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A GARCH Model for Testing Market Efficiency

ABSTRACT

In this paper we propose a generalised autoregressive conditional heteroskedasticity (GARCH) model-based test for a unit root. The model allows for two endogenous structural breaks. We test for unit roots in 156 US stocks listed on the NYSE over the period 1980 to 2007. We find that the unit root null hypothesis is rejected in 40% of the stocks, and only in four out of the nine sectors the null is rejected for over 50% of stocks. We conclude with an economic significance analysis, showing that mostly stocks with mean reverting prices tend to outperform stocks with non-stationary prices.

Keywords: *Efficient Market Hypothesis; GARCH; Unit Root; Structural Break; Stock Price*.

1. INTRODUCTION

The efficient market hypothesis (EMH) is one of the traditional hypotheses in financial economics, owing to the work of Samuelson (1965) who proposed that stock prices should follow a random walk. The implication of Samuelson's proposal was that stock returns should be entirely unpredictable due to investors' arbitrage motives.

Three forms of the EMH are popularly tested in the literature. The weak form version of the EMH is based on an information set that uses current or past asset prices (see Fama, 1970). Fama (1991) argued that the weak form EMH should also include in the information set those predictor variables, such as dividend yields and interest rates, which forecast returns. When this information set is expanded to include all public information, the EMH takes a semi-strong form. Finally, if all public and private information is contained in the information set, the EMH takes the strong form (see Fama, 1970, 1991). Our test for the EMH is based on the weak form version as it is based on the idea that current price of stocks is the best predictor of the future price of stocks, and the price change (return) is expected to be zero. This implies a random walk model where increments are identically and independently distributed. When errors from a predictive model are heteroskedastic, a martingale allows for uncorrelated increments. A martingale can be considered as a generalised form of a random walk model. Therefore, a martingale model is ideal when data on hand, such as stock price data, is best characterised by heteroskedasticity (see Kim and Shamsuddin, 2008).

The EMH has attracted a substantial interest, with voluminous empirical applications. Our interest on the EMH is based on two specific reasons. The first reason is that despite the plethora of studies on the EMH, none of the studies have examined the hypothesis at the micro level; that is, for time series of stock prices at the firm level. In other words, all empirical applications are either on aggregate stock prices (indices) or on cross-section of stocks. This is the main research gap in the extant literature. The motivation for a micro-level test of the EMH is explained in the next section. The second reason is methodological, in that, in financial economics, it has been shown that financial data suffers from heteroskedasticity. It is, therefore, important to account for heteroskedasticity. A second issue with time series data, well established in the time series applied econometrics literature, is that data tends to be characterized by structural breaks. Hence, we model both heteroskedasticity and structural breaks simultaneously.

To test for the unit root null hypothesis, following the Nelson and Plosser (1982) findings, a wide range of structural break unit root tests have been developed. These tests can be categorized into those that treat the structural breaks as exogenous and those that treat the structural breaks as endogenous. The exogenous break tests include those proposed by Perron (1989), while the endogenous class of tests include those from Lumsdaine and Papell (1997), Lee and Strazizich (2003), Sen (2003), Perron and Vogelsand (1992), and more recently Narayan and Popp (2010). A key feature of these tests is that they are based on linear models, i.e. they assume independent and identically distributed (iid) errors. Fittingly, Kim and Schmidt (1993a) show that the Dickey-Fuller type tests tend to reject the unit root null hypothesis too often in the presence of conditional heteroskedasticity.[1]

The aim of this paper is to examine the EMH for US stocks. We consider, from the New York Stock Exchange, no fewer than 156 stocks. The data series are monthly and cover the period January 1980 to December 2007. Such a historical time series analysis of the efficient market hypothesis for a large number of stocks has not been previously undertaken. The second contribution, motivated by the limiting theory for unit root processes with GARCH disturbances developed by Ling and Li (1998, 2003), Seo (1999) and Gospodinov (2008), is that we propose a GARCH (1,1) unit root model that is flexible to accommodate two endogenous structural breaks.

We also undertake an economic significance analysis through which we demonstrate the relative importance of unit root properties for investors. Generally speaking, there is limited knowledge on how beneficial the knowledge on unit roots is for investors.

The balance of the paper is organized as follows. In section 2, we describe the literature on the EMH and derive the main motivations for our study. In section 3, we present the econometric model and discuss the results. In section 4, we undertake an economic significance analysis followed by a robustness test. In the final section, we provide some concluding remarks.

2. LITERATURE AND MOTIVATION

There are two motivations for the current paper. The first motivation is empirical and has roots in the literature that has tested the EMH. The literature on the EMH has followed two strands. The first strand (see, *inter alia*, DeBondt and Thaler, 1985, 1987; Zarowin, 1990) relates to the early literature on this subject and is based on a panel data –a cross-section of stocks—analysis. These studies essentially test the return reversal behaviour of stock prices. This amounts to testing whether the prior period’s worst stock return performers (losers)

[1] The relevance of unit roots in financial time series and panel data have been demonstrated by many studies; one influential study that motivates us is Geppert et al., (2002).

outperformed the prior period's best return performers (winners) in the subsequent period. These studies can be considered as short-horizon based analysis of the EMH. The second strand of the literature considers the EMH over long horizons based on time series data (see, *inter alia*, Fama and French, 1988; Poterba and Summers, 1988; Richards, 1995, 1997; Chaudhuri and Wu, 2003; Zhong *et al*., 2003) or panel data (see Balvers *et al*. 2000); for a nonlinear mean reversion of stock prices, see Bali *et al*. (2008).

There are three distinctive features of this literature. First, there is no consensus on mean reversion. Some studies have found mean reversion, while others have rejected the mean reversion hypothesis. The more recent studies on mean reversion in stock prices, such as Balvers *et al*. (2000) based on panel data and Chaudhuri and Wu (2003) based on time series structural break unit root tests, find overwhelming evidence of mean reversion, however. The second feature is that, while a range of applications on mean reversion in stock prices are available, none of the studies have considered mean reversion in individual firm stock prices based on time series data. The third feature is that a wide range of econometric estimation techniques, ranging from simple cross-sectional regression models to sophisticated structural break unit root testing procedures have been applied, but none of the studies have considered a GARCH-based model. This is particularly important in light of the fact that high frequency data, such as daily and monthly, suffer from heteroskedasticity and a GARCH model solves this statistical problem, which if unsolved can potentially bias the results on mean reversion; see Engle (1982) and Bollerslev (1986).

From these features of the literature, the one gap that is obvious is: there are no studies that examine the EMH at the firm-level using time series data. In other words, no studies examine the validity or otherwise of the EMH for firm-level stock price. Why is this investigation important? The aggregate stock price based studies on the EMH assume that firms comprising the aggregate stock market are homogenous. It is, however, not the case. Firms are heterogeneous (see Narayan and Sharma, 2011). Firms are of different sizes and cost structures. Hence, some firms, or the heterogeneity of firms, may be contributing to the results on the EMH. For these two reasons, it is essential to test the EMH for each stock individually. As a result, we consider the unit root null hypothesis for 156 US stocks. Moreover, we divide these stocks into different sectors based on the Global Industry Classification Standard (GICS).

The second motivation is methodological in nature. In addition to financial time series data being characterized by GARCH errors, structural breaks are a stylized fact of financial time series, as demonstrated in the work of Andreou and Ghysels (2002), among others. The role of structural breaks and the fact that they contribute to volatility persistence has been highlighted in the work of Diebold (1986). Following this suggestion, an initial attempt at allowing the constant term of the conditional variance to change was made by Lamoureux and Susmel (1994).

