THE USE OF IDIOSYNCRATIC RISK TO TIME THE CANADIAN MARKET

Sébastien Weiner

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ABSTRACT

The Use of Idiosyncratic Risk to Time the Canadian Market

Sébastien Weiner

This research is aimed at testing the robustness of the positive correlation between average stock risk and stock market returns documented by Goyal and Santa-Clara (2003). This is addressed by investigating this relationship in the Canadian market by using an improved market timing methodology. We examine both the statistical and financial properties of average stock risk, as measured for equal- and value-weighted portfolios using a daily sample of all TSE-listed Canadian firms between January 1975 and December 2001. In order to further test the robustness of the relationship, we examine two sub-samples, January 1980 to December 1989 and January 1990 to December 1999. We find that the positive trend in average stock risk previously noted by Campbell et al (2001) and by Goyal and Santa-Clara (2003) is only present over our entire time period and not over each of the sub-periods. This questions the generality of the result for the entire period. Further, our findings do not support the positive correlation between average stock risk and stock market return. Our analysis shows only a weak statistical link and practically no financial timing ability when this time-series is used in an active market timing investment strategy. When macro-economic variables are introduced into our forecasting models, the in-sample statistical properties of the risk-return relationship increases significantly at the expense of the out-of-sample forecasting accuracy.

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1. Introduction

For as long as financial markets have existed, there have been investors trying to devise models or techniques to try to "beat the market". Over the last twenty years, the fast pace of technological advances in information technology has given the tools to these investors and enabled them to devise ever more sophisticated market timing models. Yet, the question remains: "Can the positive relationship between risk and return explained in financial theory be successfully used to outperform the market?"

A review of the extensive body of literature on this relationship shows that the link is weak at best and that superior market timing returns are not possible. Following the work of Campbell, Lettau, Malkiel and Xu (2001) and Goyal and Santa-Clara (2003), we hypothesize that market timing models should be developed using average stock risk instead of total market risk. There are many reasons to be interested in average stock risk and why it could lead to better market timing returns. First, corporate compensation policies lead to individuals holding undiversified portfolios with large holdings in the shares of their employer. Secondly, proper diversification described by classical portfolio theory depends on the level of idiosyncratic risk of the stocks making up the portfolio. Third, arbitrageurs stake their livelihood on idiosyncratic risk. It is this risk that they try to exploit. Fourth, firm-level volatility is the most important type of risk in event studies. Fifth, the pricing of financial derivatives is dependent on the total level of risk of the underlying security. This total risk includes average or firm-level risk.

The objective of this thesis is to examine both the statistical and the financial usefulness of average stock risk in predicting Canadian stock market returns. In doing so, the robustness of the significant positive correlation between average stock risk and the market return documented by Goyal and Santa-Clara (2003) is tested. Further, we improve on the methodology used by Goyal and Santa-Clara by employing the market timing metric of Elton and Gruber and assuming four distinct natural habitats. Also, we examine the correlation using both equal-weighted and value-weighted market indices for a different market, the Canadian market.

The thesis makes five major contributions to the literature. The first major contribution is our finding that the positive trend in average stock risk is only present when our entire sample of January 1975 to December 2001 is analyzed. Using either of the two sub-samples, January 1980 to December 1989 and January 1990 to December 1999, there is no significant positive trend in average stock risk. This questions the generality of the findings by Campbell et al (2001) and Goyal and Santa-Clara (2003). The second major contribution is the lack of support for the relationship between average stock risk and market return. Although the theory states a positive link between average stock risk and market returns, our empirical findings show a weak statistical link. The third contribution is a methodological improvement. We replace the use of the quadratic utility function by the Elton and Gruber market timing metric, and use four natural habitats and reflect trade costs. Fourth, our empirical research further reinforces the previous findings that the variance of the market has no forecasting ability for the market return. Lastly, we show that the use of two macro-variables increases the in-sample statistical properties of the risk-return relationship at the expense of the out-of-sample forecasting accuracy.

The remainder of the paper is organized as follows. Section 2 provides a detailed review of the volatility and timing performance literature as well as a review of the two main papers underlying our research. Section 3 describes the data used in this thesis. In section 4, we compute the risk measures and explore their statistical properties in forecasting market returns. Section 5 looks at the financial properties of the risk measures. Section 6 summarizes our findings and concludes the study.

2. Literature Review

This thesis combines two areas of finance, volatility and timing performance. We begin by comprehensively reviewing the existing literature of these two areas. Also, we summarize the work of Campbell, Lettau, Malkiel and Xu (2001) and Goyal and Santa-Clara (2003), as our research extends the work of these authors.

2.1 Volatility

The importance of the relationship between risk and return in the field of finance cannot be overstated. It is the most basic yet most important theoretical concept of the discipline. Commonly referred to as "no free lunch", this principal states that over the long term, it is not possible to improve returns without a proportionally larger amount of risk. All asset-pricing models are based on this. For example, Sharpe's (1964) Capital Asset Pricing Model (henceforth CAPM) introduces the beta parameter, defined as the ratio of the covariance of the return of an asset with that of the market, divided by the variance of the return on the market. Both the numerator and denominator in the beta calculation are risk measures.

Although asset-pricing models state that only systematic risk should affect returns, several authors have developed models that take idiosyncratic risk into account. Building on the principles of the CAPM, Mao's (1971), Levy (1978), Merton (1987), Malkiel and Xu (2002) elaborate models of limited diversification. Four main reasons are given to explain why individuals may chose to hold such "undiversified" or limited portfolios, namely: transaction costs, taxes, employment compensation, and private information. These extensions of the CAPM result in an additional beta with respect to a market wide measure of idiosyncratic risk.

Kryzanowski and To (1982) compare and reconcile two main contributions to the literature on asset-pricing given imperfect information and extract two testable empirical relationships. The first testable relationship is given in Levy (1978) and states that individual investor's portfolio is mean-variance efficient with regard to the number of securities held in the portfolio and that any security included in the portfolio is linearly related to the intra-portfolio risk of that security. The second testable hypothesis, albeit much less easily tested, is suggested by Mao's (1971) model.

Mayers (1976) also begins with the CAPM framework but includes a non-traded human capital factor. Barberis and Huang (2001) present a different perspective by distinguishing between different levels of loss aversion and conclude that investors exhibit loss aversion to fluctuations of owned individual stocks as opposed to fluctuations of their entire portfolio.

Over the last thirty years, there has been an enormous amount of empirical literature trying to prove the positive link established by financial theory between expected market returns and the conditional volatility of the aggregate stock market. Pindyck (1984) states that an increase in volatility during the 1970's led to an increase in the expected risk premium, defined as the difference between the market return and the risk-free rate, which in turn led to the decline in stock prices.[1] However, Pindyck (1984) fails to provide a direct test of the relationship between expected returns and volatility. French, Schwert and Stambaugh (1987) set out to test this relationship. Using two separate models, they obtain insignificantly positive empirical results. However, they do obtain a significantly negative relationship between unexpected volatilities and excess holding period returns,[2] which they interpret as supporting the positive relationship between volatility and expected returns.[3]

Turner, Startz and Nelson (1989) develop a model where the market switches between two states: a high-variance and a low-variance state. Thus, excess return is drawn from two normal densities and the state in each period determines which of the two normal densities is used for that period. This model structure is heteroskedastic by construction and has a strong time-dependence, which according to the authors improves the forecasting ability for the conditional variance of the market and, in turn, the risk-return model. By using this two-state model on post world-war two S&P data, Turner et al (1989) find a negative correlation between risk and return. Bailie and DeGennaro (1990) also examine the relationship between stock returns and volatility and conclude that the empirical evidence suggests that investors consider another measure of risk to be more important than the variance of portfolio returns in predicting returns.

Campbell and Hentschel (1992) revisit the "volatility feedback" concept first discussed by Pindyck (1984) and French, Schwert and Stambaugh (1987). They develop

[1] In order to obtain the higher expected risk premium, given a constant cash flow stream generated by the firm, one must be able to buy the stock for less, hence a lower stock price.
[2] If the standard deviation today increases, the positive relationship with the risk premium will cause the discount rate for future cash flows to increase, thereby effectively decreasing the present value of these future cash flows and the stock price.
[3] French, Schwert and Stambaugh (1987) also show that this large negative relationship is too large to be explained solely by the leverage effect proposed by Black (1979) and Christie (1982).

a complete formal model, which accounts for the asymmetric properties of volatility. This is the notion that large negative stock returns are more common than large positive stock returns (contemporaneous asymmetry), and that volatility is typically higher after stock market declines than after stock market increases (predictive asymmetry).[4] Furthermore, the Campbell and Hentschel (1992) model accounts for the excess kurtosis of stock markets and the persistence of volatility.[5,6] Campbell and Hentschel conclude that volatility feedback has little effect on returns and contributes little to the unconditional variance of stocks.

Chan, Karolyi and Stulz (1992) introduce a foreign factor into the risk return model. They find that the conditional expected US stock return is not related to the conditional US stock variance but is positively related to the conditional covariance with stock returns on a foreign index.

Glosten, Jagannathan and Runkle (1993) examine the possibility that the GARCH-M methodology used by most of the previous research is mis-specified and leads to the inconclusive results found in the literature. They apply three modifications to the methodology; specifically, they allow seasonal patterns in volatility, allow positive and negative innovations to returns to have differing impacts, and allow nominal interest rates to help predict conditional variances. Their results support the negative correlation between volatility and expected returns found by Fama and French (1977), Campbell (1987), Breen, Glosten and Jagannathan (1989) and Harvey (1991). Whitelaw (1994) also finds a negative contemporaneous correlation between risk and return. However,

[4] This is first discussed by Black (1976).
[5] Excess kurtosis refers to the fact that extreme stock price movements are more frequent than is expected if the changes are sampled from a normal distribution.
[6] Large volatility is followed by large volatility.

Whitelaw (1994) also finds a significant noncomtemporaneous positive correlation between lagged conditional volatility and returns, and a significant noncontemporaneous negative correlation between led conditional volatility and returns. Furthermore, Whitelaw (1994) finds that the size of these noncontemporaneous relationships vary over time.

Scruggs (1998) uses a two-factor model based on Merton's (1973) intertemporal capital asset pricing model (ICAPM) to test the partial relation between expected market returns and conditional volatilities.[7] He finds a significant positive partial correlation. According to Scruggs (1998), his findings support the argument that single factor models are inadequate in explaining the risk-return relationship.

In a seminal paper, Schwert (1989) analyzes the time-series relationship between aggregate stock market volatility and macro-economic or financial variables. He investigates the interactions of the following variables: PPI volatility, volatility of monetary base growth rate, volatility of growth rate of industrial production, level of economic activity,[8] dividends, earnings yields, spread between low- and high-grade corporate bonds, financial leverage, and number of trading days in a month. This paper emphasizes the puzzling fact that stock market volatility is not more closely related to other measures of economic volatility. However, Schwert (1989) does state five findings. First, he finds that the 1929-1939 great depression caused many series to be more volatile, but none were impacted as much as stock volatility which increased two to three fold. Second, financial asset returns and measures of real economic activity are more volatile during recessions. Third, weak evidence exists that macroeconomic volatility can

[7] His second factor is long-term government bond returns.
[8] Schwert (1989) includes a dummy variable that equals one for NBER recession months and zero otherwise.

help predict stock market volatility. Fourth, although financial leverage does affect stock volatility,[9] it only accounts for a small portion of the volatility. Finally, there appears to be a relationship between trading activity and stock volatility.

2.2 Timing Performance

Market timing refers to a money management strategy that attempts to generate higher returns by switching funds between the stock market and the risk-free rate based on signals generated by, for example, a statistical model. Although the efficient market hypothesis states that it is impossible for a money manager to consistently "beat the market" using information he holds, there has been a large amount of literature dealing with market timing.[10]

One of the earliest works is by Sharpe (1975) who attempts to answer the question: "How superior must one's prediction be to implement a market timing style effectively?" Using US data from 1929 to 1972, inclusively, Sharpe (1975) concludes that attempts to time the market will not improve returns by more than four percent over the long-run. Sharpe (1975) further concludes that unless a manager can predict more than seven times out of ten whether the market will be bull or bear, the manager should not attempt to time the market.

Clarke, FitzGerald, Berent and Statman (1989) develop a simulation framework that allows them to assess the effects of different levels of information on the expected returns from market timing. They find that even modest amounts of information can bring

[9] This supports the earlier findings of Black (1976) and Christie (1982).

[10] The efficient market hypothesis (henceforth EMH) states that all information that could be used to predict stock prices is already included in the price. Financial theory dictates three forms of EMH, weak, semi-strong and strong.

substantial returns. Clarke et al (1989) find that a market timing model with an R-square as small as 0.09, can generate excess returns above a buy-and-hold strategy of 5.9% annually.

Hardy (1990) uses a multiple regression methodology with four variables to forecast excess returns and to time the market in six countries.[11] His results show that risk premiums vary over time and that it is possible to predict excess returns on stocks from these six countries with similar variables. However, his research does not include transaction costs, which would limit the benefits achieved by his trading rules.

Beebower and Varikooty (1991) simulate the performance of the market over the 1926 to 1989 period in order to test different methods of measuring market timing ability. They test six different measures of timing ability: Henriksson and Merton parametric test, Henriksson and Merton nonparametric test, t-statistic test for superior performance relative to a benchmark, percentage of time a market timer has underperformed the benchmark, a nonparametric chi-square test of independence, and a probit model. Beebower and Varikooty (1991) conclude that a time period beyond human life expectancy is required in order for these measures to detect timing ability in excess of a 2% excess return.

Wagner, Shellans and Paul (1992) are the first to empirically study the track records of market timers. Using a five-year sample from 1985 to 1990, they conclude that the average market timer outperforms the market 91% of the time during declining months and 8% of the time in advancing months. The authors report that market timers do not try to beat the market during advancing months, but rather during declining months by

[11] The variables are historical dividend yields, the spread between the long and short rates, short-term interest rates, and a dummy to account for the January effect. The countries are Belgium, West Germany, Japan, the Netherlands, the United Kingdom, and the United States.

avoiding the declines. Wagner et al (1992) report that the results from all of the measures show that market timing is superior to a buy-and-hold portfolio. Brocato and Chandy (1994) replicate the study of Wagner et al (1992) for a group of random timers and find virtually identical results. Thus, they attribute the results of Wagner et al (1992) to a selection bias inherent in their sample. The sample used by Wagner et al (1992) is composed only of market timing funds that have been in operation for at least five-years, which introduces a survivorship bias. Furthermore, inclusion in their sample was voluntary on the part of the market timing funds.

Larsen and Wozniak (1994, 1995) continue the research of Wagner et al (1992) and Brocato and Chandy (1994) by extending the sample over the period of January 1977 to December 1992. They use a discrete regression model of market timing and find evidence that market timing can work in the real world. Larsen and Wozniak's (1994, 1995) principal finding is that market timing can improve the performance over a passive fixed-weight portfolio by both increasing returns and decreasing the variance. Brocato and Chandy (1995) comment on Larsen and Wozniak (1995). Brocato and Chandy (1995) state that although Larsen and Wozniak (1995) do a thorough statistical analysis of the data, they question the robustness of the results.

