Business Cycles and Mutual Fund Timing Performance: An Application of Regime Switching and GARCH Modelling

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Abstract

In this paper, we study mutual fund performance in terms of timing ability with daily data from 1998 to 2009. A novel timing model is proposed by incorporating the regime-switching framework into the Treynor and Mazuy (1966) model. The volatility follows a generalized autoregressive conditional heteroskedasticity (GARCH) process within each regime. The switching between two regimes (up and down markets) is governed by a first-order Markov process with state-dependent transition probabilities. The empirical tests are performed based on US domestic equity funds, represented by nine value-weighted portfolios based on stated investment objectives. We show that the regime switching model captures the asymmetric timing performance, whereas single regime models do not. The results of this paper show that fund managers have significant perverse timing attributes in up markets, but not in down markets. On average, institutional fund managers' timing performance is worse than that of retail funds.

JEL classification: C58; G11; G23

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1. Introduction

Mutual fund performance has long been of interest to academics, practitioners and investors. Not only because the evidence on the performance of professional fund managers relates to the market efficiency, but also its implication for investors. From a general standpoint, overall fund performance can be characterized into two broad categories according to the sources of the performance: the ability of the portfolio manager to forecast price movements of individual common stocks relative to stocks in general (i.e. selectivity performance) and the ability to forecast the direction of the overall stock market and adjust the portfolio's exposure to systematic risk (i.e. timing performance). In this paper, we extend the literature regarding the ability of mutual fund managers to time the market. In particular, the core contribution of our work relates to the assessment of how timing ability is impacted by business cycles via the implementation of a Markov switching approach to detect and estimate parameter shifts reflecting differing market states. The probability of switching from one regime to the other is time-varying and can depend on the behaviour of underlying economic fundamentals. The variance specification is allowed to have generalized autoregressive conditional heteroskedasticity (GARCH) process within each regime in order to capture volatility clustering. GARCH models have proved to be effective estimation tools for variance. The results from Coggins, Beaulieu et al. (2009) support that it significantly improve the timing performance tested with daily fund data in a GARCH framework. Retail and institutional funds are examined separately because the literature has shown that fund performance are quite different for retail and institutional funds [Jame and Karceski (2006)]. Further funds are classified on the basis of fund objective. Prior research shows that managers of growth-oriented funds have better performance than managers of income-oriented funds [Shawky (1982)]. The risk-adjusted returns of aggressive growth and growth income funds are significantly lower than growth funds in expansionary periods [Kosowski (2006)].

One of the key questions in evaluating performance is the model choice. Treynor and Mazuy (1966) (TM) were the first to propose that market timing can be estimated by adding a squared term to the usual linear index model. In the model of Henriksson and Merton (1981) (HM), a dummy variable is introduced into the timing model in which the quadratic term is replaced by an option payoff. However, Ferson and Schadt (1996) argue that the timing ability may arise due to the time-variation in the fund's beta risk and the expected market risk premium, related to public information. They propose a conditional version of TM and HM models to handle this situation. Their results show that the conditional performance measures of TM and HM generally make mutual fund managers appear better timers than their unconditional counterparts.

An extensive body of literature has applied these conditional and unconditional timing models in tests of market timing ability. Grinblatt and Titman (1989) and Ippolito (1989) report superior market timing performance. However, Lee and Rahman (1990) and Malkiel (1995) find no evidence of market timing. Many studies conclude that fund managers do not possess market timing ability [Fabozzi and Francis (1979), Grinblatt and Titman (1988), Cumby and Glen (1990), Becker, Ferson et al. (1999)]. Daniel, Grinblatt et al. (1997) also find evidence that some funds have selectivity ability but not timing ability. However, at an individual level, there is superior timing ability found by Kon (1983). Similar results are reported in Lehmann and Modest (1987), Lee and Rahman (1990) and Shukla and Trzcinka (1994). It has also been shown in the literature that funds have perverse market timing abilities. [Kon (1983), Malkiel (1995), Chang and Lewellen (1984) and Jagannathan and Korajczyk (1986)]. Recent studies by Bollen and Busse (2001) and Chance and Hemler (2001) who use daily data in evaluating the mutual fund performance show that a substantial number of funds possess significant timing ability.

In these studies, conclusions are drawn based on *single regime* models in the sense that these models assume a single structure for the mean and variance, hence the timing coefficients stay constant across different states of economy. One potential source of misspecification of single regime models is that these models have the effect of averaging the timing coefficient over the sample period. As Moskowitz (2000) noted in his paper, a single regime measure cannot answer the question of how mutual funds perform in recession periods and expansion periods, and thus such simple models hide a wide variation in the actual fund performance. To overcome this hurdle, in this paper, we propose a timing model incorporating the Markov Switching scheme into the TM model. The coefficients in this model are different in each regime so that the model can capture the time varying risks, thereby enhancing traditional performance measures by allowing an investment to have dynamic factor exposure through time. The Global financial crisis (GFC) has, in part, motivated our work using the regime switching model. After the GFC, questions which naturally arise concern the fund performance conditional upon the business cycle, that is, can fund managers correctly time the market hence provide investors a partial hedge against states where markets are going down? The GFC has led to a consideration of how a model connects fund performance with the business cycle.

There have been different approaches proposed for identifying switching points and analysing the business cycle. Moskowitz (2000) examines the fund performance over recessionary and non-recessionary periods according to the NBER classification. In an analysis of REIT mutual funds, Kallberg, Liu et al. (2000) use returns on the National Real Estate Index to identify up and down markets. Mamaysky, Spiegel et al. (2004) propose a Kalman filter model allowing for alpha and beta dynamics to be based on an unobserved factor that follows an AR(1) process. Dummy variables are used in their model. One of the limitations of using a pre-defined state indicator or dummy variables to identify the different states of the economy is that they are a binary classification and, as a result, fail to assign a state probability on the continuous interval. Moreover, the state indicator such as NBER recession dates, has its own measurement problems and only becomes available *ex post*. Hamilton (1989) introduced the Markov regime-switching model as a tool for dealing with structural breaks in time series, as well as the asymmetric effects of business cycles. A regime switching model allows the continuous state probability which overcomes the problem inherent with the above mentioned approaches. The transition between states is governed by a first-order Markov process and can be obtained recursively along with other parameters in the model using Maximum Likelihood Estimation (MLE).

Our study makes four contributions to the mutual fund performance literature. First, studies on mutual fund performance using the Markov Switching approach have been largely non-existent. Early studies have addressed the issue of the existence of switching regimes or non-stationary beta[1] in mutual fund data [Kon and Jen (1979); Miller and Gressis (1980) and

[1] Since well managed mutual funds should change their beta in accordance with their forecasts of general market movements, to find out the existence of nonstationary beta is the centre of these early studies.