As highlighted earlier, studies on structural break unit root tests are based on standard linear models, i.e. with iid innovations. This assumption is inappropriate for modeling unit roots if there is heteroskedasticity. Following this, some studies (see, *inter alia*, Phillips and Durlauf, 1986; Phillips, 1987; Chan and Wei, 1988; Kim and Schmidt, 1993b; Lucas, 1995; Herce, 1996; Seo, 1999; Ling and Li, 2003) consider testing for unit roots with non-iid errors. We extend this branch of research to include two endogenous structural breaks based on a GARCH (1,1) process. Our extension is relevant in the case of testing the EMH based on monthly data because Kim and Schmidt (1993a) show that the Dickey and Fuller test is sensitive to heteroskedasticity and the problem is compounded when the ARCH and GARCH parameters together approach unity. Ling *et al*. (2003) argue that the phenomena can be, to some extent, explained by the loss of efficiency of the least squares estimator. To give credence to this line of thought, Ling and Li (1998) derive the limiting distribution of the maximum likelihood estimator for higher order GARCH errors and prove that it was more efficient compared to the least square estimator. In the work of Seo (1999), in addition, it is shown that when the unit root test is based on the maximum likelihood estimation, which estimates the autoregressive unit root and the GARCH parameters jointly, significant power gains are achieved.

Based on this literature, we propose a model that not only allows for two endogenous structural breaks but also jointly estimates the autoregressive (AR) and the GARCH parameters based on the maximum likelihood estimator. Essentially, we merge two branches of the literature—the endogenous structural break literature and the literature on efficient estimators for unit root tests—to arrive at a model that is novel for unit root testing. It follows that our proposed GARCH (1,1)-unit root test model with two endogenous structural breaks is characterized by the salient features of the broader literature on unit roots.

3. ECONOMETRIC MODEL AND EMPIRICAL FINDINGS

3.1. Data

The data on stock prices of the US firms is from the New York Stock Exchange, obtained from BLOOMBERG. The data is monthly and for the period 1980 to 2007. The stocks are divided into nine sectors based on the GICS following Narayan and Sharma

(2011). These sectors are utilities, materials, information technology, industrial, health care, financial, energy, consumer staples, and consumer discretion. The number of firms in each sector varies, from as low as eight in the case of the info tech sector to as high as 31 in the case of the industrial sector. The complete distribution of firms by sector is noted in Table 1.

INSERT TABLE 1

3.2. Some descriptive statistics of the data

In this section, we provide some stylized facts about the data series. The results are reported in Table 1. The key features of the data are as follows. First, we notice that mean stock price varies from sector-to-sector. Returns (not reported here) follow a similar pattern. It falls in the 0.5 to 1.04% range. Three sectors (utilities, infor tech, and energy) have a mean return of around 0.5%; for four sectors (health, financial, consumer staples and consumer discretion) returns are either one or close to one; and the rest of the sectors have a mean return in the 0.7 to 0.85% range. Second, in terms of volatility, the coefficient of variation (CoV) suggests that some sectors are relatively more volatile than others. For instance, the consumer staples, financial, and health care sectors are the most volatile while utility and energy sectors appear to be least volatile. Third, the kurtosis statistic suggests that all sectors are platykurtic, except for the energy sector for which prices have a much thicker tail. Finally, one can observe a similar sectoral pattern with respect to skewness. While skewness is positive across all sectors, the magnitude varies and falls in the 0.23 (utilities) to 1.64 (energy) range.

The implication emerging from this simple statistical analysis is that the behavior of firms is different depending on their sectoral location, which is a well-known fact in financial economics. Our main reason for demonstrating this here is to motivate our categorization of stocks into sectors.

3.3. GARCH-unit root test with two endogenous structural breaks

3.3.1. Model specification

In this section, we propose a GARCH-unit root test with two endogenous structural breaks. Before we proceed with model description, it is important to address the question: why are two structural breaks sufficient? To answer this question, we draw on the Bai and Perron (1998) procedure which allows us to examine the maximum number of breaks for each of the 156 stocks in our sample. Bai and Perron (1998) suggest an F-test statistic and a double maximum statistic to identify the maximum number of breaks in the data series. The F-test statistic considers the null hypothesis of no structural break against the alternative hypothesis that there are k breaks. Essentially, this test amounts to searching for all possible break dates and minimizing the difference between the restricted and unrestricted sum of squares over all the potential breaks. The double maximum test examines the null hypothesis of no structural breaks against the alternative hypothesis of at least one through to k structural breaks. There are two forms of the double maximum statistic: $UDmax$ statistic, which is the maximum value of the F-statistic, and the $WDmax$ statistic, which weights the individual statistics so as to equalize the p-values across the values of structural breaks. Using both test statistics, we find that for 138 out of 156 stocks (88.4%) in our sample, there are a maximum of two structural breaks, while for the remaining stocks there is only one structural break. Based on this evidence, a two break model is sufficient.

We consider a GARCH (1, 1) unit root model of the following form:

$$y_t = \alpha_0 + \pi y_{t-1} + D_1 B_{1t} + D_2 B_{2t} + \varepsilon_t \qquad (1)$$

Here, α_0 being the constant, and y_{t-1} is the one lag of the dependent variable y. $B_{it} = 1$ for $t \geq T_{Bi}$ otherwise $B_{it} = 0$; T_{Bi} are the structural break points, where $i = 1, 2$. D_1 and D_2 are break dummy coefficients. Moreover, ε_t follow the first-order generalized autoregressive conditional heteroskedasticity model, denoted as GARCH (1, 1),

$$\varepsilon_t = \eta_t \sqrt{h_t}\,, \quad h_t = \varkappa + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (2)$$

Here $\varkappa > 0, \alpha \geq 0, \beta \geq 0$, and η_t is a sequence of independently and identically distributed random variables with zero mean and unit variance.

3.3.2. Simulation design

In this section, we evaluate the size and power properties of the two endogenous structural GARCH-unit root test, as described in Equations (1) and (2).

We consider different break locations in the range of 0.2 to 0.8 with various GARCH [α, β] combinations, where α and β are the ARCH and GARCH parameters, respectively. There are various approaches to estimating the equation, such as demonstrated by Ling et al. (2003), which is: first estimate π by least squares, and then obtain a series of artificial observations of the residual, ε_t, which is then used to estimate the coefficients of the variance equation $(\varkappa, \alpha, \beta)$ by using the Fortran Numerical Libraries of IMSL subroutine DBCOAH. We adopt the joint maximum likelihood (ML) estimation approach proposed by Seo (1999); that is, the unit root hypothesis is examined via the ML t-ratio for π. Since the break time is unknown, T_{Bi} $(i = 1, 2)$ in Equations (1) and (2) has to be replaced by their estimates $\widehat{T}_{Bi}$.

We conduct the estimation by using a sequential procedure;[2] that is, we search for the first break date according to the maximum absolute t-value of the break dummy coefficient D_1, i.e., $t_{\hat{D}_1}$. Hence we obtain:

$$\hat{T}_{B1} = \arg\max_{\hat{T}_{B1}.} \left| t_{\hat{D}_1} \left(T_{B1} \right) \right| \tag{3}$$

Imposing the first break estimate $\hat{T}_{B1}$, we estimate the second break date $\hat{T}_{B2}$ such that

$$\hat{T}_{B2} = \arg\max_{\hat{T}_{B2}.} \left| t_{\hat{D}_2} \left(\hat{T}_{B1}, T_{B2} \right) \right| \tag{4}$$

3.3.3. Critical values

The critical values are based on 50,000 replications and are generated for sample sizes of N = 150, N = 250, and N = 500. The break fractions considered are (0.2, 0.4), (0.2, 0.6), (0.2, 0.8), (0.4, 0.6), (0.4, 0.8), and (0.6, 0.8). We have computed critical values at the 1% and 5% levels for both cases of known break dates (exogenous case) and unknown break dates (endogenous case). To conserve space, we only report the endogenous case with critical values at the 5% level.

INSERT TABLES 2

Some observations for the critical values are in order. First, we notice that the critical values do not vary much with changing the GARCH parameters regardless of the different structural break combinations. Second, we observe that the distribution of the finite sample critical value converges to the traditional Dickey-Fuller distribution as the sample size increases. For instance, the 5% critical value moves closer to the Dickey-Fuller critical value of -2.87 when the sample size increases to 500. We also observe that the finite sample distribution further shifts leftwards when the GARCH parameter decreases, such as from 0.9 to 0.05.