Fuller and Kling (1994) extend previous research by Fama and French (1989) on the predictability of stock returns in a market-timing context. They conclude that using monthly data from 1938 to 1988, the Fama and French (1989) models predict negative excess returns, but that when considering transaction costs, subperiods, and consistency across models, it becomes doubtful that these models would be reliable.

Reichenstein and Rich (1994) show that dividend yield or price/earnings ratios can accurately predict stock market returns in the short-run, but transaction costs would eliminate the limited profits that may be gained. Secondly, these authors find that long-run returns are partially predictable. Based on this latter result, they conclude that some market timing is justified.

Lee (1997) examines the empirical relationship between stock returns and short-term interest rates using a three-year rolling regression market timing methodology. Lee finds that the relationship is unstable through time and that any market timing benefits are completely eroded by 1989. Furthermore, Lee (1997) finds that the average market timing strategy is 3.65 basis points lower, before accounting for transaction fees, than a buy-and-hold strategy.

Copeland and Copeland (1999) use the one-day percentage change in the VIX from its seventy-five day average as a timing signal to investigate the empirical relationship between size and style.[12] They conclude that following these timing rules generates positive excess returns and that market timing may be feasible.

Chung and Kryzanowski (2000) examine whether a market timing strategy based on the informational content of top-down and bottom-up consensus forecasts can generate superior investment performance. Chung and Kryzanowski (2000) conclude that investors cannot generate a "free lunch" by timing the market. This conclusion further reinforces Sharpe's (1975) finding that only investors with truly superior foresight should attempt to beat the market. Secondly, Chung and Kryzanowski (2000) find a significant optimism bias in both the top-down and bottom-up forecasts, but find that individual investors should use the less optimistic top-down forecast. Further, the authors suggest

[12] Size refers to large versus small capitalization funds and style refers to value versus growth funds.

that investors could use the informational difference between top-down and bottom-up forecasts to extract some information about the level of overoptimism. Finally, Chung and Kryzanowski (2000) find that this overoptimism decreases over the year, and that the overoptimism exhibits temporary reversal during the months of January.

2.3 Campbell, Lettau, Malkiel and Xu

Campbell, Lettau, Malkiel and Xu (2001) develop a methodology to disaggregate total stock volatility into three components; namely: aggregate market-level volatility, industry-level volatility, and firm-level volatility. They discuss several reasons to be interested in these three volatility components.

First, many investors have large holdings of individual stocks. This causes their portfolios to not be diversified in the manner suggested by classical portfolio theory. Thus, they are much more susceptible to the volatility of particular stocks. Corporate compensation policies are usually a primary cause of such lack of proper diversification.

Second, the adequacy of classical portfolio diversification depends on the levels of idiosyncratic volatility of the stocks making up the portfolio.[13] Third, arbitrageurs that trade to exploit the mispricing of individual stocks are affected by firm-level volatility and not aggregate market-level volatility. These arbitrageurs depend on idiosyncratic risk, as larger pricing errors are more frequent when idiosyncratic risk is high (Schleifer and Vishny, 1997).

[13] General financial wisdom states that a portfolio made up of 25 to 30 stocks should diversify away the idiosyncratic risk associated with each individual security.

Fourth, firm-level volatility is most important in event studies. Events affect individual stocks and the significance of event-related abnormal returns depends on the volatility of the individual stocks.

Fifth, the price of an option on a particular stock depends on the total volatility of the underlying stock, including industry- and firm-level volatilities. Finally, the three disaggregated volatility measures have important relationships in macroeconomic models. Lilien (1982) states that sectoral reallocation models imply that an increase in industry-level volatility of productivity growth could decrease the output as resources are diverted away from production. Caballero and Hammour (1994) and Eden and Jovanovic (1994), through their models of "cleansing recession", highlight the same type of relationship but at the firm level. An outside increase in the arrival rate of information about management quality could temporarily decrease output as resources are reallocated from low quality to high-quality firms. Similarly, a recession that occurs for some other reason could increase the pace of management quality information and influence the reallocation.

Campbell, Lettau, Malkiel and Xu (2001) find that market-level and industry-level volatilities have not increased over time, but that the firm-level component shows a significant positive trend over their sample period 1962 to 1997. The authors then go on to discuss possible explanations for this positive trend. It is essential at this point to state that an increase in the volatility of stocks can only be caused by an increase in the variance of cash flow shocks, an increase in the variance of discount rate shocks, or an increase in the covariance of these two terms. Increases in the variance of idiosyncratic cash flow shocks could be caused by the trend to break up conglomerates and replace them with more specialized firms. This is in essence a shift from internal to external capital markets.[14] Also, companies have begun to issue stock at an earlier stage in their development, at a stage where their long-run profitability and cash flow are less certain.[15] The increase in the use of stock options in executive compensation could also help to explain the positive trend in idiosyncratic stock volatility. Managers whose compensation relies more heavily on stock options are more prone to unnecessarily increasing the risk of their firms. Leverage is another factor that can increase the variance of cash flows to equity holders. When a company increases its leverage, equity holders bear the increase in the cash flow risk of the firm, which leads to an increase in the volatility of the stock. Finally, Campbell, Lettau, Malkiel and Xu (2001) discuss two other factors that can have an impact, albeit ambiguously, on idiosyncratic volatility: information technology and financial innovations (i.e. derivatives).

2.4 Goyal and Santa-Clara

Goyal and Santa-Clara (2003) document a link between idiosyncratic equity risk and stock market returns. They begin by confirming the findings of previous studies that the variance of the market has no predictive power for the market return. However, they find a significant positive relationship between firm-level volatility, as calculated by Campbell et al (2001), which they refer to as average stock risk, and the return on the market. They use this significant relationship to devise a market-timing model. This model leads to the conclusion that the relationship between average stock risk and market returns can be used to produce economically significant returns.

[14] A conglomerate can be thought of as being itself a diversified portfolio.
[15] This relationship is more important for the results using equal weights.

Three possible explanations for the relationship between the firm-level volatility and the market return are discussed. First, they argue that average stock risk may be a proxy for background risk. When the risk associated with the non-traded assets held by investors increases, the investors are less willing to hold other traded assets. The investor will then demand an increase in the expected return of the stock portfolio to compensate for the increase in risk. The two most widely recognized non-traded assets in the finance literature are human capital and private businesses. Second, Goyal and Santa-Clara (2003) state that their findings are consistent with models of investor heterogeneity. By assuming that individual stocks proxy the idiosyncratic income of investors, the authors treat average stock risk as the cross-sectional variance of income shocks among investors. Finally, by looking at the equity of a firm through an options perspective,[16] they demonstrate that an increase in average stock risk leads to an increase in the value of the stock at the expense of debt holders.[17]

3. DATA

The data for this thesis are gathered from the Canadian Financial Market Research Database (henceforth CFMRC). Although the CFMRC database contains stock price information for all TSX (previously known as the Toronto Stock Exchange or TSE) listed firms between 1950 and 2001, the sample is restricted to all daily stock price information from January 1975 to December 2001, inclusively. This sample corresponds to the availability of the CFMRC equal- and value-weighted market indices. This data sample is the Canadian equivalent to the samples used by Campbell, Lettau, Malkiel and Xu (2001)

[16] Owning a stock is akin to owning a call option on the value of the firm.
[17] Under this explanation, an increase in average stock risk would not have an impact on the total value of the firm, only on the split between equity holders and bondholders.

and by Goyal and Santa-Clara (2003), which cover the period from July 1962 to December 1999.[18]

The sample for the research contains 3,607 securities over a 6,804 day period (i.e., 27 years).[19] In order to calculate the risk measures used in this thesis, the following daily information was extracted from the database: ticker symbols; dates (which were also broken down into months and years); closing prices; closing bid prices; closing ask prices; and returns. Duplicate entries and entries that had missing values (represented by "." or "-9") were eliminated.[20]

Based on the assumption that monthly outstanding share data are constant within a month, capitalization is calculated as follows:

$$Mktcap_{i,t} = Cprice_{i,t} * Oshares_{i,m-1} \tag{1}$$

In equation (1), $Mktcapt_{i,t}$ is the market capitalization of stock i on day t, $Cprice_{i,t}$ is the closing price of stock i on day t, and $Oshares_{i,t}$ is the outstanding shares of stock i at the close of the previous month.

Both equal- and value-weighted portfolio returns are computed on a daily basis using all of the stocks that had valid returns for that day.

4. Statistical Properties of the Risk Measures

[18] Their sample represented the availability of CRSP daily stock information.
[19] Not every security traded over the entire sample period of 27 years.
[20] Although it may have been preferable to replace missing returns by the mid-spread, the closing bid and closing ask prices were more often than not also unavailable which made calculations impossible.

In this section, we present the risk measures and investigate their statistical properties and their relationships with the market returns.

4.1 Risk Measures

The methodology used in this thesis to derive the risk measures, was first presented by Campbell, Lettau, Malkiel and Xu (2001) and later used by Goyal and Santa-Clara (2003). The goal of this methodology is to define volatility measures that sum to the total return volatility of a stock without the complexities of calculating covariances or estimating betas.

The "market-adjusted-return-model" of Campbell, Lo and MacKinlay (1997) is given by:

$$R_{ijt} = R_{mt} + \varepsilon_{it} + \eta_{ijt} \tag{2}$$

where R_{ijt} is the return of firm j in industry i at time t, ε_{it} is the difference between industry return R_{it} and the market return R_{mt}, and η_{ijt} is the difference between the firm return and the sum of the market and industry returns.

The variance of the firm return R_{ijt} in equation (2) is given by:

$$\begin{aligned} Var(R_{ijt}) &= Var(R_{mt}) + Var(\varepsilon_{it}) + Var(\eta_{ijt}) \\ &+ 2Cov(R_{mt}, \varepsilon_{it}) + 2Cov(\varepsilon_{it}, \eta_{ijt}) + 2Cov(R_{mt}, \eta_{ijt}) \end{aligned} \tag{3}$$

Although the variance of an individual firm j includes covariance terms,[21] they can be eliminated by taking the weighted average of firm variances within each industry and then across industries. Specifically:

$$\sum_i w_{it} \sum_{j \in i} w_{ijt} Var(R_{ijt}) = Var(R_{mt}) + \sum_i w_{it} Var(\varepsilon_{it}) + \sum_i w_{it} \sigma^2_{\eta ij} \quad (4)$$

By re-arranging equation (4) to compute the firm variance without the need of first computing the industry variances, we obtain the risk measure referred to by Goyal and Santa-Clara (2003) as being the average stock variance. This measure is the arithmetic average of the monthly variances of each stock's returns, and is given by:

$$V_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \left[\sum_{d=1}^{D_t} r_{jd}^2 + 2 \sum_{d=1}^{D_t} r_{jd} r_{jd-1} \right] \quad (5)$$

where r_{jd} is the return on stock j on day t, and N_t is the number of stocks that exist in month t. The second term on the right-hand side of equation (5) follows French, Schwert and Stambaugh (1987), and adjusts for the autocorrelation in daily returns.

Equation (5) is not a true variance measure as the returns are not demeaned before taking the expectations, but for short holding periods (as is the case in this research) the impact is minimal. The benefit of this method is that it avoids the need to estimate mean stock returns.

[21] By extension, it also includes betas.

Similarly to Goyal and Santa-Clara (2003), the monthly variance of a portfolio p is computed using within-month daily return data, or:

$$V_{pt} = \sum_{d=1}^{D_t} r_{pd}^2 + 2\sum_{d=1}^{D_t} r_{pd} r_{pd-1} \tag{6}$$

where D_t is the number of days in month t, and r_{pd} is the portfolio return on day t. This variance calculation is performed for both an equal-weighted and a value-weighted portfolio to obtain two monthly portfolio variance measures, V_{pte} and V_{ptv}.

4.2 Descriptive Statistics

Table 1 reports the descriptive statistics on the variance measures and their corresponding standard deviations for the entire time period of January 1975 to December 2001. The time-series mean of the average stock standard deviations of 23.38% per month is almost six times larger than both the mean standard deviation of the equal- and value-weighted portfolios of 4.59% and 4.25% per month, respectively. This indicates that idiosyncratic risk represents a large part of total stock risk. The standard deviations of all three risk measures are approximately half their means, which implies that all three of the measures are measured accurately. This contradicts the findings of Goyal and Santa-Clara (2003) that the average stock variance is measured more precisely.

The average stock variance is highly positively skewed (13.36) and leptokurtic (200.55). In fact, the average stock variance is more than 2.7 times more skewed than the average variance of the equal-weighted portfolio, and 2.6 times more skewed than the average variance of the value-weighted portfolio. The kurtosis of the average stock variance is 5.9 times and 3.5 times higher than that of the average variance of the equal- and value-weighted portfolios, respectively.

A test of the joint hypothesis of whether the autocorrelation coefficients are zero is conducted next. This is an important test, since if the null hypothesis of autocorrelation coefficients being zero cannot be rejected, the time series is said to be white noise and there is little or no value in using a time-series model to forecast the series. The Box-Pierce statistic for white noise for the first 12 lags (BP1:12) is greater than the critical value at 10% for all series except the value-weighted returns (CFMRCv). Thus, we reject the null hypothesis of white noise for all series but the value-weighted return.

The last necessary step is to examine the stationarity of the series. A series is said to be stationary if its mean and autocovariances do not depend on time. Stationarity of a series is important for two reasons. First, if a series is non-stationary, then it is said to follow a random walk. In such a case, the Gauss-Markov theorem[22] would not hold and regressions of one variable against another could lead to false results. Secondly, if economic variables were non-stationary, then the effects of temporary economic shocks would not dissipate over time but would rather be permanent. The only way to transform a non-stationary series into a stationary series is by differencing.

The stationarity of a series can be tested using the augmented Dickey-Fuller test.[23] Suppose that a series labeled as Y_t can be described by the following equation:

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[22] The Gauss-Markov theorem states that, given the five underlying assumptions, the estimators α and β are the best linear unbiased estimates (referred to as BLUE) in the sense that they have the minimum variance of all unbiased estimators.

[23] In comparison to the original Dickey-Fuller test, which assumes no serial correlation in the error terms, the augmented Dickey-Fuller test takes serial correlation of the residuals into consideration.

$$Y_t = \alpha + \beta t + \rho Y_{t-1} + \sum_{j=1}^{p} \lambda_t \Delta y_{t-j} + \varepsilon_t \quad (7)$$

Using Ordinary Least Squares, the following unrestricted regression is run:

$$Y_t - Y_{t-1} = \alpha + \beta t + (\rho - 1)Y_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta Y_{t-j} \quad (8)$$

This is followed by estimation of the restricted regression:

$$Y_t - Y_{t-1} = \alpha + \sum_{j=1}^{p} \lambda_j \Delta Y_{t-j} \quad (9)$$

A standard F ratio is calculated to test for the presence of a unit root. The failure to reject the null hypothesis of the presence of a unit root (defined as $\beta = 0$ and $\rho = 1$ in Y_t) confirms that a given series is non-stationary and that it should be differenced before including it in a model.