Hays and Upton (1986)]. However, these studies simply identify structural shifts in the regression model in a chronological framework without explicitly identifying the timing ability[2]. The current study is the first to test the market timing performance by incorporating Markov regime-switching scheme. Therefore, the emphasis in this study is on the detection of parameter shifts in mutual funds as well as on parameter estimation.

Second, in Goetzmann, Ingersoll et al. (2000), the authors question the validity of using monthly data to detect market timing performance because the timing models may not be able to accurately assess fund managers who attempt to time the market over shorter time periods. Bollen and Busse (2001) find evidence of market timing abilities with daily data. Therefore in this study, we use daily, instead of monthly, fund data to assess timing abilities where regime-switching models are considered.

Third, the timing model developed in this study also extends the regime-switching literature by allowing the variance specification to have a generalized autoregressive conditional heteroskedasticity (GARCH) process to capture the volatility clustering phenomenon. Hence, parameter estimates from GARCH models provide an appropriate basis for performance measurement. GARCH(1,1) is considered in this study. To model the conditional variance, this study follows the non-path-dependent approach proposed by Gray (1996). Unlike the path-dependent GARCH model where conditional variance depends not just on the current regime but also on the entire past history, the non-path-dependent GARCH lets each conditional variance depend only on the current regime. Nelson (1990, 1992) support the conditional GARCH volatility model estimated with high-frequency data.

Fourth, performance differences between institutional funds and their retail counterparts will also be investigated in this study. It is important to further study institutional funds for several reasons. First institutional fund managers control a large portion of the aggregate wealth than do retail fund managers (Coggin, Fabozzi et al. (1993)). Second, institutional

[2] The way of using nonstationary beta as an indication of market timing ability has been questioned by Alexander et. al. (1982) who point out that mutual funds may have betas that follow a first-order Markov process, which is nonstationry, even if fund managers do not actively engage in timing decisions. Thereby, beta nonstationarity is not a sufficient condition for identifying the timing ability.

equity managers and retail mutual fund managers operate in different environments. For example, typical institutional funds have higher minimum investments but lower fees than retail funds.

This paper is organized as follows. Section 2 discusses the model development process. Section 3 describes the data and empirical method. Results are presented in Section 4 and Section 5 concludes.

1. **Model development**

2.1 The Treynor and Mazuy market timing measure (TM)

Treynor and Mazuy (1966) add a squared term to the usual linear index model. It is expressed as:

$$r_{jt} = \alpha_j + \beta_j RMRF_t + \gamma_j RMRF_t^{\,2} + \varepsilon_{jt} \qquad (1)$$

where r_{jt} = the return of fund j in excess of the T-bill return at time t;

α_j = measures selectivity performance of fund j;

$RMRF_t$ = the excess return on a value-weighted aggregate market proxy at time t;

γ_j = measures timing performance of fund j.

A positive γ indicates that timing activities have added value to overall portfolio performance. Comparing the γs of different funds indicates the relative importance of timing activities in their investment policies.

2.2 The Regime Switching Framework

The regime-switching framework combines two or more sets of model coefficients into one system. The particular coefficient vector that applies to a certain observation depends on the regime or "state" that the system was likely in at that time. For instance, a two-state switching model can take the form:

$$\begin{aligned} z_t &= \alpha_0 + \beta z_{t-1} + \varepsilon_t \qquad & \mathrm{s_t} = 1, \\ z_t &= \alpha_0 + \alpha_1 + \beta z_{t-1} + \varepsilon_t \qquad & \mathrm{s_t} = 2 \end{aligned} \qquad (2)$$

In equation (2), $\mathrm{s_t}$ denotes the state variable that changes through time according to a process that is unobservable to the researcher. The process by which the state variable changes through time is determined by a one-period Markov chain.

$$
\begin{aligned}
&Pr[\mathrm{S_t} = 1 | \mathrm{S_{t\text{-}1}} = 1] = P \\
&Pr[\mathrm{S_t} = 2 | \mathrm{S_{t\text{-}1}} = 1] = 1 - P \\
&Pr[\mathrm{S_t} = 2 | \mathrm{S_{t\text{-}1}} = 2] = Q \\
&Pr[\mathrm{S_t} = 1 | \mathrm{S_{t\text{-}1}} = 2] = 1 - Q
\end{aligned}
\qquad \textbf{(3)}
$$

2.3 The Regime Switching TM model (RSTM)

The regime-switching model is applied to the TM model. That is:

$$
\begin{aligned}
&r_{jt} = \alpha_{j,S_t} + \beta_{j,S_t} RMRF + \gamma_{t,S_t} RMRF^2 + e_{jt} \\
&e_{jt} \sim N(0, \sigma_{S_t})
\end{aligned}
\qquad (4)
$$

where

γ_t = timing coefficient, measures the sensitivity of the manager's beta to the private market timing signal;

S_t = Latent state variable.

2.4 The Regime Switching TM GARCH model (RSTMGARCH)

The regime-switching GARCH model is applied to the TM model. That is:

$$
\begin{aligned}
&r_{jt} = \alpha_{j,S_t} + \beta_{j,S_t} RMRF + \gamma_{t,S_t} RMRF^2 + e_{jt,S_t} \\
&e_{jt,S_t} = z_t \sigma_{jt,S_t} \qquad \mathrm{z_t} \sim D_v(0,1) \\
&\sigma^2_{jt,S_t} = b_{0,S_t} + b_{1,S_t} e^2{}_{t-1} + b_{2,S_t} \sigma_{jt-1}
\end{aligned}
\qquad (5)
$$

where

γ_t = timing coefficient, measures the sensitivity of the manager's beta to the private market timing signal;

$D_v(0,1)$ = probability density function of the residual with zero mean and unit variance, v are additional distribution parameters to describe the skewness of the distribution

S_t = Latent state variable.

2.3.1 Specification of the switching probabilities

The transition probabilities in this model are assumed to follow a first order Markov chain. The simplest model assumes that state transitions are constant over time. Recent empirical experience with Markov switching models suggests that the flexibility gained by allowing the state transitions to vary over time as a function of a predetermined variable can be very substantial [Filardo (1994)]. One way to introduce the information set on which the fund managers base their decisions, is to let the transition probabilities depend on an economic variable that reflects the future state of the economy. The Chicago Board Options Exchange Volatility Index (VIX) is used as state variable in this study. The VIX index measures the implied volatility of options on the S&P 500 Stock Index. It represents one measure of the market's expectation of volatility over the next 30-day period and is also called the “fear factor”. The VIX index is a widely used investor sentiment measure by many practitioners and researchers [Whaley (2009) and Baker and Wurgler (2007)]. We model the transition probabilities to vary depending on the level of VIX:

$$\begin{aligned} P_t &= \Phi(c_1 + d_1 \log(VIX_{t-1})) \\ Q_t &= \Phi(c_2 + d_2 \log(VIX_{t-1})) \end{aligned} \qquad \textbf{(6)}$$

where Φ (.) is the cumulative normal distribution function.