The results for the empirical size are reported in Table 3. The properties are reported for various break sizes and sample sizes. The break sizes we use are (1, 1), (3, 3) and (5, 5), while the sample size ranges from 150 observations to 500 observations. Due to the space

[2] We also applied a simultaneous grid search procedure; that is, for each potential break date combination (T_{B1}, T_{B2}), we selected the break dates according to the maximised *F*-statistic of the joint significance of both break dummy coefficients. The results of the sequential and simultaneous procedures do not differ much; hence, we adopt the sequential procedure since it is a relatively less time consuming exercise.

limitations, we only present the case for two break points of (0.2, 0.6). The results for other scenarios are qualitatively similar and are available upon request. The size properties are then estimated for two different combinations of the ARCH and GARCH parameter values, namely [0.05, 0.9] and [0.2, 0.75].

INSERT TABLE 3

Two features of the results are worth highlighting. The first feature is that when the GARCH parameter values are chosen so as to have a higher degree of persistence—a key feature of financial markets—for a small sample size (such as when N=150), the empirical size is greater than the nominal 5% level. This implies that our proposed test of GARCH unit root is oversized in small sample sizes. By contrast in large sample sizes (such as when N=500), the test converges to the nominal 5% level. This is true irrespective of GARCH orders. This implies that our test performs well in large sample sizes.

The second feature of the size results is that when the break parameters increase, regardless of the GARCH orders, in large sample sizes, the empirical size is correctly sized at 5%. That large sample size is a feature of financial data applications implies that our proposed model will work well when subjected to data where the sample size is large.

In Table 3, we also report the frequency of detecting the break dates. First we demonstrate the case of the model exactly detecting break points (0.2, 0.6), which, when N = 150, amounts to the 30^{th} and 90^{th} observations. We notice the significant improvement with increasing the break magnitude, i.e., (5, 5). In Table 4, we consider the power of the model. Essentially, we compare the GARCH two breaks model with a GARCH model without any structural breaks. We find that the GARCH model with two structural breaks is significantly powerful for larger sample size. We also find the power increases to almost 1 with higher break magnitudes.

INSERT TABLE 4

3.4.4. Is there mean reversion in stock prices?

In this section, we apply our proposed GARCH (1, 1) model with two structural breaks to test the EMH for 156 US stocks listed on the NYSE. We reject the null hypothesis for no less than 63 stocks; for 38 stocks at the 5% level of significance and for 25 stocks at the 10% level of significance (see Table 5). This implies that for 63 stocks (40%), there is evidence of mean reversion whereas for the remaining 60% of stocks, stock prices are non-stationary.

When we consider stocks by sectors, the number (and %) of rejections of the null vary from sector-to-sector. In some sectors, the null is rejected only for 16% of stocks (utilities and materials) while for the consumer discretion sector we reject the null for a large number (76%) of stocks. There are three sectors (energy, finance, and consumer staples) for which the null is only rejected for around 30% of stocks. On the other hand, for info tech, industrial, and health care sectors' the null is rejected for 50-58% of stocks.

INSERT TABLE 5

There are three messages emerging from our results. First, we find limited evidence of the "stock market overreaction" hypothesis, which posits that stock prices temporarily overreact by moving away from their fundamental values in response to news. DeBondt and Thaler (1985, 1987) were amongst the first to show this behaviour in stock prices; see also Kaul and Nimalendran (1990) and Shefrin and Statman (1985). However, the DeBondt and Thaler analysis was challenged by Conrad and Kaul (1993), who argued that there was no evidence of market overreaction.

Another hypothesis proposed to explain possible reversion of prices owes to Basu (1977), who contends that stocks with low price-earnings ratios are likely to be temporarily undervalued because investors become pessimistic following a series of bad news. However, as future earnings improve relative to the gloomy forecasts, the price reverts and adjustment takes place. Similarly, for stocks with high price-earnings ratios, equity is overvalued—in this case, a downward adjustment in price takes place. Basu (1977) called this the 'price-ratio' hypothesis.

A contrarian stock selection hypothesis, proposed by Chan (1988), argues for a strategy whereby stocks that have been losers are purchased and short stocks that have been winners are sold. This strategy is motivated by the premise that stock markets overreact to news. It follows that winners are overvalued while losers are undervalued. This ensures that an investor who exploits this situation gains when stock prices adjust to their fundamental value.

A tax-motivated trading hypothesis was proposed by Branch (1977). Jegadeesh (1991) finds empirical evidence that stock price mean reversion was concentrated in the month of January, prompting him to conclude that there is year-end tax-motivated trading on the NYSE. He argued for the possibility of a large number of securities exposed to concentrated year-end tax-loss selling following prolonged periods of market decline.

Our findings, taken on the whole, reveal mixed evidence of the stock market overreaction hypothesis, the price-ratio hypothesis, the contrarian stock selection hypothesis, and the tax-motivated trading hypothesis for 156 US stocks over the period 1980 to 2007. In total, for only 63 out of 156 stocks there is evidence of mean reversion. Moreover, in terms of sectors in only four (consumer discretion, info tech, industrial, and health care) of the nine sectors more than 50% of stocks have mean reverting prices.

Second, contrary to the voluminous literature, alluded to earlier, which has found aggregate stock prices to be mean reverting processes, our findings at the individual firm level are completely the opposite. When we consider mean reversion in stock prices for 156 US firms, we find that for 60% of stocks there is no evidence of mean reversion. Shleifer and Vishny (1997) show how the existence of specialized arbitrageurs, who invest capital of outside investors and where investors use arbitrageurs' performance as a guide for investment, may not be fully effective in reverting security prices to fundamental values. Our findings also seem to associate closely with the proposal put forward by De Long *et al*. (1990)—the noise trading hypothesis. Although the hypothesis explains channels through which price adjustment can take place, their model also shows how stock prices can potentially diverge from their fundamentals. In their model, noise trading risk is a cost that the firm must bear and both traded equity and traded long-term debt will be underpriced relative to fundamentals if their prices are subject to the whims of noise traders' opinion. Moreover, De Long *et al*. (1990) argue that as long as arbitrageurs have short horizons and are concerned about liquidating their investment in a mispriced asset they will be less aggressive even though they do not face fundamental risk. In such a situation, De Long *et al*. (1990) hypothesise that noise trading can lead to a large divergence between market prices and fundamental values.

4. ECONOMIC SIGNIFICANCE

In this section our goal is to demonstrate how the knowledge on stationarity and non-stationarity of stock prices provides different expected returns to investors. Moreover, we demonstrate how different investment strategies perform when investors incorporate the integrational properties of stock prices in devising investment strategies. To achieve the goal of this section, we closely follow the procedure recommended by Balvers *et al*. (2000) for undertaking an economic significance analysis of stock prices when their integrational properties vary. The key difference between the Balvers *et al*. (2000) approach and ours is that we implement their proposed panel test within a time series framework. We group stocks into stationary and non-stationary categories based on our unit root test results. This means that for each of the sectors we create two groups of stocks; one that contains only the stationary price stocks and the other that contains stocks with non-stationary price. Just to demonstrate this further, let us consider stocks of the financial sector. There are four stocks in this sector with stationary prices, which belongs to one group, while the remaining eight stocks have a non-stationary price, which belongs to the second group.

Our first strategy (Strategy 1) is based on a rolling-window approach. We take the in-sample period of 14 years (January 1980 to December 1993) and estimate model (1). We then use the parameter estimates to calculate the expected return for each stock at time $t_0 + 1$, and invest 100% of the portfolio in the stock with the highest expected return. At time $t_0 + 2$ (for the rest of the sample; that is, for the out-of-sample period), the estimation is conducted with one more observation and the portfolio is switched to the stock with the highest expected return. We impose transaction costs of 0.1% which is paid when switching to another stock. This process is repeated for the entire out-of-sample period until December 2007. The expected returns obtained for each group of stocks is called "maximum return" (MaR). Similarly, we define "minimum returns" (MiR) as a strategy that invests 100% of the portfolio in the stock with the lowest expected return. It follows that MaR less MiR gives us an excess payoff from the zero net investment per dollar invested in the MaR portfolio. Essentially, this strategy implies buying the MaR portfolio and shorting the MiR portfolio. Following Balvers *et al*. (2000), we also compute the average of the three stocks with the highest expected return (MaR_3) and the average of the three stocks with the lowest expected returns (MiR_3).

