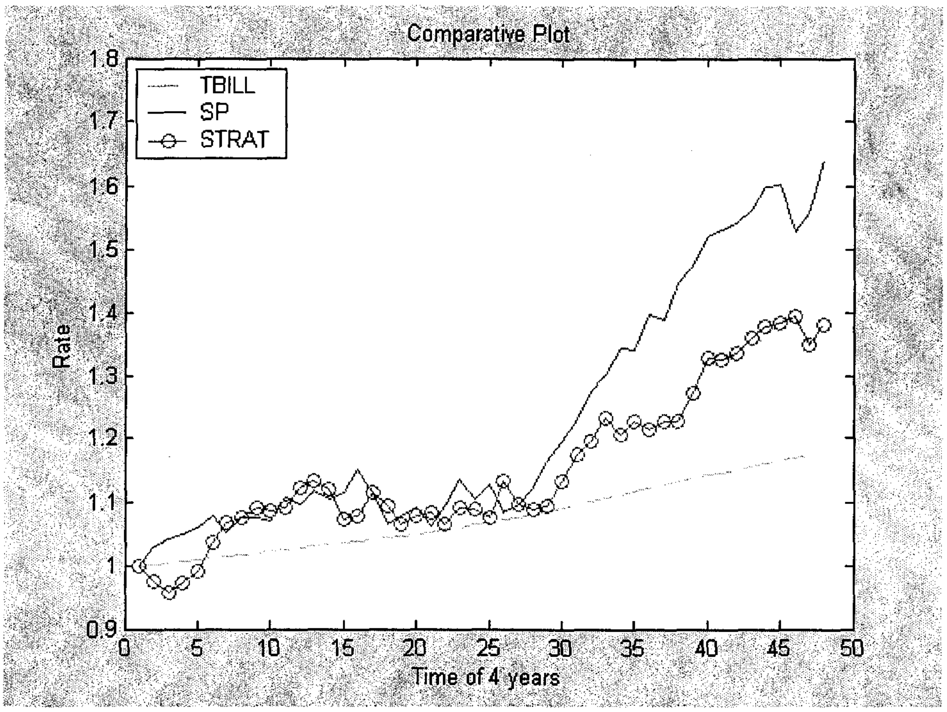


Figure 21 Performance Comparison of Interest, SP500 and IP5

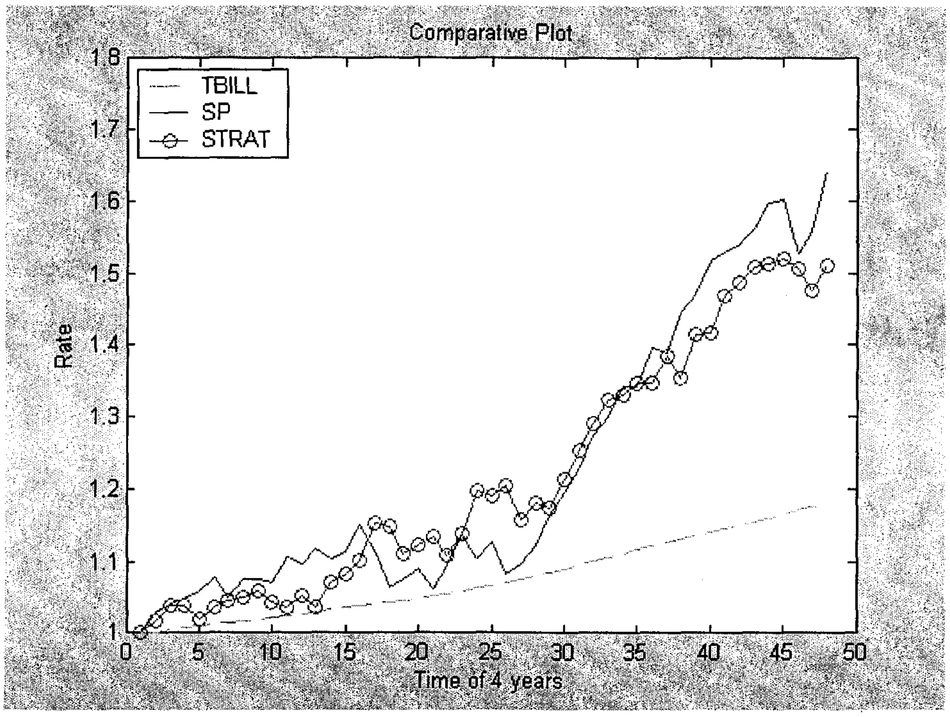