2.3.2 Specification of the error term

Common choices for the error term distribution are the Normal and Student-t. The Student-t specification is particularly useful, since it can provide the excess kurtosis in the conditional distribution that is often found in financial time series processes.

2.3.3 The construction of log-likelihood function

The construction of log-likelihood function follows Quandt (1972) and Gray (1996).

Let r_{pt} denote the mutual fund’s return in excess of benchmark return. In the Hamilton framework, the transition between states is governed by a first-order Markov process. At time t, we assume that r_{pt} follows a student’s *t*-distribution with one of the two states in S. In the next period t+1, $r_{p,t+1}$ may stay in the same regime at the given transition probability (p or q) or switch to the other regime (1-p or 1-q). Therefore the density function of r_{pt}, conditional on available information Φ, takes the following form:

$$f(r_{pt}|\Phi_{t-1}) = \sum_{t=1}^{2} f(r_{pt}|S_t = i, \Phi_{t-1}) \Pr(S_t = i|\Phi_{t-1}) = \sum_{t=1}^{2} f(r_{pt}|S_t = i, \Phi_{t-1}) P_{it} \quad \textbf{(7)}$$

$$f(r_t|S_t = i, \Phi_{t-1}) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu-2)\sqrt{\pi(\nu-2)}} \left[1 + \frac{(r_t - \mu_{it})^2}{\sigma_{it}^{\ 2}(\nu-2)}\right]^{-(\nu+1)/2} \quad (8)$$

where $\Gamma(\nu) = \int_0^\infty e^{-x} x^{\nu-1} dx$ is the gamma function and ν is the parameter that measures the tail thickness.

Since the only information used as conditional information for P_{1t} **is** ξ_{t-1}**, then**

$$P_{1t} = \Pr(S_t = 1|\xi_{t-1}) \text{ where } \xi_{t-1} = \{\xi_{t-1}, \xi_{t-2}....\} \quad \textbf{(9)}$$

According to the first-order Markov structure, $P_{1t} = \Pr(S_t = 1|\xi_{t-1})$ depends only on the regime the process is in at time t-1.

$$P_{1t} = \Pr(S_t = 1|\xi_{t-1}) = \sum_{t=1}^{2} \Pr(S_t = 1|S_{t-1} = i, \xi_{t-1}) \Pr(S_{t-1} = i|\xi_{t-1}) = p \times \Pr(S_{t-1} = 1|\xi_{t-1}) + (1-q) \times [1 - \Pr(S_{t-1} = 1|\xi_{t-1})] \quad \textbf{(10)}$$

By Bayes' rule the conditional state probability can be written as a function of $\Pr(S_{t-1} = 1|\xi_{t-2})$:

$$\Pr(S_{t-1} = 1|\xi_{t-1}) = \Pr(S_{t-1} = 1|r_{p,t-1}, \xi_{t-2}) = \frac{f(r_{p,t-1}|S_{t-1} = 1, \xi_{t-2}) \Pr(S_{t-1} = 1|\xi_{t-2})}{\sum_{i=1}^{2} f(r_{p,t-1}|S_{t-1} = i, \xi_{t-2}) \Pr(S_{t-1} = i, \xi_{t-2})} \quad \textbf{(11)}$$

Finally, the log-likelihood function can be written as

$$L = \sum_{t=1}^{t} \log\left\{ p_{1t} \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu-2)\sqrt{\pi(\nu-2)}} \left[1 + \frac{(r_t - \mu_{it})^2}{\sigma_{it}^{\ 2}(\nu-2)}\right]^{-(\nu+1)/2} \right\} + \left\{ (1 - p_{1t}) \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu-2)\sqrt{\pi(\nu-2)}} \left[1 + \frac{(r_t - \mu_{it})^2}{\sigma_{it}^{\ 2}(\nu-2)}\right]^{-(\nu+1)/2} \right\} \quad (12)$$

2. Data, Sampling and Empirical Method

3.1 Data and Sampling

Daily fund data are extracted from CRSP survivor-bias free mutual fund database. The sample period runs from 1st September 1998 to 30th June 2009. This study focuses on domestic US equity funds that invest mainly in the US stock market. Therefore, bond, money market, international, flexible, sector funds and funds of funds are eliminated. It is more appropriate to use daily data when attempting to detect shifts in the risk-return relationships [Miller and Gressis (1980), Bollen and Busse (2001)].

Funds are separated into retail and institutional funds. Funds with no information provided and funds classified as both retail and institutional are eliminated. To be included in the fund sample, funds must have at least $15million in total net assets and hold 60% of their assets in common stocks. According to the Strategic Insight (SI OBJ) classifications, funds are further classified into following three groups: aggressive growth, growth and growth and income funds, where the growth category includes “Equity USA growth”, “Equity USA midcaps” and “Equity USA small companies”. Retail and institutional funds are divided into their respective groups. The final sample for retail funds comprises: 166 aggressive growth funds, 915 growth funds and 528 growth and income funds. For institutional funds, there are 20 aggressive growth funds, 258 growth funds and 150 growth and income funds.

To ensure that the results are not due to some influential observations, we follow the process in Collins, Maydew et al. (1997), and Fama and French (1998). We exclude 0.1% of the observations from both the top and bottom tails of the return and total net assets sample distributions.

Timing abilities are analysed for funds at the aggregate level. We form nine value-weighted portfolios of all funds, retail funds, retail aggressive, retail growth, retail growth and income, all institutional funds, institutional aggressive, institutional growth and institutional growth and income. Daily return and daily total net asset value of each fund are used to construct each of the portfolios.

The S&P500 index is sourced from Datastream and is used as the proxy for market return. For the risk-free rate we use one-month Treasury bill rate and it is downloaded from Kenneth French's website. Data on the VIX are obtained from the CBOE website.

To assess the impact of global financial crisis (GFC), we further examine the time period by excluding the GFC period. In this case the sample period runs from Sept 1998 to 31 July 2007. We select July 2007 as the commencement of the financial crisis based on the fact that in late July, Bear Stearns announced that two hedge funds with subprime exposure had little value. In August, numerous quantitative long/short equity hedge funds suddenly began experiencing unprecedented losses. It highlights one of the first examples of the contagion effect of the subprime crisis spilling over into a radically different business area.