A conventional benchmark strategy in most economic significance analysis is the buy-and-hold strategy. As in Balvers *et al*. (2000), we apply the geometric average buy-and-hold strategy.

The results are reported in Table 6. There a number of features of our results. First, upon comparing the expected returns across sectors we find that the rolling estimation approach outperforms the buy-and-hold strategy. In other words, the rolling window-based strategy for both stocks with stationary and non-stationary prices outperforms the expected returns from the buy-and-hold strategy. We also report the Sharpe ratio (SR) for stationary and non-stationary stocks by sector. The SR reveals the attractiveness of the rolling estimation strategy over the buy-and-hold strategy.

INSERT TABLE 6

Second, if we compare the performance of stationary firms with non-stationary firms, across all sectors, we make the following observations. The rolling regression-based strategy suggests higher expected returns from stocks with stationary stock prices in five sectors, namely, utilities, materials, info tech, energy, and consumer discretion, while in the other four sectors returns from non-stationary price stocks are higher than those from stationary price stocks. The SR results are consistent with the trend in returns.

Based on MaR, most of the stationary price stocks have returns around the 3-3.4% range; the only exceptions are stocks of utilities and materials where returns are 2% and 1.6%, respectively. By comparison, returns for non-stationary stocks are between 1.3-1.5% in the cases of utilities and materials; around 2.5-3% for rest sectors; except with 3.2% for the financial sectors.

In our final test of economic significance, we compute investor utility when the investor incorporates the information from unit root tests. In other words, we compute investor utility for firms with mean reverting stock prices and non-stationary stock prices. We do this for all sectors. Although there are debates on the mean-variance theory, including most recent ones, Levy and Levy (2013), and Simaan (2013), we apply the parsimonious approach to compute the investor utility (U) as follows:

$$U = \hat{\mu} - \frac{1}{2}\gamma\hat{\sigma}^2 \qquad (5)$$

Where $\hat{\mu}$ and $\hat{\sigma}^2$ are the sample mean and variance, respectively, over the out-of-sample period for the return forecasts, and γ represents the risk aversion parameter. We consider, following Marquering and Verbeek (2004) and Westerlund and Narayan (2012), γ to be 3, 6 and 12, representing low, moderate and high levels of risk aversion, respectively. This effectively is a test of the robustness of the utilities. The utility is also referred to as the certainty equivalent return or the amount of portfolio management fee that an investor will be willing to pay to have access to the additional information available. In our case, the additional information refers to the knowledge available from the unit root properties of the stock prices.

The results are reported in Table 7. We find that regardless of the risk aversion parameter investor utility based on stationary price stocks is higher than non-stationary price stocks for eight of the nine sectors; the only exception is the health care sector. We also notice that investor utilities, for both stationary and non-stationary price stocks, vary from sector-to-sector. For stationary price stocks, for instance, utility (for $\gamma = 6$) is in the 0.51 (energy) to 2.35 (financial) range. For non-stationary price stocks, it is in the 2.16 (health care) to 0.43 (energy) range. We also observe that energy sector has the lowest utility, followed by utilities and materials sectors. The main message of our results is that investors are willing to pay different amounts of fees to extract information in predictive regression models depending on whether or not stock prices are mean reverting. Investor preference for paying different amounts of fees is also sector-dependent; that is, in some sectors, they are willing to pay higher fees (such as investors in financial, consumer discretion, industrial and health sectors) whereas in other sectors (such as energy, utility, and materials) investors prefer paying less fees. This finding only highlights the importance of the knowledge on the unit root properties of stock prices.

INSERT TABLE 7

5. ROBUSTNESS TEST

We undertook some robustness tests to give credence to our findings and conclusions. To conserve space, we decided to only provide a brief account of what we did and what we found with respect to the robustness test. The detailed results are available upon request. We tested the robustness of our results in two ways. First, we were concerned that even though our study, given that it is based on time series financial econometric methods, needs historical data going as far back in time as possible, it may well suffer from survivorship bias. To test this, we filtered all stocks for the period 1990 to 2007. Although from an econometric point of view this compromised the time series requirement for our model to work we more than doubled the number of stocks. We found evidence of mean reversion for 36% of stocks. We also tried with stocks covering the period 2000-2007. In this case, we ended up with close to 800 stocks. We found that for 45% of stocks there was evidence of mean reversion. Therefore, given that with 156 stocks over 1980 to 2007 we found that for 40% of stocks there is evidence of mean reversion, we can safely claim that our results are robust and do not suffer from survivorship bias.

Second, we were concerned that by including data for the period after 2007 will bias our results by unnecessarily making our test more power given that there is an obvious structural break due to the global financial crisis. We re-estimated all results for the period 1980 to 2011 and found that there is only a slight improvement in power of our test to reject the null. More specifically, we found evidence of mean reversion for 46% of stocks as opposed to 40% when using data for the period 1980 to 2007. On the basis of these results, we can claim that our results and indeed the main conclusions are unaffected even if we used more recent data covering the global financial crisis.

6. CONCLUDING REMARKS

In this paper, we revisit a traditional research topic—the efficient market hypothesis (EMH)—in financial economics. There are two motivations for doing this. First, we find that the existing research on the EMH is based on aggregate stock prices. We argue that because of the presence of heterogeneous firms, the results for the aggregate stock price may be spurious. To obviate this, we test the EMH at the firm-level using time series data.

The second motivation is that financial time series data is well- known to suffer from heteroskedasticity. Therefore, unit root testing models that do not account for heteroskedasticity are likely to suffer from over rejection of the null hypothesis of a unit root. To remedy this, we propose a generalized autoregressive heteroskedasticity (GARCH) model that not only caters for the GARCH errors but also allows for two endogenous structural breaks in the data series.

We study the size and power properties of the proposed GARCH structural break unit root test and find that statistically it performs well. This is, thus, a useful methodological addition to the applied finance literature. Using monthly data for 156 US stocks (divided into nine sectors) for the period January 1980 to December 2007, we find reasonably good although not overwhelming evidence (63 out of 156) of stock price stationarity. However, in only four (consumer discretion, info tech, industrial, and health care) of the nine sectors over 50% of stocks are found to have stationary prices.

In the final part of our analysis, we undertake an economic significance analysis. We find that rolling regression-based strategies for both firms with stationary and non-stationary stock prices outperform the expected returns from the buy-and-hold strategy. The rolling regression-based strategy suggests higher expected returns from firms with stationary stock prices in most sectors but not all. Finally, the investor utility (certainty equivalent return) analysis reveals that investors are willing to pay different amount of fees to extract information contained in the predictive regression model conditional on whether or not stock prices are mean reverting. Equally important, investors prefer certain sectors over other, in that they are willing to pay different amounts of fees depending on the sector of investment. These are fresh insights on investor behaviour from the point of view of market efficiency.

REFERENCES

Andreou, E., Ghysels, E., (2002) Detecting multiple breaks in financial market volatility dynamics, Journal of Applied Econometrics, 17, 579-600.

Bai, J., and Perron, P., (2003) Computation and analysis of multiple structural change models, Journal of Applied Econometrics, 18, 1-22.

Bali, T.G., Demirtas, K.O., and Levy, H., (2008) nonlinear mean reversion in stock prices, Journal of Banking and Finance, 32, 767-782.

Balvers, R., Wu, Y., and Gilliland, E., (2000) Mean reversion across national stock markets and parametric contrarian investment strategies, The Journal of Finance, 55, 745-772.