Panel A of table 1 reports the augmented Dickey-Fuller statistics (ADF column) for the entire sample. The ADF is larger than the 5% critical value for the rejection of unit root for all three risk measures (V_t, V_{pte} and V_{ptv}) as well as for both returns series (CFMRCe and CFMRCv). Thus, the time series used in the predictive models are stationary.

Panel B of table 1 shows that although the average stock variance is not highly correlated with either the volatilities of the equal-weighted (0.2768) or the value-weighted (0.0623) portfolios, the correlation is much stronger with the equal-weighted portfolio. This correlation is maintained when the average standard deviations are examined. Furthermore, the correlation between the equal-weighted and value-weighted portfolio variances (0.7103) is high. This shows that both are good measures of market risk but that the correlation declines when the standard deviations are calculated (0.6441).

Goyal and Santa-Clara (2003) highlight a negative correlation between the equal- and value-weighted market returns and the risk measures as support for the leverage effect of Black (1976) and Christie (1982). In contrast, the correlation between the equal-weighted return and the equal-weighted average portfolio standard deviation is a small positive (and not negative) value for our sample.

The correlation between the average stock variance and the equal-weighted market return is slightly negative (-0.0108), and that between the average stock variance and the value-weighted market return is slightly positive (0.0177). Since an equal-weighted portfolio puts greater weight on small firms, this could indicate that the relationship between returns and variance differ for small and large firms.

The time series of average stock standard deviations for the sample are depicted in Figure 1. The top panel plots the raw time series while the bottom panel displays the 12-month moving average time series. As first noted by Campbell, Lettau, Malkiel and Xu (2001) and reinforced by Goyal and Santa-Clara (2003), this figure shows an upward trend in the average stock standard deviation.[24] Panel A of table 4 gives the trend line statistics of these two time series. Both parameters are significant at the 1% level and the F-statistic is significant at the 5% level. Furthermore, the adjusted R^2 of the trend line increases significantly from 0.0721 to 0.3413 when a 12-month moving average is used.

[24] The upward trend also is present using average stock variance.

The time series of the standard deviations of the equal- and value-weighted portfolios, along with their respective 12-month moving averages, are depicted in Figure 2. The time-series of these two risk measures are essentially flat, i.e. they do not show an upward (or downward) trend. Panel B of table 4 gives the trend line statistics for these four series, none of the betas are significant and the null hypothesis of no relationship between Y and X cannot be rejected (as determined by the F-statistics).

As check of robustness, the sub-periods of 1980-1989 and 1990-1999 also are examined. The descriptive statistics for these sub-periods are presented in Tables 2 and 3, respectively.

The mean of the average stock standard deviations is still larger than the mean of both the equal- and value-weighted portfolios. This supports the argument that idiosyncratic risk represents a large part of total risk. For the 1980-1989 sub-samples, the standard deviation of average stock standard deviation (SDVt) is much lower than that in either the subsequent sub-samples or the entire sample. Thus, SDVt is measured more precisely in the first sub-sample. Furthermore, the average stock variance (Vt) during the 1980 to 1989 period displays lower skewness and is less leptokurtic.

The Box-Pierce statistic for white noise for the first sub-period (1980-1989) for both return series, average stock variance and the equal-weighted portfolio variance are smaller than the critical value of 18.55. Thus, the null hypothesis of white noise cannot be rejected. During the second sub-period (1990-1999), only the equal- and value-weighted portfolio standard deviation series have Box-Pierce statistics larger than the critical value. Although the null hypothesis of white noise is rejected for the whole period, it cannot be rejected for each of the two sub-periods. This raises some doubt about whether or not the series are in fact white noise. If they are, problems may arise later since white noise cannot be effectively modeled.

Similarly, while the augmented Dickey-Fuller (ADF) statistic is largely significant over the entire time period, it is not significant for all series for each sub-period with the exception of the return series for the second sub-period.

Panels B of Tables 2 and 3 present the cross-correlations among the time series for the two sub-periods. The correlations between average stock variances and equal-weighted portfolio variances and value-weighted portfolio variances are stronger over the 1980 to 1989 sub-period. The correlations between equal- and value-weighted portfolio variances are high during both sub-periods, which confirms that both are good measures of market risk.

Over the 1990 to 1999 sub-period, the correlation between the equal-weighted returns and equal-weighted portfolio variances is negative. During the 1980's, the correlation of the return series with average stock variances also is negative, as opposed to having alternate signs during the 1990's and over the entire time period.

The average standard deviations of stocks for each of the two sub-periods are depicted in Figure 3, while the trend line statistics are given in panel C of Table 4. The upward trend apparent in Figure 1 for the entire period is not evident for either of the two sub-periods in Figure 3, i.e. the beta parameters are not significant. The R^2 of the trend lines in figure 3 are much lower (0.0002 and 0.0014) than that obtained for the entire time period (0.075). Furthermore, the F-statistic test of a regression relationship fails to reject the null hypothesis of no relationship. This questions the robustness of the positive trend documented by both Campbell et al. (2001) and Goyal and Santa-Clara (2003) for the U.S. market.

4.3 Univariate ARMA(1,1) model of return series

We begin exploring the predictibility of the two return series, CFMRCe and CFMRCv, by running an ARMA(1,1) model for each of them. We use these two models as benchmarks for our other return forecasting models to be discussed in the following two sections.[25]

ARMA(p,q) stands for autoregressive-moving-average model. This methodology is a univariate time-series methodology developed by Box and Jenkins as a combination of a simple moving average model, MA(q), and an autoregressive model, AR(p), and is represented by:

$$y_t = \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \delta + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \tag{10}$$

We assume that this process is stationary and that its mean is constant over time.[26]

To identify the order of the ARMA(p,q) model, we examine the autocorrelation and partial-autocorrelation functions. Spikes in the autocorrelation function plot indicate moving-average terms, whereas spikes in the partial-autocorrelation function plot indicate

[25] Our single and multiple variable models should be able to provide us with more accurate forecasts of the one-period step ahead return than the ARMA (1,1) models, since ARMA(1,1) models use only past information reflected in the return series.

[26] The more general version of the ARMA(p,q) model that deals with non-stationary series is the ARIMA (p,d,q) model, where d is the number of times a series is differenced, effectively rendering it stationary. In our research, we are satisfied with the ARMA(p,q) model since the series are said to be stationary, as was tested using the Dickey-Fuller test. These results are presented in the previous section (refer to section 4.2).

autoregressive terms.[27] We conclude that for both series, the correct model to use is an ARMA(1,1) model, represented as:

$$y_t = \phi_1 y_{t-1} + \delta + \varepsilon_t - \theta_1 \varepsilon_{t-1} \tag{11}$$

Using a 60-month moving window, which moves by one-month intervals, we run consecutive ARMA(1,1) models and obtain forecasts for January 1980 to December 2001, i.e. 264 monthly forecasts.[28]

Since our main concern in this research is forecast accuracy, we then proceed to calculate two measures of forecast accuracy: the root mean squared error (RMSE), and the mean percentage error (MPE). They are calculated as follows:

$$RMSE = \sqrt{\frac{\sum (A_t - F_t)^2}{n}} \tag{12}$$

$$MPE = \frac{\sum [(A_t - F_t)/A_t]}{n} \tag{13}$$

In equations (12) and (13), A_t is the actual return at time t, F_t is the forecasted return at time t given by the ARMA(1,1) model, and n is the number of forecasted periods (in this case 264 months). RMSE is probably the most widely used measure of forecast accuracy. It is easy to interpret because of its similarity to the concept of standard

[27] By spikes we mean the number of AR and MA terms that are significantly different from zero.
[28] Since we use a moving window methodology, we have not tested the order of the ARMA model for each of the 264 model runs and have assumed that an ARMA(1,1) model is appropriate for each of these sub-periods.

deviation. The MPE is not often used because large positive errors can be offset by large negative errors, effectively giving an MPE close to zero for a very bad model. However, we have chosen to include the MPE since it is a very useful measure of forecast bias. A large negative MPE suggests that the model overstates the forecast, while a large positive MPE suggests forecasts are generally too low. For both forecast accuracy measures, a smaller number represents a more accurate forecast.

Table 5 gives summary statistics for the ARMA(1,1) model forecast of the return series. Panel A represents the equal-weighted return forecast statistics and panel B the value-weighted return statistics. For both series, we show the results for the entire sample and for the two sub-periods.

The forecasting error of the ARMA(1,1) model of equal-weighted returns ranges from 6.57% for the sub-sample of January 1990 - December 1999 to 6.73% for the entire sample. There appears to be a significant difference in the forecast bias between the two sub-samples (1.0192 versus 6.0594). This positive bias shows that the forecasts from this ARMA(1,1) model are too low and that this is even more true during the 1990's.

The ARMA(1,1) benchmark model forecast of the value-weighted market return (Panel B of Table 5), displays a lower RMSE, hence a more accurate forecast, for each of the two sub-samples and for the entire sample. The RMSEs range from 4.25% to 5.51%, or approximately 30% lower than those of the equal-weighted return forecasts. Futhermore, the value-weighted return benchmark model forecast has lower forecast bias and these biases are more constant over the three periods. The MPE of the second sub-period is 0.9518 versus 6.0594 and for the first sub-period falls to 0.9465 from 1.0192.

The MPE of the entire sample is 0.9512 as opposed to 3.3101 for the equal-weighted return series.

Thus, the ARMA(1,1) model is a more accurate and a less biased forecasting model when applied to the value-weighted return series rather than to the equal-weighted return series.

4.4 Single Variable OLS Model

We now look at the statistical linkage between the risk measures and the market return. We regress each of the two market return series, equal- and value-weighted returns, on our three risk measures, namely value-weighted portfolio variance, equal-weighted portfolio variance and average stock variance. Thus, the fitted values from these regressions give us the step-ahead one-period forecasts. The generalized forecasting regression can be written as:

$$r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{14}$$

In equation (14), r_{t+1} is each of the two market return series, and X_t represents different combinations of the market risk measures and average stock risk. Similarly to the ARMA(1,1) benchmarks discussed above, we run these models using a 60 month moving window which moves by one month intervals, thus giving us 264 regressions per model. Hence, 264 one month step-ahead forecasts are generated covering the period of January 1980 to December 2001. In order to test the robustness of the relationships, the two sub-periods are also examined. Tables 6 to 11 inclusive give the summary statistics for the regressions and for the forecasts.

Table 6 presents the summary statistics of the regressions of equal-weighted market return (CFMRCe) on equal-weighted portfolio variance (Vpte). 57.20% of these regressions show a significant relationship between CFMRCe and Vpte over the entire period, as given by the F-statistics reported in Panel A. The strength of the relationship is lower in the first sub-sample (49.17% of the regressions are significant) than in the later sub-sample (76.67% of the regressions are significant). The significance of the beta parameters follow a similar pattern, i.e. smaller in the first sub-sample but larger in the second sub-sample. However, the significances of the alpha parameters show a different pattern. A larger number of alpha parameters are significant during the first sub-sample (63.33%) than during the second sub-sample (37.50%). Panel B summarizes the adjusted R-Square values of the regressions. The mean R-Square for the entire sample is 10.84%. The R-Square is higher for both sub-samples (12.30% and 11.90%, respectively). Panel C reports the two measures of forecast accuracy, RMSE and MPE. The RMSE for the entire sample as well as for both sub-samples are marginally greater than those for the ARMA(1,1) benchmark. Thus, it does not seem possible to obtain statistically more accurate forecasts by using Vpte over the benchmark ARMA(1,1). However, the forecasts obtained by these regressions exhibit a much larger bias (given by the MPE) than the benchmark model during the second sub-sample (47.5804).

Table 7 presents the summary statistics for the regressions of equal-weighted market return (CFMRCe) on value-weighted portfolio variance (Vptv). The number of significant parameters/regressions is slightly larger than for the previous model over the entire sample, but the number increases in the first sub-sample contrary to the previous model. Since the equal-weighted market variance gives more weight to small firms, these results may be due to some extent to the tech bubble during which primarily smaller tech firms listed on Nasdaq. The adjusted R-Square is slightly higher than for the previous model at 13.32% over the entire sample (14.74% and 13.04%, respectively, for the two sub-samples). The RMSEs of the forecasts of the equal-weighted market return with the value-weighted portfolio variance are larger than the forecast using the equal-weighted portfolio variance as the independent variable. Thus, the value-weighted portfolio variance leads to less statistically precise forecasts of the equal-weighted market return. The MPE displays the same forecast bias that was present in the forecast using Vpte.

Table 8 gives the summary statistics from the regressions of equal-weighted market return (CFMRCe) on the average stock risk (Vt). The number of significant parameters/regressions is much lower than in the previous models using market risk measures. Over the entire sample, only 15 of the 264 regressions (5.68%) had F-statistics greater than their critical value. This number increases when looking at the first sub-sample (15 of 264 or 12.50%) but falls to zero for the second sub-sample. The mean adjusted R-Square of 0.12% for the entire sample is also lower than for the previous two models (tables 6 and 7). Thus, the statistical relationship between Vt and CFMRCe is significantly weaker than between Vpte or Vptv and CFMRCe. However, the two measures of forecast error (RMSE and MPE, as given in Panel C of Table 8) are the lowest of the three models of CFMRCe with a RMSE for the entire period of 0.0683. However, this is still larger than the RMSE of the benchmark ARMA(1,1) model. The MPE imply the same forecasting bias that is present in the other two models.

Tables 9 through 11 present the summary statistics of the regression models and their forecasts of value-weighted market returns (CFMRCv). The regressions of CFMRCv on Vpte (Table 9) give a slightly smaller number of significant parameters/regressions (Panel A) than the model using equal-weighted market returns. However, it becomes the first sub-sample that displays a larger number of significant parameters/regressions (63.33% versus 45.00% of significant regressions). The adjusted R-Square for this set of regressions is also lower, with a mean average of 9.63% over the entire sample (the R-Square for the first sub-sample is higher at 11.98%). Nevertheless, the forecast error is 23.46% lower than when using equal-weighted returns (RMSE of 0.0535 compared to 0.0699). The forecast errors are marginally larger than those for the benchmark ARMA(1,1) model of CFMRCv. The strong forecast bias that was present in both the entire sample and second sub-sample using CFMRCe is no longer apparent.

Table 10 reports the summary statistics from the regressions of the value-weighted market returns (CFMRCv) on the value-weighted portfolio variances (Vptv). This model gives lower numbers of significant parameters/regressions (Panel A) with 51.52% of the regressions being significant as measured by the F-statistics compared with 59.47% for the corresponding model using CFMRCe. This model is most significant (71.67%) in the first sub-sample. The mean adjusted R-Square of 11.82% for the entire period is lower than that using the equal-weighted market returns. However, the forecast error also is lower with an RMSE of 0.0561for the entire period. The forecast bias, which was present when using equal-weighted market returns, is not apparent for these regressions.