3.2 Research Method

The empirical tests are performed using a single regime TM model, regime switching TM model and regime switching TM GARCH model. The analysis proceeds in two steps: (a) model comparison and (b) timing tests.

Model comparison will be performed for two pairs. To test the existence of the second regime, we compare a single-regime TM model (TM) with a regime-switching TM model (RSTM). The comparison between a standard RSTM and RSTM GARCH model (RSTMGARCH) reveals the significance of the GARCH parameters. A Log Likelihood ratio (LLR) test will be used.

The analysis in the second step focuses on the estimates of the timing coefficients in up and down markets. Timing coefficients are also compared across fund groups. To address the question of whether a regime-switching model will lead to different conclusions about timing abilities, test results using a regime-switching model will be compared with conventional TM models. If the methods yield different performance measures, then empirical evidence obtained from using single regime could be misleading. Retail and institutional funds are analysed separately.

The timing tests based on RSTMGARCH use a two-stage estimation process. Most existing papers, employing a regime switching technique, only examine one series of data thus parameters are estimated simultaneously with time-varying transition probabilities. Our study tests the performance for nine fund categories. The transition probabilities need to consistent with economic intuition, that is, transition probabilities should be constant in cross-section, rather than allowing them to vary for each fund group. To overcome this problem, first, we identify the possible switch in regime using the VIX. The Markov switching model is directly applied to the time series of the observed daily VIX levels. This step involves estimating c1, c2, d1 and d2. Then for each fund group, we apply the regime switching model using c1, c2, d2 and d2 as constants for transition probabilities.

3. Empirical Results

Table 1 reports the summary statistics of excess returns for each fund category, where excess return is calculated as fund portfolio return in excess of the risk-free rate. Our whole sample reported in Panel A includes 2722 observations from 1st Sept 1998 to 30th June 2009. The subsample reported in Panel B excludes the GFC period. The JB test rejects the null hypothesis that the distribution is normal at the 5% level of significance for all fund portfolios. When the GFC period is included, all fund portfolios exhibit negative skewness whereas for the period before the GFC, only 3 portfolios show negative skewness. The range of maximum and minimum returns of each fund group suggests that the fund return in the sample is rich enough to capture market timing activity. All fund portfolios' returns exhibit a high level of non-normality, which is caused by skewness and/or excess kurtosis.

As stated earlier, we use VIX as state variable for the time-varying transition probabilities. The up and down markets can be identified based on coefficients reported in Table 2. The literature posits that higher VIX values correspond to a more volatile market and are associated with higher levels of investor fear or uncertainty, which generally occur during market downturns; while lower VIX levels often correspond to less stressful times or less fear, which generally occur during "normal" times (see, for example, Whaley (2009)). Since d2 is significantly positive, the probability of staying in this regime increases as the level of VIX increases. So regime 2 is identified as the downward market. Conversely, given d1 has a negative loading, the probability of staying in the low-variance regime increases as the level of VIX decreases.

Table 3 reports a summary of the Likelihood-ratio tests. The fourth column shows the LRT produced by comparing the TM model and RSTM model. All LRT statistics are significant at conventional levels. Thus, it rejects the single regime TM model in favour of RSTM model for all fund categories. The limitation of using LRT in this test is that this method is limited to comparisons among nested models. However, under the null of a single state, state transition probabilities are unidentified nuisance parameters and standard results on the distribution of likelihood ratio tests no longer apply. A standardized LRT approach has been developed in Hansen (1992) but is computationally demanding. However, given the large difference in the log-likelihood values for each fund category, even though we have not adjusted the χ^2 distribution, the result does provide indicative evidence as to the existence of the second regime.

The comparison between RSTM model and RSTMGARCH model reveals that the GARCH effect is statistically important in the regime switching setting. As shown in the final column of Table 3, the log likelihood values obtained from the RSTMGARCH model are larger than that of the RSTM model. All LRT statistics are significant at any conventional level. The results hold for both periods, including and excluding GFC. Therefore, it shows that RSTMGARCH model is statistically the best fit model in this timing model context.

The timing measures are obtained by estimating equation (1) for the TM model, equation (4) for the RSTM model and equation (5) for the RSTMGARCH model. Table 4 reports the parameter estimates for single-regime TM model, which represents a baseline for comparison purposes. Across the full sample, Panel A of Table 4 shows that timing coefficients γ are negative and statistically different from zero for all fund groups. The magnitude of the negative daily timing coefficients for retail fund groups is larger than their institutional counterparts. For example, the average timing coefficient of retail aggressive funds is -1.23 while institutional aggressive funds have average timing coefficient of -1.13. These results are not consistent with those obtained by Bollen and Busse (2001) in which the majority of the funds studied with daily data showed a significant timing coefficient. The different results might be due to differences in the sample period examined in their paper and sample settings.

The TM model is re-estimated in different subsample and results are shown in Panel B of Table 4. Again, all fund groups exhibit negative timing coefficients. Of these, all funds, retail, retail growth and income, institutional funds, institutional growth and institutional growth and income funds are statistically significant. In contrast to the overall sample results, the magnitude of the timing coefficients for retail fund groups is smaller than institutional fund groups.[3]

Table 5 presents the parameters estimated using the RSTM model. As previously shown in Table 2, regime 2 is identified as down-market regime and regime 1 is the up-market regime. In up-market periods, 4 fund portfolios are found to have significant negative timing coefficients across the full sample period. All timing coefficients are insignificant in down-market periods. None of the timing coefficients are significant during the period prior to the GFC. While RSTM is a regime switching model, it assumes a constant variance, thus does not take into consideration the GARCH effect.

Displayed in Table 6 are the results from our proposed RSTMGARCH model. At a general level we see that the number of significant timing measures differs when GARCH effects are considered in the model. In the up-market regime, three fund groups (all funds, retail funds and retail income funds) show a negative timing coefficient at the 1% significant level. The timing coefficient of the Institutional fund group is significant at the 5% level, while retail aggressive, retail growth and institutional growth funds have timing coefficients at 10% level. During the market down turn, all funds have insignificant timing coefficients.

Different results again are obtained when the non-GFC sub-period is examined. Estimated parameters in Panel B of Table 6 shows fund managers as a whole have perverse timing ability in up market, but not in a downward market. Retail funds show no timing abilities for both aggregate level and each sub groups. Results obtained from Institutional funds are similar to retail funds except at the aggregate level, institutional funds exhibit perverse timing at 10% significant level.