Basu, S., (1977) Investment performance of common stocks in relation to their price-earnings ratios: A tets of the efficient market hypothesis, The Journal of Finance, 3, 663-682.

Bollerslev, T., (1986) Generalised autoregressive conditional heteroskedasticity, Journal of Econometrics, 31, 307-327.

Branch, B., (1977) A tax loss trading rule, Journal of Business, 50, 198-207.

Chaudhuri, K., and Wu, Y., (2003) Random walk versus breaking trend in stock prices: Evidence from emerging markets, Journal of Banking and Finance, 27, 575-592.

Chopra, N., Lakonishok, J., and Ritter, J.R., (1992) Measuring abnormal performance: Do stocks overreact? Journal of Financial Economics, 31, 235-268.

Chan, K.C., (1988) On the contrarian investment strategy, The Journal of Business, 61, 147-163.

Chan, N. H., Wei, C. Z., (1988) Limiting distributions of least squares estimates of unstable autoregressive processes, Annals of Statistic, 16, 367–401.

Conrad, J., and Kaul, G., (1993) Long-term market overreaction or biases in computed returns, The Journal of Finance, 48, 39-63.

DeBondt, W.F.M., and Thaler, R.M., (1985) Does the stock market overreact? The Journal of Finance, 40, 793-805.

DeBondt, W.F.M., and Thaler, R.M., (1987) Further evidence on investor overreaction and stock market seasonality, The Journal of Finance, 42, 557-581.

De Long, J.B., Shleifer, A., Summers, L.H., and waldmann, R.J., (1990) Noise trader risk in financial markets, The Journal of Political Economy, 98, 703-738.

Diebold, F.X., (1986) Modeling the persistence of conditional variances: a comment. Econometric Reviews, 5, 51–56.

Engle, R., (1982) Autoregressive conditional heteroskedasticity with estimates of the variance of the United Kingdom inflation, Econometrica, 50, 987-1008.

Fama, E., (1970) Efficient capital markets: A review of theory and empirical work, Journal of Finance, 25, 383-417.

Fama, E., (1991) Efficient capital markets II, Journal of Finance, 46, 1575-1617.

Fama, E., and French, K., (1988) Permanent and temporary components of stock prices, Journal of Political Economy, 96, 246-273.

Geppert, J.M., Jares, T.E., and Lavin, A.M., (2002) The effect of time-series and cross-sectional heterogeneity on panel unit root test power, Journal of Financial Research, 25, 321-335.

Herce, M. A., (1996) Asymptotic theory of LAD estimation in a unit root process with finite variance errors, Econometric Theory, 12, 129–153.

Jegadeesh, N., (1991) Seasonality in stock price mean reversion: Evidence from the US and the UK, The Journal of Finance, 46, 1427-1444.

Kaul, G., and Nimalendran, M., (1990) Price reversals: Bid-asks errors or marke overreaction? Journal of Financial Economics, 28, 67-83.

Kim, J.H., and Shamsuddin, A., (2008) Are Asian stock markets efficient? Evidence from new multiple variance ratio tests, Journal of Empirical Finance, 15, 518-532.

Kim, K., Schmidt, P., (1993a) Unit root tests with conditional heteroskedasticity, Journal of Econometrics, 59, 287-300.

Kim, K., Schmidt, P., (1993b) Some evidence on the accuracy of Phillips–Perron tests using alternative estimates of nuisance parameters, Journal of Econometrics, 59, 345–350.

Lamoureux, C.G., Lastrapes, W.D., (1990) Persistence in variance structural change and the GARCH model, Journal of Business and Economic Statistics, 8, 225–234.

Lee J. and Strazicich, M.C., (2003) Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks, The Review of Economics and Statistics, 85, 1082-1089.

Levy, H and Levy, M., (2013), The benefits of differential variance-based constraints in portfolio optimization, European Journal of Operational Research, 234, 372–381.

Ling, S., Li, W.K., (1998) Limiting distributions of maximum likelihood estimators for unstable autoregressive moving-average time series with general autoregressive heteroskedastic errors, Annals of Statistics, 26, 84–125.

Ling, S., Li, W.K., (2003) Asymptotic inference for unit root with GARCH (1,1) errors, Econometric Theory, 19, 541–564.

Ling, S., Li, W.K., and McAleer, M., (2003) estimation and testing for unit root process with GARCH (1,1) errors: theory and Monte Carlo evidence, Econometric Reviews, 22, 179-202.

Lucas, A., (1995) Unit root tests based on M estimators, Econometric Theory, 11, 331–346.

Lumsdaine R. L., and Papell, D.H., (1997). Multiple Trend Breaks And The Unit-Root Hypothesis, The Review of Economics and Statistics, 79, 212-218.

Marquering, W., and Verbeek, M., (2004) The economic value of predicting stock index returns and volatility, Journal of Financial and Quantitative Analysis, 39, 407-429.

Narayan, P.K., and Popp, S., (2010) A new unit root test with two structural breaks in level and slope at unknown time, Journal of Applied Statistics, 37, 1425-1438.

Narayan, P.K., and Sharma, S., (2011) New evidence on oil price and firm returns, Journal of Banking and Finance, 35, 3253-3262.

Nelson, C.R., and Plosser, C.I., (1982) Trends and random walks in macroeconomic time series: some evidence and implications, Journal of Monetary Economics, 10, 139-162.

Gospodinov, N., (2008) Asymptotic and bootstrap tests for linearity in TAR-GARCH (1,1) model with a unit root, Journal of Econometrics, 146, 146-161.

Perron, P., (1989) the great crash, the oil price shocks, and the unit root hypothesis, Econometrica, 57, 1361-1401.

Perron, P., and Vogelsang, T.J., (1992) testing for a unit root with a changing mean: corrections and extensions, Journal of Business and Economic Statistics, 10, 467-470.

Phillips, P.C.B., (1987) Time series regression with a unit root, Econometrica, 55, 277–301.

Phillips, P. C. B., Durlauf, S. N. (1986) Multiple time series regression with integrated processes, Review of Economic Studies, LIII, 473–495.

Poterba, J., and Summers, L., (1988) mean reversion in stock prices: Evidence and implications, Journal of Financial Economics, 22, 27-59.

Richards, A.J., (1995) Comovements in national stock market returns: evidence of predictability, but not cointegration, Journal of Monetary Economics, 36, 631-654.

Richards, A.J., (1997) Winner-loser reversals in national stock market indices: Can they be explained? The Journal of Finance, 52, 2129-2144.

Samuelson, P.A., (1965) Proof that properly anticipated prices fluctuate randomly, Industrial Management Review, 6, 41-49.

Sen, A. (2003) Limiting behaviour of Dickey-Fuller t-tests under the crash model alternative, Econometrics Journal, 6, 421-429.

Seo, B., (1999) Distribution theory for unit root tests with conditional heteroskedasticity, Journal of Econometrics, 91, 113-144.

Shefrin, H.M., and Statman, M., (1985) This disposition to ride winners too long and sell losers too soon: Theory and evidence, The Journal of Finance, 41, 774-790.

Shleifer, A., and Vishny, R.W., (1997) the limits of arbitrage, The Journal of Finance, 52, 35-55.

Simaan, Y., (2013) The opportunity cost of mean–variance choice under estimation risk, European Journal of Operational Research, 234, 382–391.

Terasvirta, T., Tjostheim, D., Wurtz, A.H. (Eds.), Nonlinear Econometric Modelling in Time Series Analysis. Cambridge University Press, Cambridge, pp. 61–78.

Zhong, M., Darrat, A.F., and Anderson, D.C., (2003) Do US stock prices deviate from their fundamental values? Some new evidence, Journal of Banking and Finance, 27, 673-697.

Zarowin, P., (1990) Size, seasonality and stock market overreaction, The Journal of Financial and Quantitative Analysis, 25, 113-125.

Westerlund, J., and Narayan, P.K., (2012) Does the choice of estimator matter when forecasting returns, Journal of Banking and Finance, 36, 2632-2640.