Figure 22 Performance Comparison of Interest, SP500 and IP6

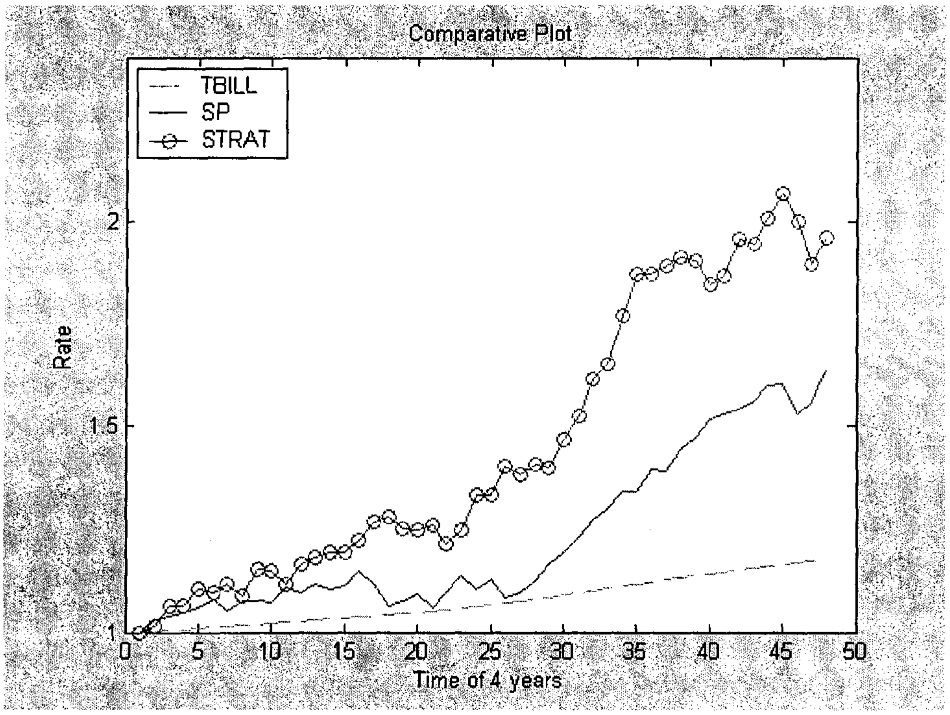