The evidence of the varying performance in up and down markets suggests that the single regime TM model has the effect of averaging parameters over the sample period. Therefore, it does not do a good job of describing data in either regime, and the results are unreliable

[3] In most finance literature, the intercept in the TM model has been interpreted as a "timing adjusted" selectivity measure. In this paper, we do not interpret the intercept α as the excess return. As Aragon and Ferson (2007) point out that the intercept does not capture the return in excess of a benchmark portfolio, because r_m^2 is not a portfolio return.

in these specific market periods. For example, under the regime switching model, retail income funds show no timing ability in the GFC excluded sub-sample while significant negative timing is detected under the TM model.

In general, we see that the magnitude of timing coefficients across fund categories during up markets is larger than that of the funds in down markets. For example, the retail fund portfolio shows a timing measure of -0.492 in up markets and -0.386 in down markets. Our results also show that beta is high in up markets and low in down markets for all fund portfolios. One potential explanation is the cash-flow hypothesis described in Ferson and Warther (1996) and Edelen (1999). Ferson and Warther (1996) document that money flows into mutual funds partly explain the changes in betas over time. They show that larger cash holdings imply lower beta. Our results are consistent with Chordia (1996) and Kosowski (2006) which find cash holdings are higher in recession periods because mutual funds hold more liquid securities when there is more uncertainty about future states of the economy.

The parameters b11, b12, b21 and b22 are ARCH and GARCH coefficients in up and down markets respectively. In the standard GARCH(1,1) model, the conventional stationary condition constrains the sum of ARCH and GARCH parameters to be less than one. However, in the regime switching model, since the conditional variance can fall into two different regimes, it is possible that conditional variance can be explosive in one regime, but strictly stationary in another regime. To obtain a variance stationary process we just need the weighted average of the sum of parameters in two regimes to be less than one:

$$\left[(b11+b21)(1-\pi)+(b12+b22)\pi\right]<1 \tag{12}$$

where $\pi=(1-\overline{Q})/(2-\overline{P}-\overline{Q})$. Since *P* and *Q* are time-varying transition probabilities, we use average values in our computations. Given the average value of *P* is 0.95 and *Q* is 0.65, all the conditional variances are stationary.

The results presented in Table 6 also reveal the timing performance difference between retail and institutional fund managers. The magnitude of timing coefficients for retail funds is smaller than that of the institutional funds as a whole. It is not surprising that retail funds and institutional funds show dissimilar performance given that the retail managed funds have relatively smaller size compared to institutional funds.

Edelen (1999) finds the source of negative market timing is attributable to the flow experienced by active mutual funds based on monthly cash flow data. We have not controlled for this effect due to the availability of daily cash flow data for our sample funds, but it can be an avenue for future research.

If the fund returns exhibit more/less skewness than the market proxy, either positive or negative, it is more likely to observe a positive/negative timing coefficient even with the absent of timing ability [Jagannathan and Korajczyk (1986)]. The Jarque-Bera (JB) test reported in Table 1 shows that all funds exhibit less skewness than the market proxy in this study. As such it would generate a positive timing coefficient, even in the absence of market timing activity. Therefore, our results of finding negative timing coefficient may not be subject to this bias.

4. Conclusion

In this paper, we propose a timing measure by incorporating a regime switching scheme into the Treynor and Mazuy (1966) model (TM), while the volatility follows a generalized autoregressive conditional heteroskedasticity (GARCH) process within each regime. The Chicago Board Options Exchange Market Volatility Index (VIX) is used as state variable for the time-varying transition probabilities. The empirical tests are performed using daily data, as Bollen and Busse (2001) shows that daily tests are more powerful to detect significant timing activity.

We first document that the regime switching TM GARCH model is statistically the best fit model using the log likelihood ratio tests. We then apply the proposed model to test timing ability in relation to the variation of market conditions for a sample of mutual funds. Funds are classified into groups according to their investment objective. In total, nine fund portfolios are examined. Results are also compared to those obtained using a single-regime TM model and a regime-switching TM model. It shows that mutual funds at the aggregate level exhibit significant perverse timing in up markets, but not in down markets. The magnitude of the timing coefficients are larger in up market than down market for all fund groups. On average, institutional fund managers' timing performance is worse than that of retail funds. Our analysis is not subject to the spurious timing phenomenon. As for future research, an analysis of the fund flow impact on timing performance would shed further light on the sources of perverse timing abilities of mutual fund managers.

Table 1 Summary Statistics of Excess Returns

investment objectives	Mean	Median	Std	Excess kurtosis	Skewness	JB test	min	max
	Panel A: Full sample period							
All funds	5.28E-05	0.00053	0.0108	0.529	-0.090	35.05	-0.034	0.033
Retail	4.99E-05	0.00049	0.0122	2.484	-0.100	700.63	-0.059	0.051
Retail Aggressive	5.43E-05	0.00063	0.0141	2.056	-0.093	480.69	-0.063	0.057
Retail Growth	6.07E-05	0.00058	0.0131	2.087	-0.070	493.13	-0.058	0.053
Retail Income	5.53E-05	0.00042	0.0112	3.362	-0.133	1283.88	-0.059	0.053
Institutional	5.19E-05	0.00046	0.0110	0.685	-0.059	54.24	-0.037	0.035
Inst Aggressive	-4.21E-06	0.00055	0.0140	3.899	-0.083	1719.45	-0.087	0.092
Inst Growth	5.76E-05	0.00058	0.0137	2.122	-0.095	511.60	-0.065	0.058
Inst Income	1.67E-05	0.00040	0.0111	1.122	-0.051	142.98	-0.040	0.038
Market index	1.39E-04	0.00049	0.0140	7.407	0.122	6201.80	-0.090	0.116
	Panel B: Pre-GFC period, 01/09/1998 – 30/07/2007							
All funds	1.31E-04	0.00060	0.0098	0.549	-0.082	30.17	-0.034	0.033
Retail	2.05E-04	0.00058	0.0106	1.774	0.116	296.57	-0.046	0.049
Retail Aggressive	2.31E-04	0.00065	0.0129	1.845	0.085	317.78	-0.049	0.057
Retail Growth	2.13E-04	0.00059	0.0116	1.631	0.117	251.36	-0.049	0.050
Retail Income	2.10E-04	0.00046	0.0094	2.348	0.105	514.97	-0.048	0.047
Institutional	1.23E-04	0.00053	0.0100	0.702	-0.060	46.79	-0.036	0.035
Inst Aggressive	1.38E-04	0.00053	0.0121	1.869	0.119	328.84	-0.057	0.053
Inst Growth	2.21E-04	0.00063	0.0116	1.058	0.061	104.84	-0.044	0.047
Inst Income	8.26E-05	0.00045	0.0100	1.260	-0.028	147.00	-0.040	0.038
Market index	2.98E-04	0.00050	0.0113	2.390	0.173	540.45	-0.058	0.057

Table 2 Transition Probability Modelling Results

This table reports parameter estimates for the Chicago Board Options Exchange market Volatility Index (VIX), in the following regime specifications (31 Aug 1998 to 29 June 2009):

$$P_t = \Phi(c_1 + d_1 \log(VIX_{t-1}))$$
$$Q_t = \Phi(c_2 + d_2 \log(VIX_{t-1}))$$

where Φ (.) is the cumulative normal distribution function. '***', '**' and'*' represent 1%, 5% and 10% significant respectively.