Table 1: Descriptive statistics of daily stock prices

This table reports the descriptive statistics for monthly stock prices for the 156 US stocks listed on the New York Stock Exchange for the period January 1980 to December 2007. Column 1 contains the nine sectors. These sectors are utilities, materials, information technology, industrial, health care, financial, energy, consumer staples, and consumer discretion. This is followed by the number of stocks in each sector; mean values and coefficient of variation (CoV) are reported in columns 3 and 4; skewness and kurtosis statistics are reported in columns 5 and 6; while in the final two columns, we report the autocorrelation (AC) coefficients for lags 10 and 20, respectively.

	No. of stocks	mean	CoV	Skewness	Kurtosis	AC(10)	AC(20)
Utilities	19	20.259	0.395	0.228	2.459	0.807	0.676
Materials	15	21.49	0.579	0.529	2.604	0.843	0.731
Info Tech	8	19.581	0.689	0.955	3.056	0.839	0.692
Industrial	31	21.455	0.698	0.749	2.569	0.855	0.745
Health	13	20.013	0.768	0.477	1.638	0.897	0.804
Financial	12	19.843	0.762	0.632	2.044	0.886	0.776
Energy	16	20.826	0.506	1.637	6.134	0.734	0.544
Con. Staples	21	19.449	0.735	0.36	1.684	0.902	0.81
Cons. Disp.	21	19.173	0.623	0.334	1.765	0.881	0.775

Table 2: 5% level critical values for endogenous structural breaks model

This table reports the 5% level critical values for the model with endogenous structural breaks at different sample sizes (N), ranging from 150 to 500. All simulations are conducted based on various GARCH's parameters $[\alpha, \beta]$ combinations with different structural break locations T_{Bi} $(\mathrm{t} = 1, 2)$ ranging from 0.2 to 0.8.

$[\alpha, \beta]$		N =150			N =250			N =500		
		0.4	0.6	0.8	0.4	0.6	0.8	0.4	0.6	0.8
	0.2	-3.8362	-3.8312	-3.8276	-3.7551	-3.7721	-3.7442	-3.6573	-3.6926	-3.6618
[0.05, 0.90]	0.4		-3.8252	-3.821		-3.7567	-3.7469		-3.6629	-3.6577
	0.6			-3.8277			-3.7526			-3.6741
		N =150			N =250			N =500		
		0.4	0.6	0.8	0.4	0.6	0.8	0.4	0.6	0.8
	0.2	-3.7866	-3.7809	-3.7618	-3.6905	-3.6916	-3.665	-3.6034	-3.592	-3.5838
[0.45, 0.5]	0.4		-3.7765	-3.7586		-3.6604	-3.6558		-3.5864	-3.5803
	0.6			-3.7692			-3.6498			-3.6048
		N =150			N =250			N =500		
		0.4	0.6	0.8	0.4	0.6	0.8	0.4	0.6	0.8
	0.2	-3.7469	-3.7546	-3.7087	-3.6527	-3.6479	-3.643	-3.5651	-3.5456	-3.5518
[0.9, 0.05]	0.4		-3.7173	-3.7423		-3.6174	-3.6536		-3.5144	-3.582
	0.6			-3.7196			-3.6237			-3.5213

Table 3: Finite sample size and power

This table reports the 5% rejection frequency with nominal 5% significance level, and the probability of detecting the true break date for one break date combination (0.2, 0.6).

				$\rho = 1$	
$[\alpha, \beta]$	Break sizes	N	rejection rate	Frequency of detecting break points range	
[0.05, 0.9]				TB	TB ± 20
		150	0.0681	0.3106	0.6863
	(1, 1)	250	0.0601	0.3679	0.7396
		500	0.0515	0.4423	0.8141
		150	0.0651	0.3505	0.7109
	(3, 3)	250	0.0602	0.4028	0.782
		500	0.0511	0.4942	0.8653
		150	0.0606	0.7098	0.9289
	(5, 5)	250	0.0575	0.7878	0.9656
		500	0.0541	0.8514	0.9873
[0.2, 0.75]					
		150	0.0641	0.2908	0.654
	(1, 1)	250	0.0567	0.3742	0.7027
		500	0.0525	0.4496	0.7922
		150	0.066	0.3317	0.705
	(3, 3)	250	0.0608	0.3973	0.7669
		500	0.0526	0.4862	0.8625
		150	0.5635	0.7381	0.9270
	(5, 5)	250	0.5287	0.8003	0.9774
		500	0.5129	0.8705	0.9839

Table 4: Empirical power of the two break GARCH unit root model

This table reports the empirical power of the two break GARCH unit root models for the break date combination (0.2, 0.6) based on various GARCH's parameters $[\alpha, \beta]$ combinations.

[0.05, 0.9]		N	Power with breaks	Power without breaks
	Break sizes			
		150	0.3691	0.1532
	(1, 1)	250	0.6653	0.3137
		500	0.9826	0.3568
		150	0.7960	0.1540
	(3, 3)	250	0.8629	0.3323
		500	0.9974	0.3469
		150	0.9535	0.1449
	(5, 5)	250	0.9833	0.2419
		500	1	0.2785
[0.2, 0.75]				
		150	0.4058	0.1475
	(1, 1)	250	0.7680	0.3481
		500	0.9767	0.3586
		150	0.8629	0.1452
	(3, 3)	250	0.9642	0.3602
		500	1	0.3543
		150	0.9751	02082
	(5, 5)	250	1	0.2866
		500	1	0.3781

Table 5: Results of the two break GARCH unit root model

This table presents empirical results for stock prices of 156 US stocks listed on the New York Stock Exchange. Stocks are categorised into nine sectors; these sectors are utilities, materials, information technology, industrial, health care, financial, energy, consumer staples, and consumer discretion. The results are based on Equation (1). The two structural breaks denoted by TB1 and TB2 are reported together with the t-test statistic used to test the null hypothesis of a unit root. ** and * denote significance at 1% and 5% level respectively.

Panel A: Utilities	TB1	TB2	t-stat	Panel C: Health Care	TB1	TB2	t-stat
AEP	30-May-80	29-Apr-83	-1.3514	ABT	31-Jan-89	31-Jan-95	-0.0184
CNP	31-Jul-84	31-May-89	-4.7249**	BAX	30-Dec-94	30-Dec-94	-0.0381
CMS	31-Aug-82	29-Jun-07	-2.1634	BDX	28-Sep-84	29-Jul-94	-3.453
ED	30-Apr-80	30-May-80	-2.7695	BMY	31-Aug-94	30-Nov-99	-3.1121
DTE	31-Aug-88	30-Jun-97	-5.4461**	BCR	31-Jan-85	28-Feb-03	-4.2246*
DUK	29-Jun-84	28-Apr-89	-3.572	LLY	31-Oct-84	31-Aug-94	-5.1467**
EIX	30-Apr-80	31-Dec-02	-3.3038	HUM	31-Jan-89	30-May-03	-5.0185**
EXC	31-Oct-90	30-Apr-03	-2.9466	JNJ	30-Apr-80	30-Apr-80	-0.0056
NEE	31-Aug-94	30-Jun-04	-2.9124	MRK	29-Nov-85	31-Aug-94	-4.9762**
NI	29-Jan-88	30-Nov-94	-4.1771*	PKI	30-Sep-82	30-Jan-98	-5.119**
NU	30-Nov-81	31-May-06	-3.6206	PFE	31-May-90	29-Apr-94	-4.8376**
PCG	31-Jan-84	31-May-84	-2.174	THC	31-Dec-81	31-May-82	-3.5887
PPL	31-Mar-80	31-Jul-80	-0.1674	VAR	30-Oct-92	31-Mar-99	-4.106*
PGN	28-Sep-90	31-Oct-90	-2.7058	Panel D: Finance	TB1	TB2	t-stat
PEG	30-Apr-80	30-May-80	-0.0051	AFL	31-Aug-81	30-Sep-81	-2.7701
SCG	30-Apr-80	31-Jul-80	-0.7485	AXP	29-Apr-94	30-May-03	-4.5787**
SO	31-Mar-80	29-Aug-80	-0.0033	JPM	31-Mar-80	28-Apr-95	-0.087
TE	30-Jan-80	30-Apr-89	-0.013	LNC	30-Apr-80	30-Sep-96	-2.4306
XEL	30-Apr-80	30-May-87	-2.4374	L	31-Aug-82	31-Oct-03	-3.7329*
Panel B: Materials	TB1	TB2	t-stat	MMC	31-Mar-80	29-Jun-84	-0.0287
APD	31-Oct-90	31-Aug-06	-2.5107	PNC	31-Jul-87	30-Sep-96	-10.2971**
AA	31-Mar-88	28-Apr-95	-3.9972*	TRV	31-Mar-80	30-Apr-87	-0.0084
BLL	31-Mar-00	31-Jul-06	-3.1043	USB	31-Mar-80	31-Jan-95	-0.0225
BMS	30-May-80	30-Sep-82	-3.2119	VNO	30-Apr-80	30-Nov-07	-1.3194
CLF	31-Mar-80	30-Jun-03	-1.7849	WFC	31-Oct-01	31-Oct-07	-0.0019
DOW	29-Nov-85	31-Jan-96	-5.3306**	WY	31-Jan-92	30-May-03	-5.7944**
DD	30-Sep-82	30-Nov-90	-3.5022	Panel G: Consumer staples	TB1	TB2	t-stat
FMC	31-Jul-86	29-Jul-94	-8.0013**	MO	29-Nov-85	30-May-03	-4.2025*
IFF	31-May-82	31-Jan-89	-3.6201	ADM	30-Sep-82	31-Dec-07	-1.8143
IP	29-Nov-85	31-Oct-90	-5.8168**	AVP	31-Jan-89	28-Apr-95	-3.245