Figure 23 Performance Comparison of Interest, SP500 and IP7

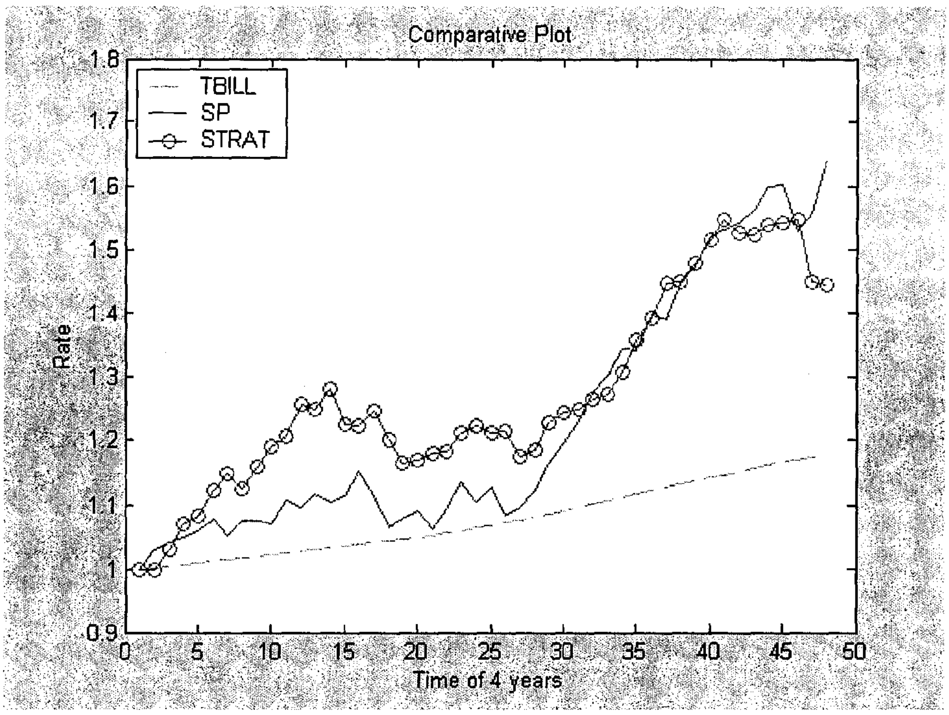


Figure 24 Performance Comparison of Interest, SP500 and IP8