	Parameter estimate	Std error	t-statistic
c1	2.13	0.42	5.07***
c2	-1.63	1.06	1.53
d1	-0.15	0.136	1.10
d2	0.67	0.33	2.03***

Table 3 Log likelihood Ratio Tests (LRT)

This table reports the log likelihood evaluated at the Maximum Likelihood Estimation (MLE) for three models: TM model, RSTM model and RSTMGARCH model. The log-likelihood function can be written as:

$$L = \sum_{t=1}^{t} \log \left\{ p_{1t} \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu-2)\sqrt{\pi(\nu-2)}} \left[1 + \frac{(r_t - \mu_{it})^2}{\sigma_{it}^{2}(\nu-2)} \right]^{-(\nu+1)/2} \right\} + \left\{ (1-p_{1t}) \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu-2)\sqrt{\pi(\nu-2)}} \left[1 + \frac{(r_t - \mu_{it})^2}{\sigma_{it}^{2}(\nu-2)} \right]^{-(\nu+1)/2} \right\}$$

where $\Gamma(\nu) = \int_0^\infty e^{-x} x^{\nu-1} dx$ is the gamma function and ν is the parameter that measures the tail thickness. The Likelihood-ratio test examines whether a reduced model provides the same fit as a full model. The likelihood-ratio test statistic is given by:

$$LRT = -2\left[L(\hat{\Theta}_r | z) - L(\hat{\Theta} | z) \right]$$

where $L(\hat{\Theta}_r | z)$ is the maximum of the likelihood function, subject to the restriction that *r* parameters unconstrained in the full model and $L(\hat{\Theta} | z)$ is the likelihood evaluated at the MLE for the full model. The LRT statistic is χ^2 distribution.

Panel A: Full sample period				
(1) TM	(2) RSTM	(3) RSTMGARCH	LRT statistic (1)&(2)	LRT statistic (2)&(3)
-10539.4	-12881.4	-13137.1	4683.9	511.5
-11088.8	-13207.9	-13497.3	4238.2	578.8
-9944.04	-11129.5	-11620.6	2371.0	982.1
-10557.9	-11901	-12261.3	2686.3	720.6
-11414.7	-13954.7	-14195.5	5080.1	481.5
-10172.2	-13007.2	-13269.0	5670.1	523.6
-10729.8	-11647.2	-12080.2	1834.8	865.8
-10382.7	-11275.6	-11542.0	1785.8	532.7
-10229.5	-14610.2	-15048.0	8761.5	875.6
Panel B: pre-GFC period, 01/09/1998 – 30/07/2007				
(1) TM	(2) RSTM	(3) RSTMGARCH	LRT statistic (1)&(2)	LRT statistic (2)&(3)
-10066.4	-10854.9	-11047.8	1577.0	385.9
-10651.7	-10977.0	-11290.5	650.7	627.1
-8671.3	-9186.6	-9696.2	1030.6	1019.1
-9559.9	-9908.0	-10261.4	696.1	706.8
-11421.4	-11594.4	-11859.3	346.0	529.8
-9993.8	-11044.7	-11169.0	2101.6	248.8
-9314.2	-9724.4	-10121.1	820.6	793.2
-9302.6	-9444.9	-9653.7	284.6	417.7
-10071.2	-12452.5	-12776.5	4762.6	648.1

Table 4 Estimation Results for the TM Model

This table reports the timing measure based on the TM model for the full sample (Panel A) and the sub-period before the GFC (Panel B): $r_{jt} = \alpha_j + \beta_j RMRF_t + \gamma_j RMRF_t^2 + \varepsilon_{jt}$ where r_{pt} is the fund return in excess of risk-free rate at time t, γ_p measures timing ability. Daily returns are used. The coefficient γ is estimated based on fund excess returns of value-weighted portfolios of the following investment objectives: Aggregate (all funds), Retail (all retail funds), ragg (retail aggressive), rgro (retail growth), rincome (retail growth and income), institutional (all institutional funds), iagg (institutional aggressive), igro (institutional growth) and iincome (institutional growth and income). The second row below the estimates are t-statistics. '***', '**' and'*' represent 1%, 5% and 10% significance, respectively.

	Panel A: Full sample period				Panel B: Pre-GFC period, 01/09/1998 – 30/07/2007			
	α	β	γ	LLF	α	β	γ	LLF
All funds	0.00015	0.68	-0.69	10539.43	0.00026	0.84	-2.29	10066.35
	1.51	98.57	-4.23***		4.17	164.81	-10.64***	
retail	0.00022	0.82	-1.04	11088.77	0.00009	0.92	-0.44	10651.67
	2.60	145.12	-7.81***		1.83	234.78	-2.67***	
ragg	0.00026	0.91	-1.23	9944.042	0.00011	1.05	-0.54	8671.34
	2.05	104.85	-6.10***		0.92	110.50	-1.33	
rgro	0.00023	0.87	-1.05	10557.87	0.00009	0.99	-0.43	9559.94
	2.27	126.36	-6.49***		1.09	154.76	-1.59	
rincome	0.00022	0.76	-1.01	11414.66	0.00011	0.82	-0.41	11421.38
	2.92	151.00	-8.54***		3.05	296.11	-3.51***	
institutional	0.00016	0.68	-0.72	10172.16	0.00028	0.86	-2.52	9993.85
	1.35	85.03	-3.85***		4.30	162.77	-11.32***	
iagg	0.00018	0.95	-1.13	10729.84	-0.00000	1.02	-0.36	9314.15
	1.90	146.54	-7.45***		-0.03	143.62	-1.18	
igro	0.00022	0.90	-1.02	10382.72	0.00014	0.97	-0.78	9302.57
	2.05	122.77	-5.94***		1.60	135.49	-2.59***	
iincome	0.00011	0.69	-0.65	10229.45	0.00028	0.86	-2.83	10071.17
	0.94	88.11	-3.55***		4.41	169.04	-13.18***	

Table 5 Estimation Results for the RSTM model

This table reports the parameters estimated by using regime switching TM model for the full sample period (Panel A) and the sub-period before the GFC (Panel B):

$$r_{jt} = \alpha_{j,S_t} + \beta_{j,S_t} RMRF + \gamma_{t,S_t} RMRF^2 + e_{jt}$$
$$e_{jt} \sim N(0, \sigma_{S_t})$$

where r_{pt} is the fund return in excess of risk-free rate at time t. γ_p measures timing ability, Daily returns are used. The coefficient γ is estimated based on fund excess returns of value-weighted portfolios of the following investment objectives: Aggregate (all funds), Retail (all retail funds), ragg (retail aggressive), rgro (retail growth), rincome (retail growth and income), institutional (all institutional funds), iagg (institutional aggressive), igro (institutional growth) and iincome (institutional growth and income). The second row below the estimates are t-statistics. '***', '**' and'*' represent 1%, 5% and 10% significance, respectively.