Table 11 summarizes the regression statistics and the forecast errors of the regression of CFMRCv on Vt. As was the case for the previous model using average stock variance (refer to Table 8), the number of significant parameters/regressions is much lower when using market risk measures. However, the significance is much improved over the model that regresses CFMRCe on Vt (F-statistic is significant 22.73% of the times versus 5.68%). The adjusted R-Square values remain low with a mean value of 1.95%. Although the forecast error is lower than for all of the previous models over every sample period (Panel C), it is still larger than it is for the benchmark model (hence, less statistically precise).

4.5 Inclusion of Macro Variables in the OLS Model

In order to confirm the relationships of the previous six models and to potentially improve the forecasting ability of these models, we expand our models by adding two variables known to control for the business cycle; namely, dividend yield and treasury bill yield. Campbell, Lettau, Malkiel and Xu (2001) show that for American data, average stock variance (Vt) is counter-cyclical. Following the work of Campbell (1991), Campbell and Shiller (1988), Chen, Roll and Ross (1986), Fama (1990), Fama and French (1988, 1989), Ferson and Harvey (1991) and Keim and Stambaugh (1996), Goyal and Santa-Clara test the robustness of their model by including four variables known to control for the business cycle.

We follow the same methodology as in the previous sections. Using a 60-month moving window, we run 264 multiple regressions for each of the six models. The summary statistics for each of these models are presented in Tables 12 to 17, inclusive.

By introducing the dividend yield (DivYield) and the treasury bill yield (TB) into the regressions of CFMRCe against Vpte, the in-sample statistical precision increases. The number of significant regressions increases to 69.32% (Panel A of Table 12) from 57.20%. Furthermore, the significance of the Vpte parameter also increases. Also, contrary to the corresponding single variable model, the number of significant regressions is larger in the first sub-sample than in the second sub-sample. The mean adjusted R-Square value for the entire period more than doubles to 22.29%, while the standard deviation only increases from 12.42% to 14.98%. The forecast error increases to 9.73% (RMSE, Panel C of Table 12), which means that out-of-sample forecasting ability has decreased. The previously recorded forecast bias, although still present, is much less severe with an MPE for this model for the entire period of 4.6850 (compared to 22.4472).

Table 13 presents the summary statistics for the regressions of CFMRCe on Vptv, DivYield and TB. The number of significant regressions has once again increased to 62.12% (from 59.47%), and the number of times that the Vptv parameter is significant also has increased to 60.61% from 59.47%. These in-sample statistical improvements occur for both sub-samples. The mean adjusted R-Square has a large increase over the entire sample and the first sub-sample to 24.86% and 34.51%, respectively. The mean adjusted R-Square of the second sub-period also increases, although less dramatically, to 18.88%. While the RMSE of these forecasts is higher than for the corresponding single-variable model for all sample periods, the forecast bias is less severe.

The summary statistics for the regressions of CFMRCe on Vt, DivYield and TB are presented in Table 14. By including the two macro variables, the number of significant regressions increases by 5.6 times to 31.82% for the entire sample. However, the number of significant Vt parameters drops by half to 3.41%. Thus, the inclusion of these two new variables increases the significance of the overall model at the expense of the risk parameter. This relationship holds for both sub-samples. The mean adjusted R-Square also jumps from 0.12% to 10.40%. As is the case for the first two models using macro variables, the forecast error increases slightly to 7.37% over the complete sample, while the MPE forecast error decreases.

Tables 15 to 17 summarize the regression statistics for the models using the value-weighted market returns (CFMRCv). The regressions of CFMRCv on Vpte, DivYield and TB result in a lower number of significant regressions than the corresponding models using equal-weighted market returns and a higher number than the model without macro-variables. Thus, the impact associated with including the two macro variables is not as pronounced for the value–weighted returns. The significance of the Vpte parameter does not decrease over the entire sample, and only decreases marginally for each of the two sub-samples. The mean adjusted R-Square increases from 9.63% to 16.98% with no significant change in the standard deviation. The RMSE increases to 6.26%, 7.35% and 4.95% for the entire sample, first and second sub-samples, respectively. This indicates a reduction in out-of–sample forecasting ability.

The number of significant regressions for value-weighted market returns on Vptv, DivYield and TB (Table 16) is lower (54.92% of regressions have significant F-statistics) than for its equal-weighted counterpart but higher than the similar model without macro variables. This relationship holds for both sub-samples and also for the significance of the Vptv parameter. The mean adjusted R-Square of 20.45% is less than that for the equal-weighted model, and is significantly higher than that for the no macro variable regressions. The forecast error of 0.0706 is again larger.

The summary statistics for the value-weighted market return model using average stock risk and macro variables are presented in Table 17. The number of significant regressions increases only slightly to 23.48% from 22.73%. As was the case for the model relating equal-weighted market returns to average stock risk, the increase in the significance of the regressions is at the expense of the significance of the average stock risk parameter. The mean adjusted R-Square increases to 8.16%, and forecast error increases to 6.05%.

Thus, introducing two macro variables into our models produces two contrasting effects. First, it increases in-sample statistical precision (as measured by an increased number of significant regressions/parameters and larger adjusted R-Square values). Second, it decreases the out-of-sample forecasting precision (larger RMSE). The financial properties of these models are examined in Section 5.

5. Financial Properties of Risk Measures for Market Timing

Having investigated the statistical properties of the risk measures, we now turn our attention to the financial properties of these variables, i.e., can these risk measures be successfully used in a market timing strategy.

5.1 Test procedures

The test procedures used in this thesis are those suggested by Chung and Kryzanowski (2000). We examine the timing portfolio performance for investors under three distinct preferred or natural habitats. The first preferred habitat is when investors prefer to stay in stock. The second preferred habitat is when investors prefer to stay in cash and the third is when investors have no preference. We assume a 1% transaction cost for each switch away from the preferred habitat. For the no preference habitat, we assume two scenarios: 1% transaction costs on all switches, and no transaction costs on any switch. Table 18 summarizes these switching rules.

In order to measure the market-timing ability of our portfolios, we apply the performance metric developed by Elton and Gruber (1991). This metric refines the performance measure of Dybvig and Ross (1985) by assuming the existence of additional information available to outside investors. Elton and Gruber (1991) assume that the outside investor knows not only the portfolio's time series of returns but also the portfolio proportions at various points in time. The Elton and Gruber (1991) performance metric (henceforth EG) can be written as:

$$d = E[R_p] - E[R_{\beta=\bar{\beta}}] \tag{15}$$

In equation (15), R_p is the return on the timing portfolio in month t and $R_{\beta=\bar{\beta}}$ is the return that would have been obtained if the portfolio maintained its average actual beta at all points in time. The average actual beta represents the beta of a buy-and-hold portfolio with a holding horizon equal to our sample size, which in this thesis is 264 months.

We test the statistical significance of both the mean and median EG performance measure. The statistical significance of the mean is tested using a standard t-test. The median is tested using a large-sample Wilcoxon nonparametric sign test. The Wilcoxon test is of the null hypothesis that returns are distributed symmetrically around a specified center, i.e. the median. The Wilcoxon test is usually applied in cases where differences are used. In our case, the EG metric measures the difference between the timing return and the average beta buy-and-hold return. We test the null hypothesis that the EG metrics are distributed symmetrically around zero. Failure to reject this null hypothesis would help us to conclude that market timing does not work.

To perform the Wilcoxon test, we begin by eliminating the EG metrics that are equal to zero. We then rank the absolute values of the deviations from the median of the remaining EG metrics. We compute the sum of the ranks above the median and below the median. The null hypothesis is rejected if the smallest of the two sums is less than or equal to:

$$z = \frac{T \ - [n(n+1)/4]}{\sqrt{[n(n+1)(2n+1)]/24}} \tag{16}$$

In equation (16), T is the smallest of the two sums, and n is the number of deviations from the median (i.e., 264 herein).

5.2 "Perfect Timing"

We begin by examining a perfect timing strategy, or one where stocks are held when monthly stock returns are larger than treasury-bill returns and treasury-bills are held when monthly stock returns are lower than treasury-bill returns. This perfect timing strategy acts as an "outside benchmark"; that is, the highest possible return that a market timing strategy could generate.[29] A 1% transaction cost is used for all switches.

Table 19 presents the monthly and annual average returns and standard deviations for treasury-bills, CFMRCe, CFMRCv, the perfect timing strategy using CFMRCe, and the

[29] The perfect timing strategy generates the highest attainable returns since it assumes that the market timer accurately predicts 100% of the time when to get into and out of stocks.

perfect timing strategy using CFMRCv. Over the entire sample (Panel A), treasury bills yielded an average annual return of 8.01%, with a standard deviation of 3.52%. The equal-weighted stock index return averaged 17.82%, but with a standard deviation of 27.44%, or more than 1.5 times its average return. The value-weighted index return averaged a lower 11.25%, also with a lower standard deviation of 14.20%. The perfect timing strategy using the CFMRCe greatly improved returns with an average annual return of 34.72%, and a lower standard deviation of 17.72%. The value-weighted perfect timing portfolio also greatly improved returns and decreased the associated risk, yielding an average return of 25.61% and a standard deviation of 9.72%.

During the first sub-sample (Panel B of Table 19), treasury-bill returns improved to 10.69%, with a decrease in the standard deviation over the corresponding full period results. The CFMRCe return dropped significantly to 12.96%, while its standard deviation remained approximately the same as for the full period at 26.29%. The value-weighted index average return increased slightly to 12.98% and its standard deviation decreased slightly to 12.85%. Both perfect timing portfolios were as lucrative during the first sub-sample as during the entire sample. The CFMRCe and CFMRCv perfect timing portfolios registered average returns of 33.84% and 28.87%, respectively, while their standard deviations were 17.94% and 11.06%.

Compared to the first sub-sample, during the second sub-sample (Panel C of Table 19) the average risk-free return decreases to 6.04%, while the average equal-weighted stock index return increased to 22.58%. The CFMRCe average standard deviation also increased to 31.83%. The average value-weighted stock index return remained relatively constant at 12.76%, with an average standard deviation of 15.22%. Compared to the previous sub-sample, the two perfect timing strategies registered relatively constant average returns. The CFMRCe perfect timing return over the second sub-sample was 33.79% with a standard deviation of 19.77%, while the CFMRCv perfect timing return over the second sub-sample was 22.51%, with a standard deviation of 8.23%.

Table 20 summarizes the mean and median values of the EG metric for the perfect timing portfolios, as well as giving the number of switches and the average betas.

5.3 Test Results

Tables 21 to 34 summarize the mean and median values of the EG performance metric for the various timing portfolios. The market timing statistics for the two benchmark portfolios are presented in tables 21 and 22. Although overall these benchmark portfolios show no signs of market timing ability, we will point out several interesting findings. Over the entire sample, the CFMRCe benchmark (panel A of table 21) shows a relatively small number of switches for both the stock and none-1% natural habitats, with 3 and 2 switches, respectively. The other two habitats, i.e. cash and none, show a significantly higher number of switches, 16 and 17 switches, respectively. During the first sub-sample, the number of switches for both cash and none decreased to 3 and 4, respectively. The natural habitats of stock and none-1% both saw no switches during the second sub-sample. When looking at the second benchmark portfolio, i.e. CFMRCv (table 22), we find similar results, except that the first sub-sample now has the smallest number of switches.

Table 23 summarizes the mean and median EG metrics of the portfolio using Vpte to time CFMRCe. Over the entire sample and over all natural habitats, neither the mean nor the median EG metric is significant. During the first sub-sample, only the median EG metric for the none natural habitat is significant at the 5% level. The significance of the median performance metrics improves during the second sub-sample over the first sub-sample, when the median of all four natural habitats are significant at the 10% level. (The cash natural habitat median is significant at the 5% level.) Also, compared to the benchmarks, the number of switches for this portfolio increases markedly.

Table 24 presents the results of the mean and median EG measures of the portfolio using Vptv to time CFMRCe. Using the value-weighted portfolio variance to time CFMRCe does not greatly improve the results over the use of the equal-weighted portfolio variance. The mean EG metric for the stock and none natural habitats become significant at the 10% level over the entire sample. However, during the first sub-sample, the mean EG metric for cash and none are the only two means that are significant at the 10% level. During the second sub-period, none of the means are significant, and the medians are significant. The median of the EG metric for stock is only significant at the 10% level. For this portfolio, the number of switches is still relatively high.

Table 25 summarizes the mean and median EG performance metrics for the actively managed portfolio using average stock risk, Vt, to time CFMRCe. The two important observations that can be drawn from this table are, firstly, that none of the means or medians are significant for any of the natural habitats over any of the sample periods. Secondly, compared to the previous two portfolios (i.e., Vpte - CFMRCe and Vptv CFMRCe), the number of switches declines markedly. In fact, during the second sub-sample, the stock and none-1% natural habitats register no switches.

The mean and median EG measures for the timing portfolio using Vpte to forecast CFMRCv are presented in table 26. Once again, the results are entirely insignificant. This further reinforces the notion that equal-weighted portfolio variance cannot be used to successfully beat the market. Table 27 provides similar results only when the value-weighted portfolio variance is used to time CFMRCv. Except for two mean EG measures, the timing performance results are also insignificant. Over the entire sample, the mean EG measure of the stock natural habitat is significant at the 10% level. During the first sub-sample, the mean EG metric of the cash natural habitat is significant at the 10% level.

Table 28 summarizes the mean and median EG performance metrics for the actively managed portfolio using Vt to time CFMRCv. During both the entire sample and the first sub-sample, neither the means nor medians are significant. However, during the second sub-period, the mean of the stock, cash and none natural habitats are significant at the 10% level. At best, the results provide very weak support for market timing ability using average stock risk.

Table 29 to 34 summarize the results of the mean and median EG performance metrics for the actively managed portfolios using the three risk measures, as well as dividend and t-bill yields to time CFMRCe and CFMRCv. Table 29 presents the timing results of the portfolio using Vpte, dividend yields and t-bill yields to time CFMRCe. The only significant results are the median EG metrics for the second sub-sample. The stock natural habitat median is significant at the 1% level, the cash natural habitat median is significant at the 10% level, and the none-1% and none natural habitats are both significant at the 5% level.

When using the value-weighted portfolio dividend, dividend yields and treasury-bill yields to time the equal-weighted market index (table 30), the significance of the metrics improve. Over the entire sample, the mean EG metric for the cash natural habitat is significant at the 10% level, whereas the mean of the none-1% natural habitat is significant at the 5% level. During the first sub-sample, the only significant metric is the mean under the none-1% natural habitat. However, the second sub-sample displays much more significant results. The medians under all four natural habitats are significant at the 1% level. The mean under the cash and none habitats is significant at the 5% level, while the mean under the none-1% habitat is significant at the 10% level.

Table 31 presents the timing results for the portfolio using average stock risk, dividend yields and t-bill yields to time CFMRCe. For the first time over the entire sample, the mean EG metric is significant for all habitats. Furthermore, the median EG metric is significant for three of the four habitats. However, the first sub-sample does not help us confirm the robustness of these findings since only the mean under the cash and none habitats are significant at the 10% level, and none of the medians are significant. During the second sub-sample, the significance of the medians greatly improve, as they all become significant above the 5% level. Also during the second sub-sample, the mean EG measure under the cash natural habitat is significant at the 10% level.