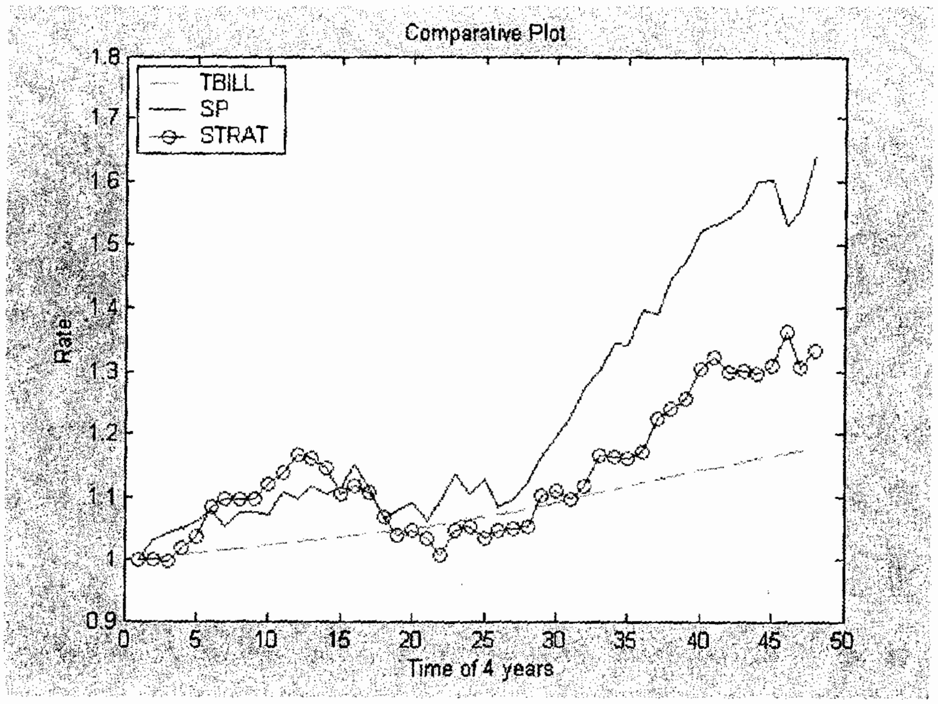
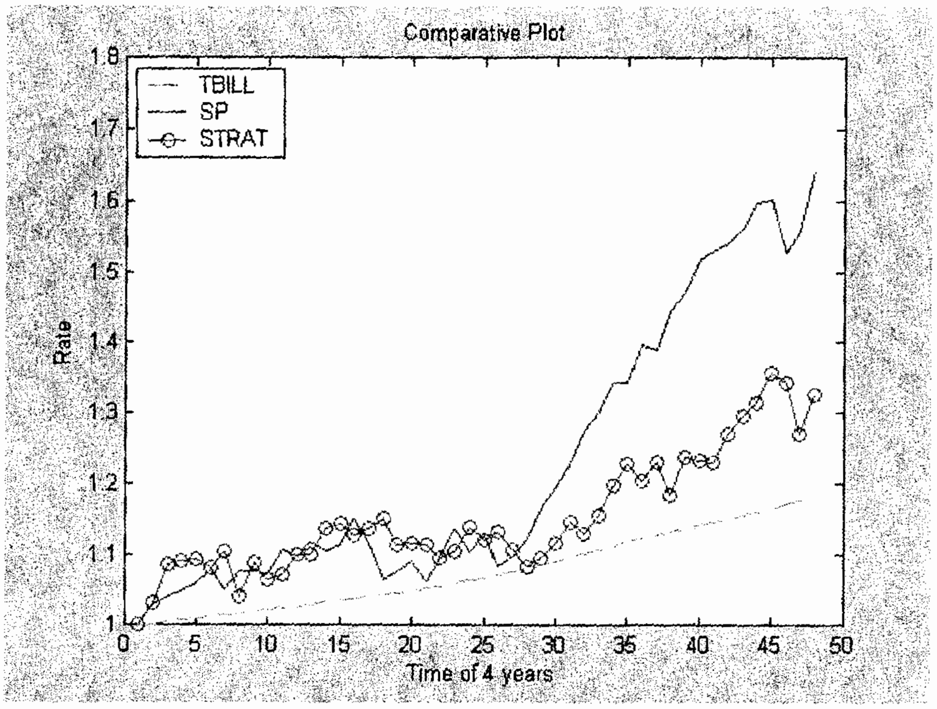
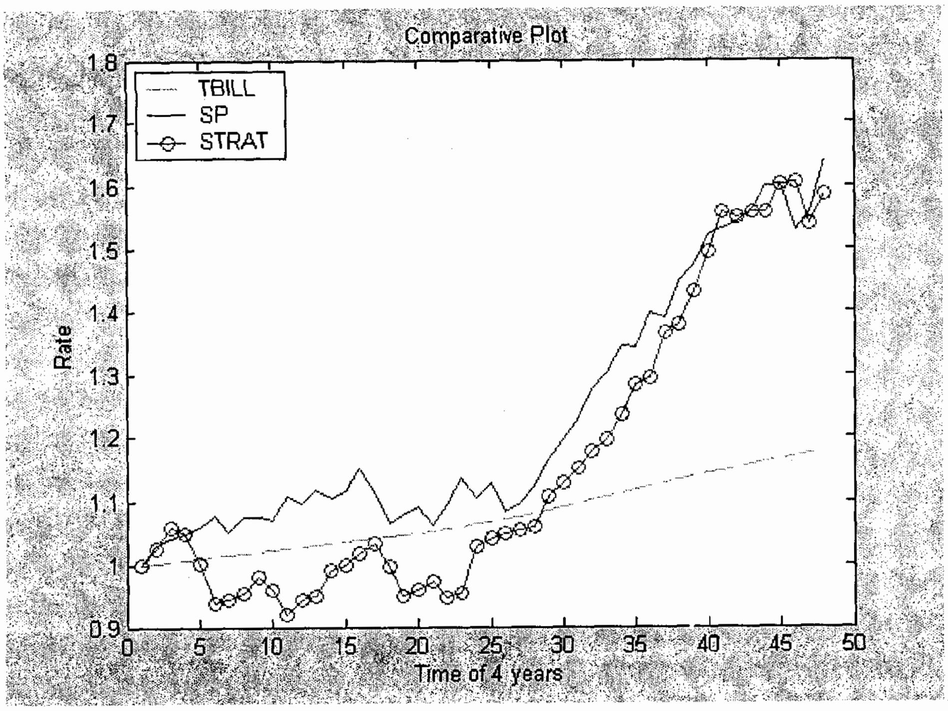