NEM	31-Mar-80	29-Aug-86	-5.1289**
NUE	31-Oct-90	30-May-03	-3.3801
PPG	29-Jun-84	30-Nov-90	-4.3001*
SHW	30-Nov-90	30-Nov-99	-0.0187
VMC	31-Aug-06	29-Jun-07	-1.0587

Panel E: Info Tech	TB1	TB2	t-stat
AMD	31-Aug-92	30-Nov-07	-3.382
CSC	28-Sep-84	31-Oct-90	-3.529
GLW	31-Mar-80	29-Dec-95	-2.1851
HRS	30-Oct-92	30-May-03	-3.9294*
HPQ	31-Aug-94	30-Jun-05	-4.2974*
IBM	31-Dec-81	30-Aug-96	-4.4766**
TER	30-Jun-93	31-Jul-07	-4.4922**
XRX	31-Jan-91	31-Aug-97	-0.0469

Panel F: Industrial	TB1	TB2	t-stat
MMM	31-Jan-89	29-Sep-95	-3.7187*
AVY	31-Aug-82	31-Aug-94	-4.6595**
BA	30-Jun-82	31-Mar-95	-4.1697*
CAT	30-Oct-92	30-May-97	-0.0275
CBE	30-Nov-88	29-Nov-02	-3.9434*
CMI	30-May-03	28-Feb-07	-3.6657
DE	31-Dec-92	31-Aug-06	-3.0545
DOV	31-May-89	31-Jan-95	-4.8232**
ETN	28-Sep-90	30-Nov-90	-1.9533
EMR	30-Apr-80	30-Jun-87	-0.0051
EFX	29-Jan-82	30-Nov-92	-3.8395*
FDX	31-Dec-80	31-Aug-95	-2.9943
GD	29-Mar-91	30-May-03	-3.9729*
GE	30-Sep-88	30-Dec-94	-4.4279**
GR	31-Mar-80	28-Apr-95	-2.6412
ITW	30-Sep-82	31-Mar-95	-3.8069*
IR	28-Sep-84	31-Jan-96	-2.8989
MAS	30-Sep-82	31-Jan-95	-4.6506**
NOC	31-Mar-95	30-Nov-05	-4.001**
PH	29-Apr-94	29-Apr-98	-0.0334
PBI	26-Feb-82	30-Nov-07	-3.1829
RTN	28-Sep-90	30-Nov-05	-3.7258*
R	28-Feb-85	31-Aug-87	-4.9517**
SNA	29-Nov-85	31-Mar-95	-3.7199*
LUV	31-Oct-90	30-May-97	-5.7249**
SWK	30-Sep-82	31-Aug-95	-4.1482*
TXT	31-Oct-90	30-May-03	-3.4451

BEAM	30-Apr-87	30-Sep-87	-1.2867
CPB	31-Dec-81	31-Aug-88	-3.5826
CLX	30-Nov-81	31-Aug-94	-4.1337*
KO	30-Apr-82	31-Aug-88	-3.829
CL	30-Apr-80	31-Jul-80	-0.9886
CAG	30-May-80	30-Jan-81	-1.6579
CVS	30-Apr-80	29-Feb-96	-4.2796*
GIS	31-Jan-89	31-Oct-00	-3.6287
HSY	30-Apr-80	31-Aug-94	-3.5574
HNZ	31-Mar-80	31-Aug-94	-2.6149
K	28-Sep-84	31-Oct-90	-4.8336**
KMB	31-May-85	31-Mar-95	-5.133
KR	31-Jul-95	28-Feb-06	-4.4382**
PEP	30-Apr-80	28-Feb-85	-2.5725
PG	30-Apr-80	30-Jun-87	-0.0008
SVU	30-Jun-82	30-Apr-03	-4.6505**
WMT	30-Apr-80	31-Jan-97	-5.001
WAG	30-Apr-80	30-Nov-94	-3.7623*

Panel H: Consumer dis.	TB1	TB2	t-stat
	T1	T2	t-stat
CCL	28-Jun-91	30-Sep-96	-13.2295**
FDO	30-Apr-82	29-Feb-96	-4.7179**
F	29-Jan-82	31-Mar-00	-3.6366
GCI	30-Dec-94	31-Jul-07	-3.4713
GPS	29-Apr-88	29-Sep-95	-5.0018**
GPC	30-Apr-80	30-Nov-90	-2.9142
GT	29-Jun-90	31-Oct-90	-3.7936*
HRB	31-May-89	29-Dec-00	-3.6631
IPG	30-Apr-80	29-Feb-00	-0.0649
JCP	29-Nov-85	31-Oct-07	-3.0996
JCI	30-Apr-80	30-Nov-07	-0.6921
LEG	28-Sep-90	30-Nov-90	-3.7048*
LEN	30-Nov-90	31-Jul-07	-2.3988
LOW	30-Nov-92	31-Oct-97	-4.7852**
MCD	31-Jul-02	30-Apr-03	-2.1729
MHP	30-Aug-96	30-Sep-90	-3.1887
NWL	30-Nov-82	31-Dec-87	-4.0658*
TGT	31-Aug-88	30-Apr-96	-4.4084**
VFC	29-Aug-03	30-Nov-07	-2.5065
DIS	29-Jun-84	31-Jul-87	-2.8844
WHR	28-Sep-90	30-Nov-99	-4.4547**

TYC	31-May-82	31-Jul-07	-3.053				
UNP	30-Nov-90	29-Jul-05	-4.3143**				
UTX	30-Dec-94	30-May-03	-4.5026**				
GWW	30-May-80	30-Nov-90	-3.6791				
Panel I: Energy	TB1	TB2	t-stat		TB1	TB2	t-stat
APA	30-Apr-80	29-May-81	-0.3499	MUR	31-Mar-99	31-Mar-99	-0.0317
COP	31-Dec-87	30-Sep-03	-3.7881*	OXY	30-Apr-80	30-Sep-03	-2.9475
EQT	30-Apr-80	31-Dec-80	-1.976	RRC	30-Sep-96	27-Feb-98	-1.1405
XOM	30-Apr-80	30-Apr-87	-0.2146	RDC	30-Jan-81	29-Dec-95	-4.5146**
HAL	31-Dec-80	31-Aug-95	-3.2303	SLB	31-Dec-80	28-Feb-86	-0.8476
HP	31-Dec-80	29-Dec-95	-2.7108	SUN	30-Apr-03	30-Sep-05	-0.0942
HES	31-Dec-07	31-Dec-07	-0.0022	TSO	29-Jun-84	30-Sep-03	-4.6679**
MRO	31-Jan-91	29-Mar-91	-31.559**	WMB	31-Jul-92	31-Jan-95	-4.1612*