Tables 32 and 33 summarize the results of the actively managed portfolios using Vpte and Vptv, respectively, along with dividend yields and treasury-bill yields to time the value-weighted market index. None of the mean or median EG metrics are significant for any of the natural habitats of either of these portfolios. This confirms our previous findings that the equal- or the value-weighted portfolio variance does not allow us to profitably time the market.

Table 34 reports the summary statistics of the mean and median EG performance metrics for the portfolio using Vt, dividend yields and t-bill yields to time CFMRCv. This portfolio shows slightly more significant results than the previous two portfolios. Over the entire sample, the mean performance measure of the stock, none-1% and none habitats are significant, while the median is only significant under the stock natural habitat. However, the first sub-sample does not display any significance. During the second sub-sample, only the mean metric of the stock and none natural habitats are significant at the 5% level.

6. Conclusions, Implications and Avenues for Future Research

The risk-return relationship is the most basic of all financial relationships. Financial theory dictates that to achieve a higher return, an investor must bear a proportionally larger amount of risk. In an attempt to outperform the stock market, market timers have tried to devise trading rules around this positive relationship. The empirical results have been inconclusive at best. In this thesis, we revisited the issue using a risk measure known as idiosyncratic or average stock risk, which was developed by Campbell, Lettau, Malkiel and Xu (2001) and later used by Goyal and Santa-Clara (2003). We tested the statistical and financial properties of this risk measure for timing the Canadian market.

To study the market timing properties of average stock risk, we constructed a sample comprised of all publicly traded companies on the Toronto Stock Exchange from January 1975 until December 2001. This sample corresponds to the availability of the equal- and value-weighted CFMRC indices. We regressed average stock risk, equal-weighted portfolio variance and value-weighted portfolio variance on both the equal- and value-weighted indices and compared the results to that for two benchmark ARMA(1,1) models. We also introduced two macro-level variables known to control for the business cycle: dividend yield and treasury bill yield. We further tested the robustness of our results by examining two 10-year sub-samples.

Our results do not support those of Goyal and Santa-Clara (2003). Although our research confirms the long-term positive trend of average stock risk over our entire sample period, this trend is not present during either of the two sub-samples. This questions the validity of the trend upwards in average stock risk. Average stock risk is found to be a large part of total risk, but contrary to GSC's findings average stock risk is not measured more accurately than equal- or value-weighted portfolio variances. We find that the risk-return relationship using average stock risk differs between large and small firms. Our results show that using the single variable regression models, the statistical relationship of average stock risk to the market return was much lower than between equal- or value-weighted portfolio variances and market returns. The RMSE forecasting ability metric was however also smaller, indicating that average stock risk is a better forecasting variable. The introduction of the two macro variables greatly increased the in-sample statistical significance of all models at the expense of the out-of-sample forecasting ability.

The results of our examination of the financial properties of the risk measures concluded that none of these risk metrics contain significant market timing ability. These results reaffirm Sharpe's (1975) finding that only investors with truly superior information, i.e. quasi-clairvoyant investors, should attempt market timing. Further, these results cast a shadow of doubt over the results of Goyal and Santa-Clara (2003) that average stock risk can be used to time the stock market.

This thesis opens up several avenues for future research. First, GSC's (2003) claim of market timing ability of average stock risk is based on a flawed methodology. Their use of a quadratic utility function to translate the returns into a measure of investor welfare is quite restrictive. Hence, as we do in our study, the Elton and Gruber metric could be used in an American setting. Further, the American data could be analyzed using Chung and Kryzanowski's four natural habitats. The research reported herein could also be extended by including a different combination of macro-variables; even the introduction of a country covariance measure as in Chan, Karolyi and Stulz (1992). Lastly, the empirical relationship between average stock risk and market return could be analyzed econometrically using more advanced forecasting techniques.

TABLES

Table 1
Descriptive Statistics for Returns and Volatility Measures - Entire Sample

This table presents descriptive statistics on returns and measures of volatility for stocks listed on the Toronto Stock Exchange. The sample period is January 1975 to Decembre 2001 (324 monthly observations). The variable r is the typical stock return. The variables CFMRCe and CFMRCv are the equal- and value-weighted index returns given by the CFMRC database. The variable Vt is the average stock variance, while SDVt is the average stock standard deviation, calculated as the square root of Vt. Vpte and Vptv are the equal- and value-weighted portfolio variances, whereas SDVpte and SDVptv are their respective standard deviations. "Skew" is the skewness, "Kurt" is the kurtosis, "AR1" is the first-order autocorrelation, and "BP1:12" is the chi-square autocorrelation checked for white noise for the first 12 lags (the critical value at 10% is 18.55; series that reject the null hypothesis are represented by *). "ADF" is the augmented Dickey-Fuller statistic for the presence of unit root calculated with an intercept and 12 lags. The critical values for rejection of unit root are 8.43, 6.34 and 5.39 at one percent, five percent and 10 percent levels (represented by ***, **, * respectively).

Panel A: Univariate Statistics

	Mean	Median	StdDev	Min	Max	Skew	Kurt	AR1	BP1:12	ADF
r	0,0019	0,0000	0,0700	-0,9970	45,6667	141,3702	74024,6500	0,0283		
CFMRCe	0,0183	0,0154	0,0651	-0,2835	0,3723	0,3553	5,1609	0,2037	19,1000 *	11,5200 ***
CFMRCv	0,0114	0,0115	0,0501	-0,2302	0,1854	-0,6008	3,0294	0,0372	9,9700	13,0200 ***
Vt	0,0742	0,0402	0,2298	0,0173	3,7090	13,3620	200,5465	0,0118	36,9300 *	6,6300 **
SDVt	0,2338	0,2005	0,1400	0,1314	1,9259	7,4574	76,2647	0,1489	91,0800 *	3,9500
Vpte	0,0027	0,0016	0,0039	0,0000	0,0405	4,8850	34,2793	0,2500	45,1400 *	7,3100 **
SDVpte	0,0459	0,0397	0,0251	0,0027	0,2012	2,1340	7,0765	0,3712	136,9400 *	5,0200
Vptv	0,0021	0,0015	0,0024	-0,0003	0,0293	5,9027	57,5061	0,2320	49,0100 *	8,7900 ***
SDVptv	0,0425	0,0388	0,0184	0,0084	0,1713	1,9038	8,1750	0,3273	122,0200 *	8,1100 **

Panel B: Cross Correlations

	CFMRCe	CFMRCv	Vt	SDVt	Vpte	SDVpte	Vptv	SDVptv
CFMRCe	1,0000							
CFMRCv	0,8192	1,0000						
Vt	-0,0108	0,0177	1,0000					
SDVt	0,0085	-0,0071	0,9169	1,0000				
Vpte	-0,0722	-0,1554	0,2768	0,4103	1,0000			
SDVpte	0,0297	-0,0557	0,2901	0,4413	0,9398	1,0000		
Vptv	-0,2079	-0,1998	0,0623	0,1763	0,7103	0,6533	1,0000	
SDVptv	-0,1428	-0,1273	0,0591	0,1664	0,6250	0,6441	0,9320	1,0000

Table 2

Descriptive Statistics for Returns and Volatility Measures - January 1980 to December 1989

This table presents descriptive statistics on returns and measures of volatility for stocks listed on the Toronto Stock Exchange. The sample period is January 1975 to Decembre 2001 (324 monthly observations). The variable r is the typical stock return. The variables CFMRCe and CFMRCv are the equal- and value-weighted index returns given by the CFMRC database. The variable Vt is the average stock variance, while SDVt is the average stock standard deviation, calculated as the square root of Vt. Vpte and Vptv are the equal- and value-weighted portfolio variances, whereas SDVpte and SDVptv are their respective standard deviations. "Skew" is the skewness, "Kurt" is the kurtosis, "AR1" is the first-order autocorrelation, and "BP1:12" is the chi-square autocorrelation checked for white noise for the first 12 lags (the critical value at 10% is 18.55; series that reject the null hypothesis are represented by *). "ADF" is the augmented Dickey-Fuller statistic for the presence of unit root calculated with an intercept and 12 lags. The critical values for rejection of unit root are 8.43, 6.34 and 5.39 at one percent, five percent and 10 percent levels (represented by ***, **, * respectively).

Panel A: Univariate Statistics

	Mean	Median	StdDev	Min	Max	Skew	Kurt	AR1	BP1:12	ADF
CFMRCe	0,0184	0,0172	0,0640	-0,2835	0,2869	-0,2345	4,5472	0,1858	16,0700	4,9000
CFMRCv	0,0141	0,0116	0,0532	-0,2302	0,1854	-0,6095	3,4761	0,0388	14,9300	4,1300
Vt	0,0441	0,0338	0,0585	0,0173	0,7456	10,0883	117,3215	-0,0120	14,2600	2,5200
SDVt	0,1982	0,1838	0,0693	0,1314	0,8635	5,8425	49,3804	0,0675	21,8300 *	2,0100
Vpte	0,0029	0,0016	0,0045	0,0000	0,0405	4,7072	29,5685	0,1470	18,3800	2,1400
SDVpte	0,0467	0,0397	0,0275	0,0143	0,2012	2,3241	7,4677	0,2535	43,8700 *	1,7400
Vptv	0,0022	0,0015	0,0026	-0,0003	0,0293	6,5881	62,9362	0,2108	54,6400 *	1,8000
SDVptv	0,0428	0,0394	0,0192	0,0084	0,1713	2,1808	10,7727	0,2422	62,5300 *	1,4500

Panel B: Cross Correlations

	CFMRCe	CFMRCv	Vt	SDVt	Vpte	SDVpte	Vptv	SDVptv
CFMRCe	1,0000							
CFMRCv	0,8948	1,0000						
Vt	-0,0612	-0,0643	1,0000					
SDVt	-0,0824	-0,1235	0,9434	1,0000				
Vpte	-0,1541	-0,2365	0,3409	0,4835	1,0000			
SDVpte	-0,0198	-0,1040	0,3369	0,4815	0,9449	1,0000		
Vptv	-0,1924	-0,2165	0,2289	0,3423	0,8206	0,7264	1,0000	
SDVptv	-0,0916	-0,1271	0,1631	0,2704	0,7417	0,7288	0,9219	1,0000

Table 3

Descriptive Statistics for Returns and Volatility Measures - January 1990 to December 1999

This table presents descriptive statistics on returns and measures of volatility for stocks listed on the Toronto Stock Exchange. The sample period is January 1975 to Decembre 2001 (324 monthly observations). The variable r is the typical stock return. The variables CFMRCe and CFMRCv are the equal- and value-weighted index returns given by the CFMRC database. The variable Vt is the average stock variance, while SDVt is the average stock standard deviation, calculated as the square root of Vt. Vpte and Vptv are the equal- and value-weighted portfolio variances, whereas SDVpte and SDVptv are their respective standard deviations. "Skew" is the skewness, "Kurt" is the kurtosis, "AR1" is the first-order autocorrelation, and "BP1:12" is the chi-square autocorrelation checked for white noise for the first 12 lags (the critical value at 10% is 18.55; series that reject the null hypothesis are represented by *). "ADF" is the augmented Dickey-Fuller statistic for the presence of unit root calculated with an intercept and 12 lags. The critical values for rejection of unit root are 8.43, 6.34 and 5.39 at one percent, five percent and 10 percent levels (represented by ***, **, * respectively).

Panel A: Univariate Statistics

	Mean	Median	StdDev	Min	Max	Skew	Kurt	AR1	BP1:12	ADF
CFMRCe	0,0186	0,0163	0,0638	-0,2835	0,3723	0,2985	5,8562	0,1741	13,7600	6,3600 **
CFMRCv	0,0127	0,0115	0,0489	-0,2302	0,1854	-0,6374	3,7618	0,0413	10,5400	5,6100 *
Vt	0,0727	0,0390	0,2386	0,0173	3,7090	12,9202	186,8009	-0,0021	1,1100	5,2000
SDVt	0,2285	0,1976	0,1435	0,1314	1,9259	7,5779	75,8847	0,0580	2,6600	5,1100
Vpte	0,0027	0,0015	0,0040	0,0000	0,0405	4,9050	33,6614	0,2732	15,7200	2,8100
SDVpte	0,0453	0,0393	0,0253	0,0027	0,2012	2,2589	7,5651	0,4302	63,7200 *	1,9000
Vptv	0,0021	0,0014	0,0024	-0,0003	0,0293	6,1999	60,4436	0,1900	9,1600	4,0900
SDVptv	0,0417	0,0381	0,0183	0,0084	0,1713	2,0866	9,4558	0,3325	36,5800 *	3,1700

Panel B: Cross Correlations

	CFMRCe	CFMRCv	Vt	SDVt	Vpte	SDVpte	Vptv	SDVptv
CFMRCe	1,0000							
CFMRCv	0,8295	1,0000						
Vt	-0,0157	0,0176	1,0000					
SDVt	-0,0005	-0,0035	0,9239	1,0000				
Vpte	-0,0948	-0,1760	0,2755	0,4047	1,0000			
SDVpte	0,0088	-0,0686	0,2906	0,4319	0,9414	1,0000		
Vptv	-0,2074	-0,1920	0,0564	0,1552	0,7120	0,6468	1,0000	
SDVptv	-0,1384	-0,1086	0,0518	0,1377	0,6269	0,6363	0,9294	1,0000

Table 4
Volatility Series Trend Line Statistics

This table presents the trend line statistics of the volatility series presented in figures 1, 2 and 3, respectivelly. The critical t-statistic values for rejection of the null hypothesis that the parameters are zero are 2.576, 1.960 and 1.645 at the 1%, 5% and 10% levels (represented by ***, **, *, respectively). The critical F-statistic values for rejection of the null hypothesis of no relationship between Y and X are 3.84 and 6.63 at the 5% and 1% levels (represented by **, * respectively).

Panel A: Figure 1 Trend Line Statistics

	SDVt						12-Month Moving Average of SDVt					
	Parameters	t-Stats		Adj. R-Square	F-Stat		Parameters	t-Stats		Adj. R-Square	F-Stat	
Alpha	0,1673	11,1382	***	0,0721	26,0916	**	0,1682	28,6357	***	0,3413	162,6457	**
Beta	0,0004	5,1080	***				0,0004	12,7533	***			

Panel B: Figure 2 Trend Line Statistics

	SDVpte					12-Month Moving Average of SDVpte				
	Parameters	t-Stats		Adj. R-Square	F-Stat	Parameters	t-Stats		Adj. R-Square	F-Stat
Alpha	0,0474	16,8932	***	-0,0018	0,4208	0,0470	31,2540	***	0,0012	1,3732
Beta	0,0000	-0,6487				0,0000	-1,1718			
	SDVptv					12-Month Moving Average of SDVptv				
	Parameters	t-Stats		Adj. R-Square	F-Stat	Parameters	t-Stats		Adj. R-Square	F-Stat
Alpha	0,0417	20,2180	***	-0,0029	0,0806	0,0402	37,5674	***	0,0046	2,4531
Beta	0,0000	0,2839				0,0000	1,5662			

Panel C: Figure 3 Trend Line Statistics

	SDVt - 1980-01 to 1989-12					SDVt - 1990-01 to 1999-12				
	Parameters	t-Stats		Adj. R-Square	F-Stat	Parameters	t-Stats		Adj. R-Square	F-Stat
Alpha	0,2067	8,6406	***	-0,0083	0,0208	0,2245	1,8055	*	-0,0071	0,1620
Beta	0,0000	-0,1444				0,0002	0,4025			

Table 5

Summary Statistics for ARMA(1,1) Model Forecast of Return Series - Benchmark

This table presents the summary statistics of the ARMA(1,1) benchmark model forecast.These forecasts were performed using a moving window of 60 months. Panel A displays the results for the equal weighted returns, while Panel B displays the results for the value weighted returns. Both panels present the results for the entire sample period as well as for the two sub-samples (January 1980 to December 1989 and January 1990 to December 1999). "RMSE" is the root mean squared error and "MPE" is the mean percentage error.