Figure 25 Performance Comparison of Interest, SP500 and IP9



munoz@sfu.ca, kchub@sfu.camunoz@sfu.ca, kchub@sfu.ca

Figure 26 Performance Comparison of Interest, SP500 and IP10



munoz@sfu.ca, kchub@sfu.ca

Figure 27 Performance Comparison of Interest, SP500 and IP11

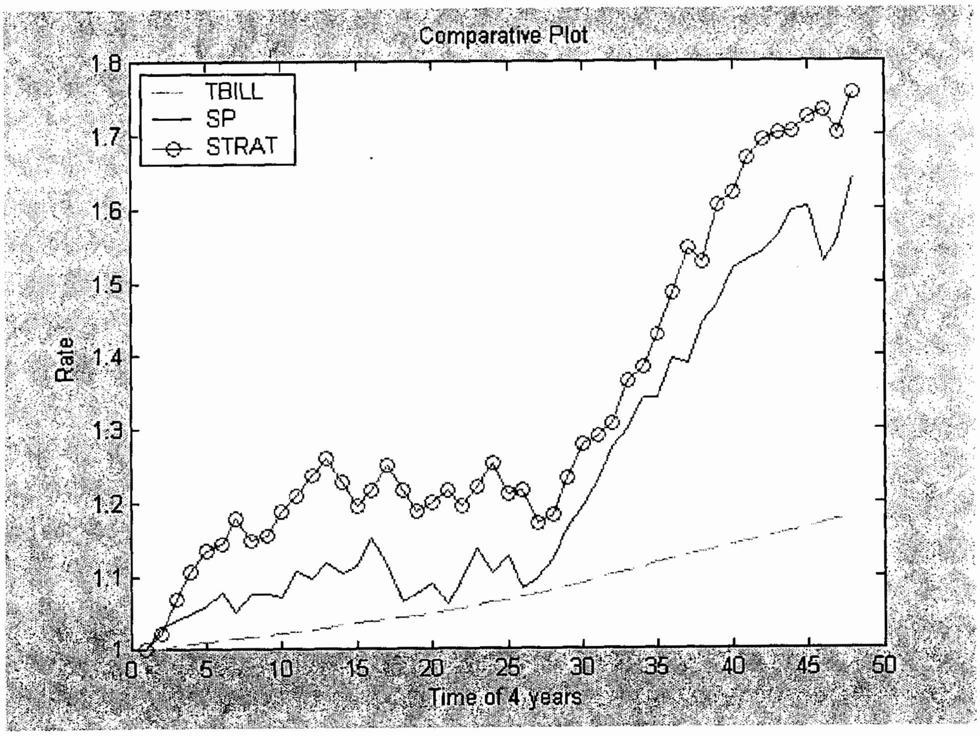
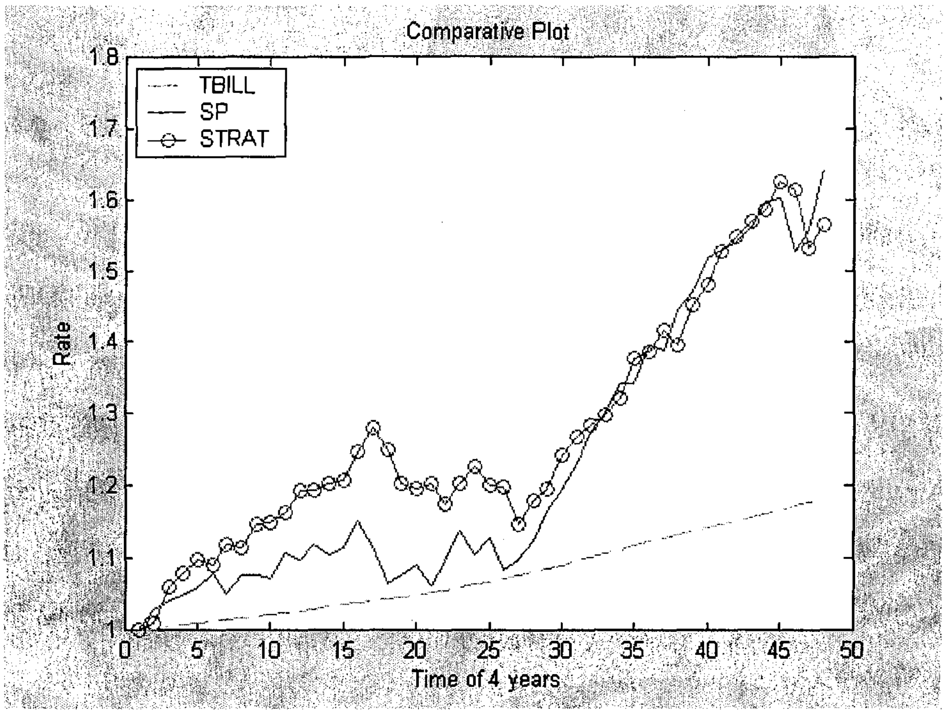