	Panel A: Full sample period									
	α1	α2	β1	β2	γ1	γ2	b01	b02	√	LLF
All funds	1.94E-04	2.06E-04	0.905	0.902	-1.037	-1.061	0.06227	0.06527	2.001	-12881.39
	1.75	0.26	107.49	19.14	-2.52***	-0.52	0.02	0.02	25.21	
retail	1.39E-04	1.48E-04	0.913	0.911	-0.423	-0.427	0.00279	0.00290	2.470	-13207.89
	1.42	0.22	139.32	28.66	-1.71*	-0.46	8.26	2.47	21.25	
ragg	2.00E-04	2.40E-04	0.983	0.977	-0.312	-0.332	0.11947	0.12472	2.001	-11129.52
	0.99	0.17	69.72	13.70	-0.64	-0.17	0.01	0.01	19.33	
rgro	1.98E-04	2.15E-04	0.957	0.953	-0.501	-0.502	0.00460	0.00479	2.441	-11901.04
	1.25	0.20	89.22	18.15	-1.29	-0.34	7.38	2.40	19.17	
rincome	1.33E-04	1.41E-04	0.851	0.852	-0.594	-0.617	0.00191	0.00201	2.664	-13954.73
	1.66	0.25	160.11	31.96	-2.84***	-0.72	10.25	2.33	22.29	
institutional	1.30E-04	1.37E-04	0.940	0.938	-0.650	-0.679	0.09637	0.10135	2.000	-13007.23
	1.25	0.18	117.34	20.58	-1.56	-0.32	0.01	0.01	28.40	
iagg	9.34E-05	1.25E-04	0.990	0.985	-0.246	-0.291	0.00482	0.00498	2.512	-11647.23
	0.55	0.11	86.38	17.82	-0.71	-0.23	8.07	2.41	17.19	
igro	2.17E-04	2.29E-04	0.996	0.993	-0.830	-0.849	0.00442	0.00461	3.291	-11275.60
	0.99	0.15	72.45	14.80	-1.68*	-0.45	12.94	2.53	18.06	
iincome	4.41E-05	4.31E-05	0.962	0.962	-0.295	-0.299	0.09195	0.09745	2.000	-14610.18
	0.75	0.10	234.22	40.93	-1.41	-0.28	0.00	0.00	37.91	
	Panel B: Pre-GFC period, 01/09/1998 – 30/07/2007									
	α1	α2	β1	β2	γ1	γ2	b01	b02	√	
All funds	1.76E-04	1.80E-04	0.900	0.897	-0.983	-0.998	0.00240	0.00248	2.820	-10854.87
	1.24	0.17	73.03	11.54	-1.42	-0.25	9.02	1.61	17.63	
retail	1.36E-04	1.37E-04	0.916	0.914	-0.502	-0.496	0.00229	0.00236	2.796	-10977.00
	1.05	0.14	77.36	12.41	-0.85	-0.15	8.49	1.56	13.69	
ragg	1.72E-04	1.90E-04	1.011	1.006	-0.787	-0.778	0.12635	0.13212	2.001	-9186.63
	0.66	0.10	41.65	6.51	-0.68	-0.12	0.01	0.01	15.53	
rgro	1.93E-04	2.01E-04	0.971	0.967	-0.858	-0.848	0.00402	0.00416	2.575	-9907.99
	0.95	0.13	50.23	7.97	-0.94	-0.17	6.87	1.53	13.92	
rincome	1.31E-04	1.30E-04	0.834	0.834	-0.401	-0.420	0.00154	0.00160	3.445	-11594.37
	1.19	0.16	91.19	14.48	-0.90	-0.17	10.48	1.62	11.39	
institutional	1.22E-04	1.22E-04	0.926	0.923	-0.480	-0.482	0.00208	0.00214	3.075	-11044.66
	0.92	0.12	86.41	13.76	-0.80	-0.14	9.89	1.62	19.74	
iagg	2.92E-05	3.55E-05	1.014	1.008	-0.402	-0.407	0.00475	0.00487	2.440	-9724.45
	0.13	0.02	50.71	8.20	-0.43	-0.08	5.77	1.59	14.36	
igro	2.48E-04	2.56E-04	0.977	0.970	-1.309	-1.299	0.00381	0.00391	4.232	-9444.87
	0.88	0.12	37.67	5.77	-1.16	-0.20	11.79	1.77	10.82	
iincome	5.54E-05	5.30E-05	0.948	0.948	-0.144	-0.147	0.04481	0.04700	2.000	-12452.48
	0.89	0.11	189.28	30.40	-0.50	-0.09	0.01	0.01	22.70	

Table 6 Regime Switching TMGARCH model

The regime-switching GARCH model is based on the TM model. That is:

$$r_{jt} = \alpha_{j,S_t} + \beta_{j,S_t} RMRF + \gamma_{t,S_t} RMRF^2 + e_{jt,S_t}$$
$$e_{jt,S_t} = z_t \sigma_{jt,S_t} \qquad \mathrm{z_t} \sim D_v(0,1)$$
$$\sigma^2_{jt,S_t} = b_{0,S_t} + b_{1,S_t} e^2{}_{t-1} + b_{2,S_t} \sigma_{jt-1}$$

where r_{pt} is the fund return in excess of risk-free rate at time t. γ_p measures timing capabilities. S_t is the latent state variable. $D_v(0,1)$ is the probability density function of the residual with zero mean and unit variance, v are additional distribution parameters to describe the skewness of the distribution. Daily returns are used. The coefficient γ is estimated based on fund excess returns of value-weighted portfolios of the following investment objectives: All funds, Retail (all retail funds), ragg (retail aggressive), rgro (retail growth), rincome (retail growth and income), institutional (all institutional funds), iagg (institutional aggressive), igro (institutional growth) and iincome (institutional growth and income). The second rows below estimates are t-statistics. '***', '**' and'*' represent 1%, 5% and 10% significance, respectively.