Panel A: CFMRCe

		1980-01 to 2001-12	1980-01 to 1989-12	1990-01 to 1999-12
# of forecasts		264	120	120
Forecast	**Mean**	0,0028	0,0033	0,0024
	Median	0,0023	0,0028	0,0022
	Min	0,0010	0,0012	0,0010
	Max	0,0118	0,0118	0,0084
	Std Dev.	0,0015	0,0017	0,0011
Std. Error	**Mean**	0,0037	0,0042	0,0033
	Median	0,0032	0,0042	0,0031
	Min	0,0009	0,0022	0,0009
	Max	0,0060	0,0059	0,0060
	Std Dev.	0,0014	0,0009	0,0017
RMSE		0,0673	0,0659	0,0657
MPE		3,3101	1,0192	6,0594

Panel B: CFMRCv

		1980-01 to 2001-12	1980-01 to 1989-12	1990-01 to 1999-12
# of forecasts		264	120	120
Forecast	**Mean**	0,0021	0,0022	0,0019
	Median	0,0019	0,0021	0,0017
	Min	0,0010	0,0012	0,0010
	Max	0,0072	0,0039	0,0072
	Std Dev.	0,0008	0,0006	0,0010
Std. Error	**Mean**	0,0021	0,0021	0,0019
	Median	0,0017	0,0017	0,0011
	Min	0,0001	0,0013	0,0001
	Max	0,0038	0,0038	0,0038
	Std Dev.	0,0010	0,0009	0,0012
RMSE		0,0505	0,0551	0,0425
MPE		0,9512	0,9465	0,9518

Table 6

Summary Statistics of Regressions of CFMRCe on Vpte

This table presents the summary statistics of the regressions of equal-weighted market returns (CFMRCe) on equal-weighted portfolio variances (Vpte). The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-vale of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Beta	F
1975-2001	264	131	151	151
		49,62%	57,20%	57,20%
1980-1989	120	76	59	59
		63,33%	49,17%	49,17%
1990-1999	120	45	92	92
		37,50%	76,67%	76,67%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,1084	0,0823	0,1242	-0,1550	0,4563
1980-1989	0,1230	0,0464	0,1388	-0,0172	0,4563
1990-1999	0,1190	0,0942	0,1050	-0,1550	0,3743

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0699	22,4472
1980-1989	0,0692	1,5569
1990-1999	0,0682	47,5804

Table 7

Summary Statistics of Regressions of CFMRCe on Vptv

This table presents the summary statistics of the regressions of equal-weighted market returns (CFMRCe) on value-weighted portfolio variances (Vptv). The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-vale of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Beta	F
1975-2001	264	207	157	157
		78,41%	59,47%	59,47%
1980-1989	120	73	88	88
		60,83%	73,33%	73,33%
1990-1999	120	110	53	53
		91,67%	44,17%	44,17%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,1332	0,0668	0,1513	-0,0172	0,5380
1980-1989	0,1474	0,1155	0,1321	-0,0172	0,4527
1990-1999	0,1304	0,0211	0,1744	-0,0171	0,5300

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0737	15,530948
1980-1989	0,0729	1,4729278
1990-1999	0,0715	32,423477

Table 8

Summary Statistics of Regressions of CFMRCe on Vt

This table presents the summary statistics of the regressions of equal-weighted market returns (CFMRCe) on average stock variances (Vt). The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-vale of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Beta	F
1975-2001	264	99	16	15
		37,50%	6,06%	5,68%
1980-1989	120	99	16	15
		82,50%	13,33%	12,50%
1990-1999	120	29	0	0
		24,17%	0,00%	0,00%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,0012	-0,00815	0,0242362	-0,0172	0,0884
1980-1989	0,0125	0,0021	0,0307033	-0,017	0,0884
1990-1999	-0,0066	-0,00865	0,0100967	-0,0172	0,0180

Panel C: Forecast errors

	RMSE	MPE
1975-2001	0,0683	21,123149
1980-1989	0,0683	1,1647999
1990-1999	0,0656	45,069159

Table 9
Summary Statistics of Regressions of CFMRCv on Vpte

This table presents the summary statistics of the regressions of value-weighted market returns (CFMRCv) on equal-weighted portfolio variances (Vpte). The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-vale of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Beta	F
1975-2001	264	151	129	130
		57,20%	48,86%	49,24%
1980-1989	120	83	75	76
		69,17%	62,50%	63,33%
1990-1999	120	54	54	54
		45,00%	45,00%	45,00%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,0963	0,0478	0,1141	-0,0172	0,7050
1980-1989	0,1198	0,0748	0,1231	-0,0168	0,7050
1990-1999	0,0904	0,0463	0,1069	-0,0172	0,3689

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0535	0,2862442
1980-1989	0,0591	0,2786678
1990-1999	0,0443	0,1520664

Table 10
Summary Statistics of Regressions of CFMRCv on Vptv

This table presents the summary statistics of the regressions of value-weighted market returns (CFMRCv) on value-weighted portfolio variances (Vptv). The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-vale of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Beta	F
1975-2001	264	157	135	136
		59,47%	51,14%	51,52%
1980-1989	120	72	86	86
		60,00%	71,67%	71,67%
1990-1999	120	61	39	39
		50,83%	32,50%	32,50%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,1182	0,04965	0,1488218	-0,0172	0,4481
1980-1989	0,1406	0,11235	0,1228832	-0,0172	0,4477
1990-1999	0,1100	-0,01045	0,1795145	-0,0172	0,4481

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0561	0,5924401
1980-1989	0,0629	0,3556501
1990-1999	0,0453	0,7286551

Table 11

Summary Statistics of Regressions of CFMRCv on Vt

This table presents the summary statistics of the regressions of value-weighted market returns (CFMRCv) on average stock variances (Vt). The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-vale of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Beta	F
1975-2001	264	104	60	60
		39,39%	22,73%	22,73%
1980-1989	120	69	52	52
		57,50%	43,33%	43,33%
1990-1999	120	24	8	8
		20,00%	6,67%	6,67%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,0195	-0,0079	0,0543043	-0,0172	0,1967
1980-1989	0,0506	0,026	0,064322	-0,0172	0,1967
1990-1999	-0,0049	-0,012	0,023963	-0,0172	0,0856

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0524	0,5284226
1980-1989	0,0579	0,1839451
1990-1999	0,0433	0,8014858

Table 12
Summary Statistics of Regressions of CFMRCe on Vpte, Dividend Yield and T-Bill Yield

This table presents the summary statistics of the regressions of equal-weighted market returns (CFMRCe) on equal-weighted portfolio variances (Vpte), dividend yields and treasury bill yields. The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-value of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Vpte	DivYield	TB	F
1975-2001	264	175	160	85	79	183
		66,29%	60,61%	32,20%	29,92%	69,32%
1980-1989	120	117	67	48	69	109
		97,50%	55,83%	40,00%	57,50%	90,83%
1990-1999	120	48	93	31	1	74
		40,00%	77,50%	25,83%	0,83%	61,67%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,2229	0,2176	0,1498	-0,0261	0,5071
1980-1989	0,3030	0,3227	0,1150	0,0658	0,5071
1990-1999	0,1842	0,1650	0,1395	-0,0082	0,5069

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0973	4,6850
1980-1989	0,1205	1,4318
1990-1999	0,0708	8,6214

Table 13

Summary Statistics of Regressions of CFMRCe on Vptv, Dividend Yield and T-Bill Yield

This table presents the summary statistics of the regressions of equal-weighted market returns (CFMRCe) on value-weighted portfolio variances (Vptv), dividend yields and treasury bill yields. The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-value of 4.000).

Panel A: Number of significant parameters / regressions

	Number of regressions	Alpha	Vptv	DivYield	TB	F
1975-2001	264	185	160	83	78	164
		70,08%	60,61%	31,44%	29,55%	62,12%
1980-1989	120	118	91	57	71	117
		98,33%	75,83%	47,50%	59,17%	97,50%
1990-1999	120	55	58	25	6	47
		45,83%	48,33%	20,83%	5,00%	39,17%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,2486	0,26165	0,1771	-0,0244	0,6051
1980-1989	0,3451	0,357	0,1015	0,1241	0,5392
1990-1999	0,1888	0,08	0,1976	-0,0244	0,6051

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0978	5,1852
1980-1989	0,0806	1,0868
1990-1999	0,0984	9,8879

Table 14

Summary Statistics of Regressions of CFMRCe on Vt, Dividend Yield and T-Bill Yield

This table presents the summary statistics of the regressions of equal-weighted market returns (CFMRCe) on average stock variances (Vt), dividend yields and treasury bill yields. The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-value of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Vt	DivYield	TB	F
1975-2001	264	166	9	102	90	84
		62,88%	3,41%	38,64%	34,09%	31,82%
1980-1989	120	110	0	61	79	63
		91,67%	0,00%	50,83%	65,83%	52,50%
1990-1999	120	46	9	34	2	21
		38,33%	7,50%	28,33%	1,67%	17,50%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,1040	0,0573	0,1249	-0,0446	0,4778
1980-1989	0,1743	0,1374	0,1355	-0,0359	0,4778
1990-1999	0,0531	0,0331	0,0803	-0,0331	0,3159

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0737	3,3026
1980-1989	0,0758	1,0607
1990-1999	0,0680	5,9228

Table 15

Summary Statistics of Regressions of CFMRCv on Vpte, Dividend Yield and T-Bill Yield

This table presents the summary statistics of the regressions of value-weighted market returns (CFMRCv) on equal-weighted portfolio variances (Vpte), dividend yields and treasury bill yields. The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-value of 4.000).

Panel A: Number of significant parameters / regressions

	Number of regressions	Alpha	Vpte	DivYield	TB	F
1975-2001	264	193	160	72	54	143
		73,11%	60,61%	27,27%	20,45%	54,17%
1980-1989	120	93	66	42	39	86
		77,50%	55,00%	35,00%	32,50%	71,67%
1990-1999	120	77	91	20	6	57
		64,17%	75,83%	16,67%	5,00%	47,50%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,1698	0,1533	0,1126	-0,0289	0,4088
1980-1989	0,2152	0,2313	0,1001	0,0533	0,4084
1990-1999	0,1474	0,1183	0,1126	-0,0289	0,4088

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0626	0,4818
1980-1989	0,0735	-0,9968
1990-1999	0,0495	1,8597

Table 16

Summary Statistics of Regressions of CFMRCv on Vptv, Dividend Yield and T-Bill Yield

This table presents the summary statistics of the regressions of value-weighted market returns (CFMRCv) on value-weighted portfolio variances (Vptv), dividend yields and treasury bill yields. The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-value of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Vptv	DivYield	TB	F
1975-2001	264	207	152	80	54	145
		78,41%	57,58%	30,30%	20,45%	54,92%
1980-1989	120	106	90	57	48	106
		88,33%	75,00%	47,50%	40,00%	88,33%
1990-1999	120	78	51	18	0	39
		65,00%	42,50%	15,00%	0,00%	32,50%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,2045	0,1928	0,1589	-0,0509	0,4973
1980-1989	0,2831	0,3109	0,0914	0,0822	0,4602
1990-1999	0,1512	0,0609	0,1873	-0,0509	0,4973

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0706	0,4928
1980-1989	0,0862	-0,6972
1990-1999	0,0526	1,6713

Table 17

Summary Statistics of Regressions of CFMRCv on Vt, Dividend Yield and T-Bill Yield

This table presents the summary statistics of the regressions of value-weighted market returns (CFMRCv) on average stock variances (Vt), dividend yields and treasury bill yields. The associated one month step ahead forecast statistics are also given. These forecasts were performed using a moving window of 60 months. Panel A gives the number of significant parameters/regressions both in absolute number and in percentage of number of regressions. Panel B gives summary statistics of the adjusted R-Square. Panel C displays the forecast error statistics. "RMSE" is the root mean squared error and "MPE" is the mean percentage error. The significance of the parameters was tested at the 5% level (critical t-value of 2.000) and the significance of the relationship was also tested at the 5% level (critical F-value of 4.000).

Panel A: Number of significant parameters/regressions

	Number of regressions	Alpha	Vt	DivYield	TB	F
1975-2001	264	141	44	73	67	62
		53,41%	16,67%	27,65%	25,38%	23,48%
1980-1989	120	82	35	37	56	53
		68,33%	29,17%	30,83%	46,67%	44,17%
1990-1999	120	46	9	28	0	9
		38,33%	7,50%	23,33%	0,00%	7,50%

Panel B: Adjusted R-Square

	Mean	Median	Std.Dev.	Min	Max
1975-2001	0,0816	0,0393	0,1141	-0,0485	0,4135
1980-1989	0,1431	0,1063	0,1357	-0,0485	0,4135
1990-1999	0,0311	0,0132	0,0551	-0,0402	0,1749

Panel C:Forecast errors

	RMSE	MPE
1975-2001	0,0605	0,2170
1980-1989	0,0667	-0,8505
1990-1999	0,0471	1,1302

Table 18

Switching rules for classical market timing for various habitats

This table presents the switching rules used for the market timing tests. A transaction fee of 1% is used when switching away from the natural habitat. For the market timing switches assuming no preferred habitat, i.e. "none", the performance of the switches are evaluated using both with and without the 1% transaction fee.

Switch to:	**Natural habitat**			
	Stock	**Cash**	**None**	**None**
Cash if predicted return is	Less than (Rf-1%)	Less than Rf	Less than (Rf-1%)	Less than Rf
Stock if predicted return is	Greater than Rf	Greater than (Rf-1%)	Greater than (Rf-1%)	Greater than Rf

Table 19
Summary Statistics for "perfect timing" strategy of actively managed portfolio

This table presents the summary statistics for a "perfect timing" strategy. "Perfect timing" is defined as holding stocks when monthly stock returns are larger than treasury-bill returns and holding treasury bills when stock returns are lower than treasury bill returns. A 1% transaction cost is charged for all switches. Panel A represents the entire period, while Panels B and C, represent the first and second sub-samples, respectively.