Figure 28 Performance Comparison of Interest, SP500 and IP12



4.6 Discussion of the EMH Assumptions and Anomalies' Behavioural Biases

In favour of semistrong-form efficiency, Malkiel (2005) argues that it's very hard to argue that information is not being properly incorporated into stock prices. Consistently, EMH implies that a stock prices is always at the "fair" level (or fundamental value), that a stock prices reacts to news immediately, and that a stock price changes only when the fair level changes. Fundamental value[32], refers to the present value of an asset or a cash stream an investor will receive, can be related to earnings, dividend prospects, expectations for future interest rates, and risk evaluation of the firm. EMH associates with the concept of "random walk", in which the subsequent price changes represent the random departure from its previous price changes (Malkiel, 2003). And also news information by definition is unpredictable. Therefore, stock price changes are

[32] It is also called the "theoretical futures price, which equals the spot price continuously compounded at the cost of carry rate for some time interval" (Harvey, 2006).

unpredictable because no one knows tomorrow's news and it is attributed to randomness of probability distribution. In the other word, the notion of EMH is that any information that can be used to predict stock performance should have already be reflected in the stock prices. This infer that stocks always trade at fair value and thus no arbitrate of buying low and selling high can be implemented. If so, this might infer that the management fee is charged for expert stock selection and market timing[33] ability. As well, part of a fund manager's workload is to take into account an investor's risk appetite, time horizon, level of desired returns and taxations before evaluating a risky portfolio in case such manager lacks expert stock selection and market timing ability. In this logic, it is not quite true to support EMH that implies that abnormal returns, if exist, are chance results and that investors can throw darts to select stocks.

On the other hand, the dominant view in finance literature is that if "beating the market" is possible, it would be difficult to implement a strategy to trade profit, because to do so requires resources such as time, money – these are needed to extract data, to have computer power, to develop ideas and insight, etc. Malkiel (2005) argue that "I am skeptical that any of the 'predictable patterns' that have been documented in the literature were ever sufficiently robust so as to have created profitable investment opportunities and after they have been discovered and publicized, they will certainly not allow investors to earn excess returns" (pg. 6). In a sense, this may be true for individual investors who would not afford such considerable transaction costs, but may not necessary applicable to some fund managers who are paid to compensate their time and are endowed with resources to do the analysis and investigation. It would be reasonable to assume the fund managers would not easily reveal their analytical work without commensurable

[33] Hence the evidence of timing ability of a model might serve as a counterargument against EMH.

compensations. With the similar viewpoint, Grossman and Stiglitz (1980) argue that there may not be incentives for fund managers to uncover the information that gets to be reflected in the price. Some arguments show that fund managers' preferences might have influence on the fund performance and psychological factors do influence securities prices. For example, the supervisorship bias (as stated in attribution theory) results in data on fund performance being tainted by overrepresentation of good funds in a sense that fund managers keep the good funds to lower the risk exposure, especially when foreseeing bad times. Moreover, there are evidences against EMH: stock prices are not close to random walk. Inspection of Figure 7-12 demonstrates that not only stock returns can have considerable serial correlation in the short run, but also they can be predictable to some extent in low lags as shown in our testing result. A very handful financial investors might be able to predict the trending, to exploit the opportunity, and to realize a fortune, e.g. *Berkshire Hathaway Inc* owned by Warren Buffet (2004) has outperformed the S&P index 34 times out of 39 tries for annual investment returns from 1965 to 2003 an 87% successful rate of beating the market index in a span of 39 fiscal years. Other well-known investors outperforming the market, or S&P 500 index, include Bill Miller of Legg Mason Capital Management (15 consecutive years since 1991) and Peter Lynch of Fidelity Investment. *Fideltity Magellan fund* records an average yearly return of 28% in contrast with S&P500 at 17.5%, beating the market index 11 out of 13 times (Lim, 2006). These investors made consistently excessive returns over the market proxy in a considerable time length – this apparently can not be well explained by the EMH that assumes randomness of probability distribution of stock returns. Some further suspects if long-term predictability of some unknown asset pricing model were plausible. There are also empirical evidence that potentially undermine the EMH such as anomalies that include bubbles, momentum effect, calendar effect, reversals, post-earnings announcement drift, small-firm effect, and book-to-market effect, and other multivariate relation not recognized by existing asset pricing theories. A well known example would be Black Monday – stock market crash of October 19 1987, where most stock exchange crashed at the same time and "the Dow [Jones Industrial Average (DJIA)] lost 22.6% of its value or $500 billion dollars.[34]"