Table 6: Economic significance analysis

In this table, we report the economic significance analysis based on a buy-and-hold strategy and the rolling window-based strategy. We take the in-sample period of 14 years (January 1980 to December 1993) of the sample and estimate model (1). We then use the parameter estimates to calculate the expected return for each stock at time $t_0 + 1$, and invest 100% of the portfolio in the stock with the highest expected return. At time $t_0 + 2$ (for the rest of the sample; that is, for the out-of-sample period), the regression is run with one more observation and the portfolio is switched to the stock with the highest expected return. This process is repeated for the entire out-of-sample period until December 2007. The expected returns obtained for each group of stocks is called "maximum return" (MaR). Similarly, we define "minimum returns" (MiR) as a strategy that invests 100% of the portfolio in the stock with the lowest expected return. It follows that MaR less MiR gives us an excess payoff from the zero net investment per dollar invested in the MaR portfolio. Essentially, this strategy implies buying the MaR portfolio and selling short the MiR portfolio. Following Balvers *et al*. (2000), we also compute the average of the three stocks with the highest expected return (MaR_3) and the average of the three stocks with the lowest expected returns (MiR_3). The Sharpe ratio is presented in column 5 and 6.

Strategy	**Type**	**Mean return**		**Sharpe ratio**	
Panel A: Utilities		Util_3_S	Util_16_NS	Util_3_S	Util_16_NS
1. buy and hold	equal-weighted	0.121	0.107	0.514	0.335
2. rolling estimation	MaR1	1.978	1.45	2.544	1.051
	MaR1-MiR1	0.958	0.756	1.078	0.897
	MaR3	2.327	1.455	1.005	0.799
	MaR3-MiR3	-0.889	-1.152	-0.401	-0.483
Panel B: Materials		Mat_6_S	Mat_9_NS	Mat_6_S	Mat_9_NS
1. buy and hold	equal-weighted	0.412	0.399	1.063	0.664
2. rolling estimation	MaR1	1.637	1.325	0.085	0.062
	MaR1-MiR1	0.97	0.725	1.089	1.022
	MaR3	1.486	1.143	0.135	0.11
	MaR3-MiR3	0.597	0.512	2.144	1.896
Panel C: Info Tech		IT_4_S	IT_4_NS	IT_4_S	IT_4_NS
1. buy and hold	equal-weighted	0.897	0.312	0.890	-0.564
2. rolling estimation	MaR1	3.055	2.842	3.542	3.005
	MaR1-MiR1	0.073	0.048	-0.477	-0.459
	MaR3	3.149	2.955	5.459	5.556
	MaR3-MiR3	0.08	0.068	-1.231	-1.316
Panel D: Industrial		Ind_18_S	Ind_13_NS	Ind_18_S	Ind_13_NS
1. buy and hold	equal-weighted	0.686	0.840	0.566	1.616
2. rolling estimation	MaR1	3.12	3.143	3.943	4.665
	MaR1-MiR1	-0.083	-0.243	-0.703	-1.114

	MaR3	3. 25	3.21	6.056	6.309
	MaR3-MiR3	-0.102	-0.125	-1.481	-1.596
Panel E: Health care		Health_7_S	Health_6_NS	Health_7_S	Health_6_NS
1. buy and hold	equal-weighted	0.906	0.727	1.331	0.336
2. rolling estimation	MaR1	2.964	3.248	3.034	4.461
	MaR1-MiR1	-0.137	0.029	-0.553	-0.576
	MaR3	3.085	3.309	4.909	6.527
	MaR3-MiR3	-0.098	-0.028	-0.922	-1.228
Panel F: Financial		Fin_4_S	Fin_8_NS	Fin_4_S	Fin_8_NS
1. buy and hold	equal-weighted	0.746	0.878	0.546	0.968
2. rolling estimation	MaR1	3.189	3.134	5.027	3.872
	MaR1-MiR1	-0.048	-0.158	-0.761	-1.024
	MaR3	3.26	3.142	6.63	4.868
	MaR3-MiR3	0.012	-0.105	-2.029	-1.65
Panel G: Energy		Energy_5_S	Energy_11_NS	Energy_5_S	Energy_11_NS
1. buy and hold	equal-weighted	1.134	1.249	2.635	1.353
2. rolling estimation	MaR1	3.356	2.49	2.875	1.983
	MaR1-MiR1	-0.118	-0.243	0.051	-0.632
	MaR3	2.827	2.66	2.924	3.3
	MaR3-MiR3	-0.081	-0.115	1.299	-1.023
Panel H: Con. Staples		CS_10_S	CS_11_NS	CS_10_S	CS_11_NS
1. buy and hold	equal-weighted	0.787	0.711	1.045	0.903
2. rolling estimation	MaR1	2.899	3.018	3.4	5.244
	MaR1-MiR1	-0.35	-0.211	-1.029	-1.257
	MaR3	3.015	3.116	5.352	7.048
	MaR3-MiR3	-0.243	-0.13	-1.456	-1.881
Panel I: Con. Dis.		CD_9_S	CD_12_NS	CD_9_S	CD_12_NS
1. buy and hold	equal-weighted	0.571	0.424	0.079	-0.161
2. rolling estimation	MaR1	3.184	2.932	4.516	3.274
	MaR1-MiR1	0.001	-0.004	-0.719	-0.477
	MaR3	3.203	3.072	5.831	5.555
	MaR3-MiR3	-0.025	0.007	-1.301	-0.79

Table 7: Investor utility

This table reports the investor utility based on: $U = \hat{\mu} - 1/2\,\gamma\hat{\sigma}^2$, where $\hat{\mu}$ and $\hat{\sigma}^2$ are the sample mean and variance, respectively, over the out-of-sample period for the return forecasts, and γ represents the risk aversion parameter. “_S” and “_NS” represent stationary and non-stationary stock prices, respectively

Panel A: Utility	Util_3_S	Util_16_NS	Panel F: Financial	Fin_4_S	Fin_8_NS
Υ = 3	1.401	1.395	Υ = 3	2.781	2.578
Υ = 6	1.063	0.465	Υ = 6	2.348	1.879
Υ = 12	0.014	0.004	Υ = 12	1.483	0.48
Panel B: Materials	Mat_6_S	Mat_9_NS	Panel G: Energy	Energy_5_S	Energy_11_NS
Υ = 3	1.388	0.871	Υ = 3	1.958	1.496
Υ = 6	0.857	0.432	Υ = 6	0.514	0.433
Υ = 12	0.106	0.048	Υ = 12	0.075	0.081
Panel C: IT	IT_4_S	IT_4_NS	Panel H: Con. St	CS_10_S	CS_11_NS
Υ = 3	2.378	1.971	Υ = 3	2.304	2.143
Υ = 6	1.56	1.052	Υ = 6	1.558	1.495
Υ = 12	-0.076	-0.785	Υ = 12	0.064	0.097
Panel D: Industrial	Ind_18_S	Ind_13_NS	Panel I: Con. Disc.	CD_9_S	CD_12_NS
Υ = 3	2.578	2.771	Υ = 3	2.812	2.151
Υ = 6	1.911	1.786	Υ = 6	2.278	1.317
Υ = 12	0.576	0.316	Υ = 12	1.21	-0.352
Panel E: Health	Health_7_S	Health_6_NS			
Υ = 3	2.051	2.734			
Υ = 6	1.059	2.161			
Υ = 12	-0.924	1.015			