Panel A: Entire Sample - January 1980 to December 2001

		Stocks		Perfect timing	
	Cash equivalent	**CFMRCe**	**CFMRCv**	**CFMRCe**	**CFMRCv**
Average monthly return	0,0067	0,0148	0,0094	0,0289	0,0213
Standard deviation of monthly returns	0,0030	0,0663	0,0501	0,0419	0,0254
Average annual return	0,0801	0,1782	0,1125	0,3472	0,2561
Standard deviation of annual returns	0,0352	0,2744	0,1420	0,1772	0,0972

Panel B: January 1980 to December 1989

		Stocks		Perfect timing	
	Cash equivalent	**CFMRCe**	**CFMRCv**	**CFMRCe**	**CFMRCv**
Average monthly return	0,0089	0,0108	0,0108	0,0282	0,0241
Standard deviation of monthly returns	0,0023	0,0658	0,0548	0,0362	0,0285
Average annual return	0,1069	0,1296	0,1298	0,3384	0,2887
Standard deviation of annual returns	0,0261	0,2629	0,1285	0,1794	0,1106

Panel C: January 1990 to December 1999

		Stocks		Perfect timing	
	Cash equivalent	**CFMRCe**	**CFMRCv**	**CFMRCe**	**CFMRCv**
Average monthly return	0,0048	0,0182	0,0082	0,0295	0,0191
Standard deviation of monthly returns	0,0021	0,0667	0,0460	0,0462	0,0224
Average annual return	0,0604	0,2258	0,1276	0,3379	0,2251
Standard deviation of annual returns	0,0261	0,3183	0,1522	0,1977	0,0823

Table 20

Summary statistics for performance, risk and activity of actively managed portfolio using "perfect timing" strategy

This table presents the summary statistics of the Elton and Gruber (1991) market-timing performance metric for actively managed portfolios using "perfect timing" strategy. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectivelly. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-periods, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***),

Panel A: Entire Sample - January 1980 to December 2001

Statistics	CFMRCe	CFMRCv
Mean	0,01768 ***	0,01324 ***
Median	0,01102 ***	0,00953 ***
# of switches	148	139
Beta	0,56061	0,52652

Panel B: January 1980 to December 1989

Statistics	CFMRCe	CFMRCv
Mean	0,01832 ***	0,02407 ***
Median	0,01193 ***	0,01154 ***
# of switches	62	63
Beta	0,51667	0,52500

Panel C: January 1990 to December 1999

Statistics	CFMRCe	CFMRCv
Mean	0,01325 ***	0,01876 ***
Median	0,00519 **	0,00859 ***
# of switches	86	76
Beta	0,71667	0,63333

Table 21

Summary statistics for performance, risk and activity of actively managed portfolios using an ARMA (1,1) process to forecast and time CFMRCe - Benchmark

This table presents the summary statistics of the Elton and Gruber (1991) market-timing performance metric for actively managed portfolios using an ARMA (1,1) process to forecast and time CFMRCe. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for these two sub-samples.

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00156	-0,00007	0,00181 **	-0,00032
Median	0,00081 *	-0,00071	0,00023 *	-0,00039
# of switches	3	16	2	17
Beta	0,90530	0,13636	0,97348	0,06818

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00211	0,00117	0,00359 *	-0,00031
Median	0,00154	-0,000625295	0,00038	-6,81074E-05
# of switches	3	3	2	4
Beta	0,79167	0,175	0,95000	0,016666667

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00000	-0,00191	0,00000	-0,00191
Median	0,00000	-0,000761783	0,00000	-0,000761783
# of switches	0	10	0	10
Beta	1,00000	0,1	1,00000	0,1

Table 22

Summary statistics for performance, risk and activity of actively managed portfolios using an ARMA (1,1) process to forecast and time CFMRCv - Benchmark

This table presents the summary statistics of the Elton and Gruber (1991) market-timing performance metric for actively managed portfolios using an ARMA (1,1) process to forecast and time CFMRCv. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respect

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00031	0,002870989	0,00200	0,000561638
Median	-0,00018	0,0011161 *	0,00031 **	-7,02104E-05
# of switches	1	10	4	7
Beta	0,19318	0,803030303	0,95076	0,045454545

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00000	0,004287817 **	0,00429 **	0
Median	0,00000	0,000579084	0,000579084	0
# of switches	0	4	4	0
Beta	0,00000	0,9	0,9	0

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00077	2,7236E-05	0,00000	0,000797544
Median	-0,00007	0,00046237	0	-0,000194682
# of switches	1	5	0	6
Beta	0,22500	0,841666667	1	0,066666667

Table 23

Summary statistics for performance, risk and activity of actively managed portfolios using Vpte to time CFMRCe

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte to time CFMRCe. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels. respectively, for the two sub-samples

Panel A: Entire sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00059	-0,00103	0,00029	-0,00191
Median	0,00049	0,00001	0,00054	-0,00131
# of switches	34	52	40	46
Beta	0,86742	0,80682	0,90909	0,76515

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00081	-0,00119	0,00021	-0,00221
Median	-0,00017	-0,00319	0,00041	-0,00474 **
# of switches	18	24	20	22
Beta	0,85000	0,71667	0,90000	0,66667

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00075	-0,00140	0,00026	-0,00241
Median	0,00075 *	0,00077 **	0,00080 *	0,00067 *
# of switches	16	26	20	22
Beta	0,86667	0,87500	0,90833	0,83333

Table 24

Summary statistics for performance, risk and activity of actively managed portfolios using Vptv to time CFMRCe

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolios using Vptv to time CFMRCe. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the two sub-samples.

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00234 *	-0,00214	-0,00147	-0,00301 *
Median	-0,00034	0,00026	0,00005	-0,00031
# of switches	50	74	56	68
Beta	0,79924	0,76894	0,83333	0,73485

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00318	-0,00441 *	-0,00301	-0,00458 *
Median	-0,00368	-0,00347	-0,00244	-0,00432
# of switches	24	36	28	32
Beta	0,74167	0,69167	0,78333	0,65000

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00272	0,00022	-0,00169	-0,00081
Median	0,00062 *	0,00130 **	0,00067 **	0,00103 **
# of switches	18	26	20	24
Beta	0,86667	0,85833	0,89167	0,83333

Table 25

Summary statistics for performance, risk and activity of actively managed portfolios using Vt to time CFMRCe

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vt to time CFMRCe. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively,

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00022	0,00081	0,00028	0,00074
Median	0,00016	0,00103	0,00012	0,00106
# of switches	8	28	8	28
Beta	0,97348	0,81818	0,98106	0,81061

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00010	-0,00091	0,00034	-0,00116
Median	0,00006	-0,00086	0,00012	-0,00129
# of switches	8	18	8	18
Beta	0,95000	0,86667	0,96667	0,85000

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00000	0,00323	0,00000	0,00323
Median	0,00000	0,00420	0,00000	0,00420
# of switches	0	10	0	10
Beta	1,00000	0,74167	1,00000	0,74167

Table 26

Summary statistics for performance, risk and activity of actively managed portfolios using Vpte to time CFMRCv

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte to time CFMRCv. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively,

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00081	-0,00008	-0,00051	-0,00038
Median	0,00037	0,00088	0,00033	0,00087
# of switches	28	56	30	54
Beta	0,89394	0,77652	0,91667	0,75379

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00083	-0,00102	-0,00082	-0,00103
Median	0,00025	0,00024	0,00022	0,00027
# of switches	18	22	18	22
Beta	0,86667	0,84167	0,88333	0,82500

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00080	0,00099	-0,00024	0,00043
Median	0,00059	0,00256	0,00049	0,00221
# of switches	10	30	12	28
Beta	0,90833	0,69167	0,94167	0,65833

Table 27

Summary statistics for performance, risk and activity of actively managed portfolios using Vptv to time CFMRCv

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vptv to time CFMRCv. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively,

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00183 *	-0,00139	-0,00148	-0,00175
Median	-0,00069	-0,00107	-0,00036	-0,00165
# of switches	38	76	48	66
Beta	0,80682	0,73106	0,85985	0,67803

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00297	-0,00394 *	-0,00300	-0,00391
Median	-0,00210	-0,00278	-0,00089	-0,00339
# of switches	26	42	32	36
Beta	0,68333	0,65833	0,76667	0,57500

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	-0,00105	0,00110	-0,00027	0,00032
Median	-0,00007	0,00111	0,00003	0,00058
# of switches	10	26	14	22
Beta	0,90833	0,80000	0,94167	0,76667

Table 28

Summary statistics for performance, risk and activity of actively managed portfolios using Vt to time CFMRCv

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vt to time CFMRCv. Panel A gives the mean and median differential performances, numbers of switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two 120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively,

Panel A: Entire sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00021	0,00074	0,00030	0,00064
Median	0,00024	0,00081	0,00012	0,00100
# of switches	14	38	14	38
Beta	0,93939	0,79545	0,96591	0,76894

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00001	-0,00060	0,00047	-0,00107
Median	0,00019	-0,00016	0,00009	0,00001
# of switches	12	24	12	24
Beta	0,90000	0,88333	0,94167	0,84167

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00042 *	0,00305 *	0,00014	0,00333 **
Median	0,00021	0,00395	0,00006	0,00459
# of switches	2	14	2	14
Beta	0,97500	0,67500	0,99167	0,65833

Table 29

Summary statistics for performance, risk and activity of actively managed portfolios using Vpte, dividend yield and T-bill yield to time CFMRCe

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte, dividend yield and T-bill yield to time CFMRCe. Panel A gives the mean and median differential performances, number sof switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the tw

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00214	0,00172	0,00207	0,00179
Median	0,00134	0,00123	0,00125	0,00129
# of switches	22	42	22	42
Beta	0,83712	0,78030	0,84848	0,76894

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00167	0,00164	0,00167	0,00164
Median	0,00075	0,00106	0,00075	0,00106
# of switches	16	24	16	24
Beta	0,81667	0,74167	0,81667	0,74167

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00275	0,00161	0,00246	0,00190
Median	0,00247 ***	0,00151 *	0,00210 **	0,00169 **
# of switches	6	16	6	16
Beta	0,83333	0,79167	0,85833	0,76667

Table 30

Summary statistics for performance, risk and activity of actively managed portfolios using Vptv, dividend yield and T-bill yield to time CFMRCe

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte, dividend yield and T-bill yield to time CFMRCe. Panel A gives the mean and median differential performances, number sof switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the tw

Panel A: Entire sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00265	0,00327 *	0,00372 **	0,00221
Median	0,00146	0,00216	0,00167	0,00163
# of switches	29	51	29	51
Beta	0,80303	0,76136	0,81818	0,74621

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00373	0,00235	0,00481 *	0,00128
Median	0,00117	0,00130	0,00129	0,00112
# of switches	14	30	14	30
Beta	0,81667	0,73333	0,82500	0,72500

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00342	0,00506 **	0,00381 *	0,00466 **
Median	0,00252 ***	0,00406 ***	0,00336 ***	0,00393 ***
# of switches	12	14	12	14
Beta	0,78333	0,78333	0,80000	0,76667

Table 31

Summary statistics for performance, risk and activity of actively managed portfolios using Vt, dividend yield and T-bill yield to time CFMRCe

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte, dividend yield and T-bill yield to time CFMRCe. Panel A gives the mean and median differential performances, number sof switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the two sub-samples.

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00301 *	0,00486 ***	0,00336 **	0,00451 **
Median	0,00190 **	0,00215	0,00168 **	0,00236 *
# of switches	14	36	18	32
Beta	0,80682	0,76515	0,82955	0,74242

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00382	0,00549 *	0,00382	0,00549 *
Median	0,00164	0,00197	0,00164	0,00197
# of switches	8	20	8	20
Beta	0,80833	0,73333	0,80833	0,73333

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00278	0,00481 *	0,00327	0,00432
Median	0,00379 ***	0,00251 **	0,00294 ***	0,00284 **
# of switches	6	16	10	12
Beta	0,77500	0,75833	0,82500	0,70833

Table 32

Summary statistics for performance, risk and activity of actively managed portfolios using Vpte, dividend yield and T-bill yield to time CFMRCv

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte, dividend yield and T-bill yield to time CFMRCe. Panel A gives the mean and median differential performances, number sof switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the two sub-samples.

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00170	0,00126	0,00176	0,00120
Median	0,00102	0,00125	0,00105	0,00116
# of switches	34	64	38	60
Beta	0,80303	0,75758	0,81439	0,74621

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00131	0,00088	0,00131	0,00088
Median	0,00053	0,00063	0,00053	0,00063
# of switches	20	28	20	28
Beta	0,81667	0,78333	0,81667	0,78333

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00149	0,00111	0,00155	0,00105
Median	0,00177	0,00288	0,00160	0,00266
# of switches	8	30	12	26
Beta	0,81667	0,75000	0,84167	0,72500

Table 33

Summary statistics for performance, risk and activity of actively managed portfolios using Vptv, dividend yield and T-bill yield to time CFMRCv

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte, dividend yield and T-bill yield to time CFMRCe. Panel A gives the mean and median differential performances, number sof switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the two sub-samples.

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00190	0,00150	0,00200	0,00141
Median	0,00122	0,00118	0,00113	0,00127
# of switches	28	46	32	42
Beta	0,80303	0,79924	0,82576	0,77652

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00215	0,00099	0,00215	0,00099
Median	0,00104	0,00095	0,00095	0,00102
# of switches	14	22	14	22
Beta	0,79167	0,77500	0,80833	0,75833

Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00124	0,00135	0,00123	0,00136
Median	0,00133	0,00117	0,00112	0,00136
# of switches	8	18	12	14
Beta	0,84167	0,84167	0,86667	0,81667

Table 34

Summary statistics for performance, risk and activity of actively managed portfolios using Vt, dividend yield and T-bill yield to time CFMRCv

This table presents the summary statistics of the Elton and Gruber (1991) market timing performance metric for actively managed portfolio using Vpte, dividend yield and T-bill yield to time CFMRCe. Panel A gives the mean and median differential performances, number sof switches and average betas over the entire 264 month sample. The statistical significance of the mean differential performance is tested using a t-test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.576, 1.960 and 1.645, respectively. The statistical significance of the median differential performance is tested using the large sample Wilcoxon nonparametric sign test. The critical values for rejection of the null hypothesis at the 1%(***), 5%(**) and 10%(*) levels are 2.575, 1.960 and 1.645, respectively. The number of switches is the number of switches from equity to cash and vice versa. Panels B and C give the same summary statistics for each of the two120 month sub-samples, respectively. The critical values for rejection of the null hypothesis of the mean being equal to zero are adjusted to 2.617, 1.980 and 1.658 for the 1%(***), 5%(**) and 10%(*) levels, respectively, for the two sub-samples.