Panel A: Full sample period

	α1	α2	β1	β2	γ1	γ2	b01	b02	b11	b12	b21	b22	DoF	LLF
all funds	2.05E-04	2.06E-04	0.909	0.906	-1.179	-1.058	6.93E-08	1.23E-06	0.137	0.065	0.867	0.658	3.676	-13137.1
t-stat	2.88	0.34	145.28	22.19	-4.74***	-0.85	0.88	1.93	5.68	0.95	29.87	5.25	16.74	
retail	1.58E-04	1.45E-04	0.911	0.912	-0.492	-0.386	1.00E-15	7.49E-07	0.129	0.070	0.890	0.659	5.569	-13497.3
t-stat	2.73	0.31	208.08	38.99	-2.67***	-0.49	0.15	3.82	5.32	0.85	37.33	6.85	13.63	
retail agg	1.66E-04	1.63E-04	0.989	0.986	-0.604	-0.442	1.00E-15	1.06E-06	0.113	0.060	0.911	0.767	6.290	-11620.6
t-stat	1.48	0.18	123.00	24.12	-1.92*	-0.39	0.01	2.35	5.37	0.89	40.07	8.39	10.19	
retail gro	1.92E-04	1.88E-04	0.956	0.954	-0.503	-0.440	1.00E-15	1.13E-06	0.109	0.081	0.909	0.723	6.555	-12261.3
t-stat	1.87	0.23	137.75	26.51	-1.80*	-0.40	0.01	3.11	4.29	0.80	38.21	7.06	10.77	
retail income	1.25E-04	1.25E-04	0.855	0.853	-0.517	-0.491	1.00E-15	5.90E-07	0.175	0.128	0.853	0.571	5.033	-14195.5
t-stat	3.20	0.37	240.29	45.22	-3.30***	-0.77	0.08	4.21	4.31	0.76	28.13	4.38	16.97	
inst	1.34E-04	1.37E-04	0.944	0.940	-0.713	-0.687	1.92E-07	1.10E-06	0.158	0.102	0.814	0.652	3.459	-13269
t-stat	1.72	0.21	134.56	20.06	-2.37**	-0.41	1.87	1.50	4.95	1.07	20.74	4.22	19.34	
inst agg	-2.17E-06	2.25E-05	1.001	0.995	-0.211	-0.166	1.00E-15	4.15E-07	0.094	0.001	0.930	0.847	7.510	-12080.2
t-stat	-0.03	0.04	181.43	45.26	-0.86	-0.22	0.01	2.31	7.24	0.39	74.68	20.38	10.44	
inst gro	1.97E-04	2.08E-04	0.994	0.989	-0.711	-0.670	1.00E-15	2.33E-06	0.079	0.076	0.923	0.763	7.640	-11541.9
t-stat	1.32	0.17	104.57	18.98	-1.73*	-0.40	0.24	3.13	3.17	0.67	37.05	6.90	10.02	
inst income	6.03E-05	6.09E-05	0.969	0.967	-0.264	-0.275	5.85E-08	2.69E-07	0.691	0.531	0.656	0.512	2.566	-15048
t-stat	2.19	0.24	382.42	57.73	-1.61	-0.29	1.60	0.82	4.27	0.86	15.17	2.64	24.00	

Panel B: Pre-GFC period, 01/09/1998 – 30/07/2007

	α1	α2	β1	β2	γ1	γ2	b01	b02	b11	b12	b21	b22	DoF	LLF
all funds	2.06E-04	2.14E-04	0.904	0.901	-1.250	-1.219	5.46E-04	8.56E-03	0.138	0.108	0.857	0.657	4.895	-11047.8
t-stat	2.50	0.29	115.28	16.63	-2.95***	-0.48	0.51	1.09	2.78	0.42	13.13	1.76	13.09	
retail	1.46E-04	1.46E-04	0.913	0.911	-0.530	-0.484	5.54E-06	3.18E-03	0.084	0.111	0.917	0.781	10.924	-11290.5
t-stat	1.96	0.23	121.72	18.40	-1.23	-0.22	0.02	1.15	2.28	0.42	24.68	3.02	4.39	
retail agg	1.02E-04	1.07E-04	1.008	1.004	-0.609	-0.487	1.00E-11	4.29E-03	0.074	0.056	0.935	0.853	12.504	-9696.2
t-stat	0.68	0.08	90.48	14.83	-0.82	-0.14	263.44	1.43	2.38	0.30	31.49	4.66	3.99	
retail gro	1.62E-04	1.63E-04	0.965	0.962	-0.601	-0.541	4.00E-15	5.86E-07	0.075	0.099	0.927	0.812	11.940	-10261.4
t-stat	1.28	0.15	79.88	12.05	-0.87	-0.16	0.00	0.00	1.99	0.39	28.04	3.65	4.03	
retail income	1.33E-04	1.32E-04	0.845	0.843	-0.491	-0.476	2.92E-05	1.73E-03	0.113	0.138	0.891	0.775	10.607	-11859.3
t-stat	2.37	0.25	149.24	21.65	-1.38	-0.25	0.12	0.76	2.76	0.54	20.79	3.17	4.29	
inst	1.47E-04	1.51E-04	0.934	0.929	-0.715	-0.693	1.67E-05	9.83E-05	0.170	0.121	0.793	0.588	4.386	-11169.0
t-stat	1.70	0.20	117.69	17.27	-1.73*	-0.28	1.04	0.92	2.82	0.41	9.05	1.20	16.61	
inst agg	-5.79E-05	-5.72E-05	1.013	1.009	-0.061	-0.038	2.76E-06	1.21E-05	0.059	0.102	0.940	0.865	11.022	-10121.1
t-stat	-0.35	-0.05	76.91	13.10	-0.09	-0.01	0.35	0.21	1.74	0.45	28.30	4.01	4.23	
inst gro	2.16E-04	2.26E-04	0.978	0.969	-1.044	-0.943	4.60E-08	1.45E-06	0.067	0.108	0.927	0.787	14.283	-9653.7
t-stat	1.14	0.14	62.79	9.44	-1.30	-0.21	0.00	0.00	1.93	0.43	20.78	2.54	3.51	
inst income	7.18E-05	7.32E-05	0.963	0.960	-0.234	-0.245	3.34E-04	1.18E-03	0.489	0.512	0.654	0.526	3.194	-12776.5
t-stat	2.27	0.25	321.86	45.84	-1.25	-0.21	1.27	0.52	2.65	0.46	7.05	0.96	20.22	

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