5 SUMMARY AND CONCLUSION

Fama et al (1969) introduce the Efficient Market Hypothesis in a simple way to produce useful evidence on how stock prices respond to information (Fama, 1998, pg. 283). The strength of his contention is that apparent anomalies are attributable to chance results, whereas the model's lack of predictability for long-term market return is attributable to methodology. The hypothesis has been widely accepted, used and recognized by mass financial economists, fund managers, investors and speculators. As a simple and powerful hypothesis (as shown in section 4.2), it helps explore the dynamics and functions of investing activities in the past, aids decision-making process for financial agents, justifies asset pricing models, and sheds light on price elasticity to information in a variety of industries and markets.

However, such a hypothesis is subject to scrutiny after empirical results have provided counter-intuitive arguments against it. Recent findings from the finance literature have identified predictive candidates for long-term return anomalies (see section 4.4, for an example) and some

[34] Stock Market Crash! Net: http://www.stock-market-crash.net/1987.htm

evidence of information bias such as public information leaking, imposing a great challenge to the Efficient Market Hypothesis and its conclusions. A significant result that seems to challenge the EMH comprises the momentum effect and market learns hypothesis. The former stresses that some predictive candidates are statistically reliable, that momentum effect takes place in both short-window and that long window of up to 30 lags (see section 4.1), and there should be no firm-specific risk believed to be of importance especially with a well-diversified portfolio. The latter implies that information bias and incomplete information by market infrastructure and agents lead to over-reaction or under-reaction as a market outcome, providing a counter-intuitive argument to the EMH.

Many of these studies indicate that market is neither perfectly efficient (see section 4.5) nor perfectly inefficient: on one hand return anomalies seems to disappear; one the other hand they have a tendency to persist. Some financial analysts argue that disappearance of abnormal returns are not random results as appearance of them, but rather a consequence of when market learns to exploit the arbitrage from academic studies on anomalous behavior (see Schwert, 2003). Moreover, although apparent anomalies could possibly occur by chance and bad-model problems (see section 4.3) could possibly be a rational outcome, lacking the alternative does not necessarily justify for the EMH and its conclusions. Although it is difficult to test for the EMH, investors should not claim the Pyrrhic victory for the EMH at this point in time, when the EMH still seems to be an incomplete tool (see section 4.7) to explain return anomalies that can be present when an investment strategy is implemented and when transact cost can be quantified if the stock-picking tactic were presumably made purely by chance (see section 4.5 – 4.6). We report evidence of considerable transaction cost. This helps explain the general market could be inefficient, to some degree, that the fund management fee could charge as maximum as 7.5% per annum with respect to the dataset consist of 12 US Industry Portfolios, and that the general market, to some extent, is predictable – such predictability depends on the interplay of the correlation of the 'fit' and the general market and the correlation of each IP and the general market, which implicitly caused the abnormal returns (or return anomalies) to the underlying asset or investment.

The decision to campaign for this developing theory is a bit early. But until a better alternative is found, it is likely that within a linear programming domain of fund management Fama's EMH will continue to provide a framework that is commonly used by most financial economists because the EMH, along with the three-factor model, is rather a simple, no-rival tool with considerable degrees of explanatory prowess on market returns, than an easy-out solution to the market complications. An extension of this study may beneficially contribute to the discourse of market efficiency hypothesis, to the rethinking of effectiveness and sophistication of active fund management, and, if possible, to the understanding of the formation of return anomalies on the industry-to-industry basis.

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