Panel A: Entire Sample - January 1980 to December 2001

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00255 **	0,00161	0,00135 *	0,00281 *
Median	0,00224 *	0,00088	0,00090	0,00200
# of switches	12	30	20	22
Beta	0,78788	0,82955	0,85606	0,76136

Panel B: January 1980 to December 1989

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00287	0,00355	0,00287	0,00355
Median	0,00087	0,00089	0,00087	0,00089
# of switches	8	16	8	16
Beta	0,82500	0,77500	0,82500	0,77500

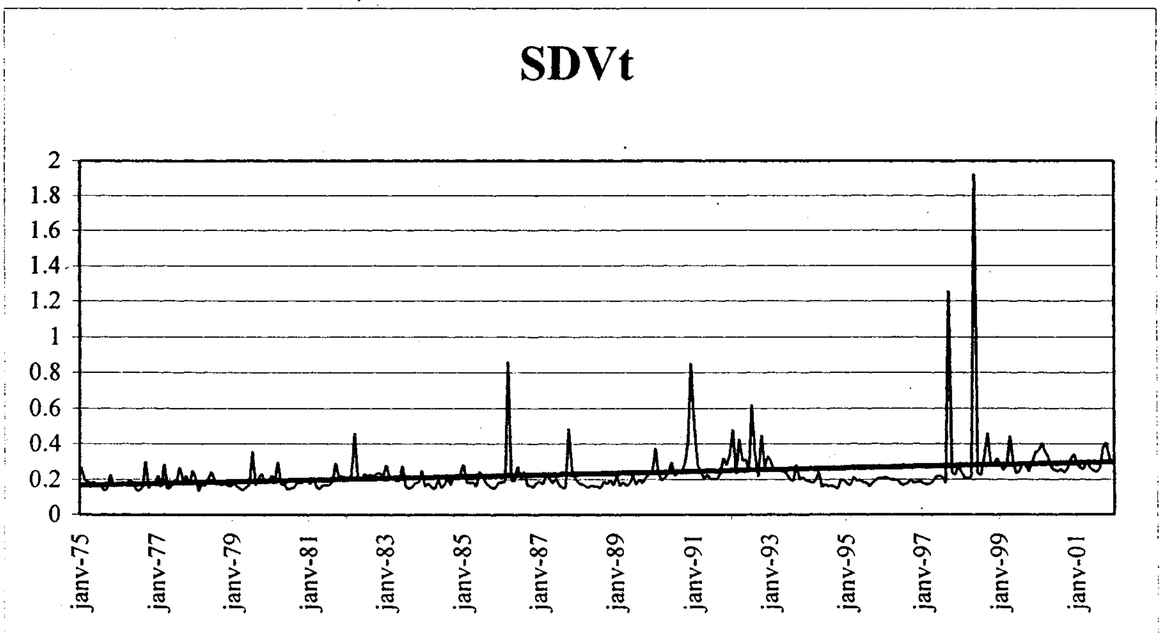
Panel C: January 1990 to December 1999

	Natural habitat			
Statistics	**Stock**	**Cash**	**None (1%)**	**None**
Mean	0,00349 **	0,00028	0,00041	0,00336 **
Median	0,00473	0,00112	0,00113	0,00431
# of switches	2	12	10	4
Beta	0,72500	0,86667	0,87500	0,71667

FIGURES

Figure 1

This figure plots the average standard deviations of stocks along with their trend lines for the period January 1975 to December 2001. Average stock variance is calculated using daily data from equation (2). The bottom panel uses a 12-month simple moving average of the top panel.



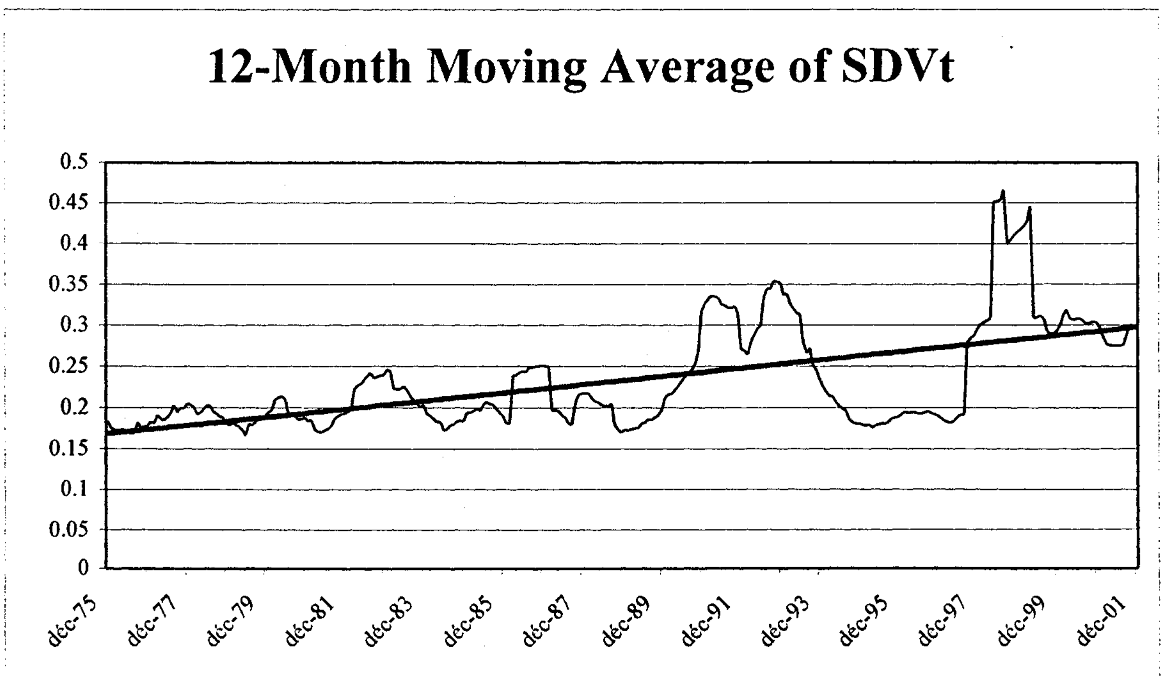


Figure 2

This figure plots the standard deviations of the equal- and value-weighted portfolios along with their respective trend lines for the period January 1975 to December 2001. Portfolio volatility is calculated using equation (1). The right two panels use a 12-month simple moving average of the data in their respective left panels.

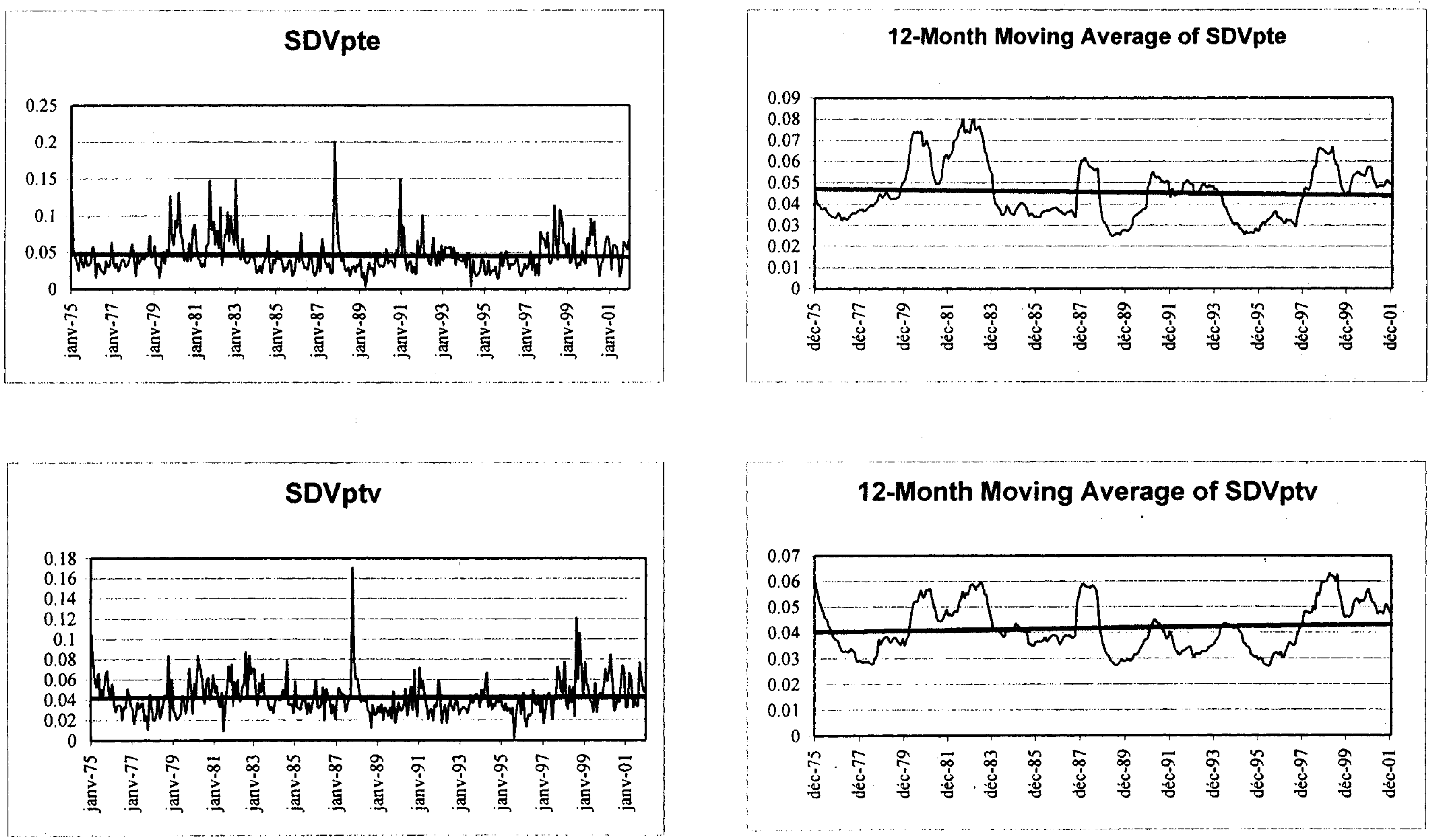
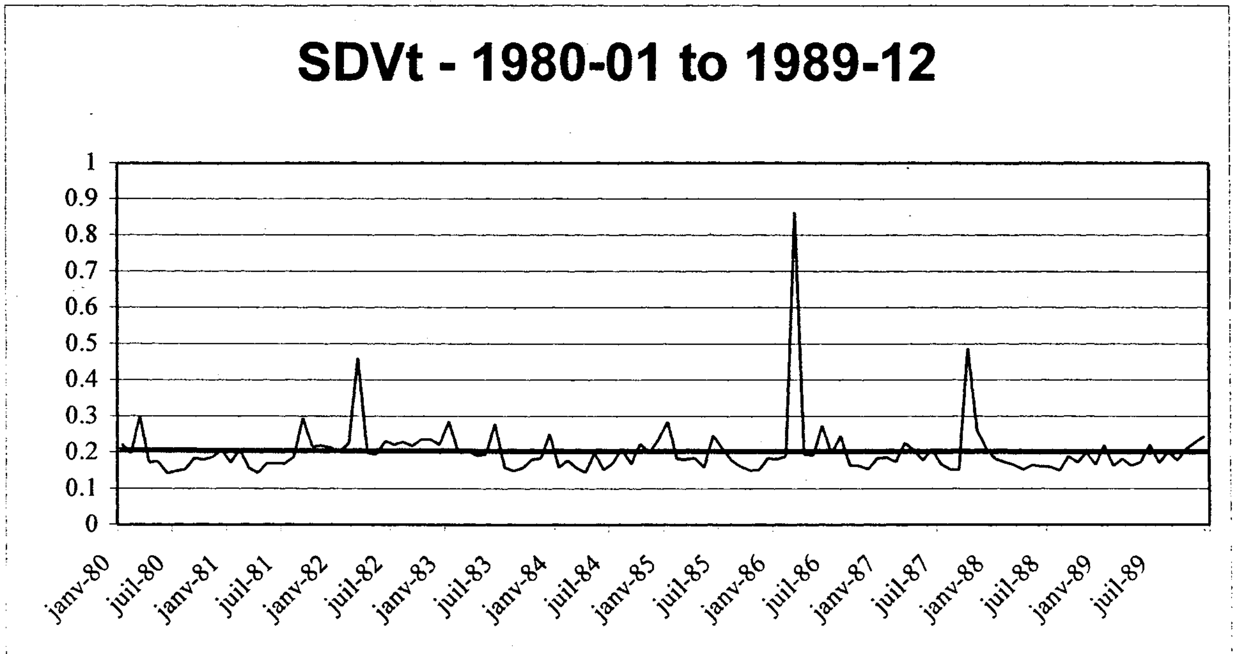
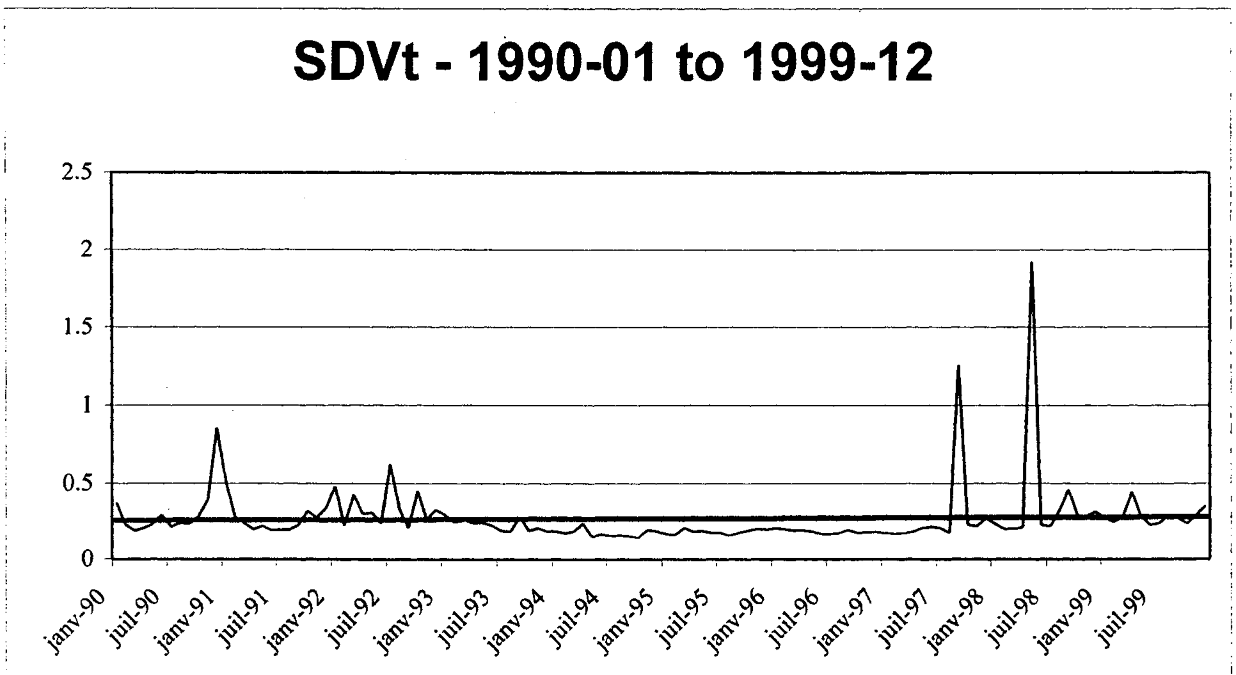


Figure 3

This figure plots the average standard deviations of stocks along with their respective trend lines for each of the two sub-samples: top graph - January 1980 to December 1989 and bottom graph – January 1990 to December 1999.





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