The Empirical Study on Volatility Timing Ability of Chinese Growth Style Mutual Funds

by

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Abstract

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The purpose of this paper is to examine the volatility timing abilities of Chinese growth style mutual fund managers by constructing single factor model with Busse volatility timing model, choosing the growth style mutual funds which found before 2007 as the sample, January 4, 2007 to December 30, 2011 as the sample interval. And the model is incorporated return timing factor in order to remove the influence of return timing abilities. The empirical result shows that the majority of the funds' volatility timing coefficients are negative, but only 33.33% pass the significance test, which shows that small part of Chinese growth style mutual funds has significant volatility timing abilities. And the volatility timing coefficient is small, indicating that volatility timing skills of fund managers are weak. The reasons are unpredictability of the policy in China and lack of Short-Mechanism which limit volatility timing abilities of fund managers.

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Introduction

1.1 Purpose of Study

After the establishment of two stock exchanges, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), the Chinese mutual funds market has become one of the most important emerging markets. More and more experts in this field step into explore this new market. Volatility timing skills are an important component of mutual fund managers' performance. In order to help investors learn and choose mutual funds, the volatility timing skills of Chinese mutual fund managers must be taken into consideration.

1.2 Background

Mutual funds are investment vehicles that are derived from stocks, bonds, money market securities and other assets. As a professional financial instrument, mutual funds provide management, diversification, liquidity, convenience, low cost and high security, thus it has become an important investment tool in developed countries. Compared to western countries, the mutual fund market is new in China, it is still preferred by Chinese investors, especially during the downturn of the stock market. The mutual fund market in mainland China started in 1998 and it has gone through three stages: experimental fund stage, market reroute stage and development stage. Through the past 14 years, the Chinese mutual fund industry has followed trends in the development of the capital market and made great progress. With the advantage of professional managers' investment experiences and improved operational ability, inside control and risk management have been strengthened in China. The appropriate supervisory system was established and the related law on mutual funds investment has been made better. With the expanding scale of the mutual fund industry, the influence on capital market is deeper and the different fund styles have emerged. There are three primary mutual fund styles: growth, value and balanced. The purpose of the growth style is capital appreciation; this kind of mutual funds invests in the securities of companies that are in their growth stage. Value investing is considered to be a conservative strategy. Its basic goal is to invest in securities with stable regular income, such as blue chips, corporate bonds and government bonds. Balanced mutual fund style employs a combination of growth style and value style. This distinction can help investors choose the suitable mutual funds.

Nowadays, as investors face a wider and wider range of choices of mutual funds, it becomes more difficult for them to choose a suitable mutual fund. For this reason, investors focus on the performance of mutual fund managers. Market timing skill is an important component of fund managers' performance. Return timing ability measures fund managers' ability to forecast average market returns. If fund managers can forecast the overall trend of the market in the future, they will modify their portfolio holdings to increase the expected rate of return.

1.3 Need for the Study

Many scholars have done a lot of research on the market timing skills of fund managers, but there is still no unique conclusion drawn so far. This is because it is very hard to predict when the market will go up or down. There are various kinds of indicators for measuring the return timing skills, which tend to yield different results. Based on these factors, many scholars tend to focus on the volatility timing skills; and they have found that the characteristics of the market return volatility, such as cluster and persistence, increase the predictability. Compared to return timing ability, volatility timing skill is described as fund managers modify their holding portfolios' risks to increase the efficiency of their investments based on forecasting future volatility of the portfolio. As a new market, the stock market in China has been volatile over the past few years. Based on this point, this paper will examine the volatility timing skills of Chinese mutual fund managers, and see whether this skill can help investors choose mutual funds and fund managers based on their performances with respect to their volatility timing skills.

Literature Review

2.1 Modern Portfolio Theory

Harry Markowitz (1952) introduced Modern Portfolio Theory (MPT) in 1952. MPT is a financial theory which attributes how rationale investors take advantage of investment diversifications to optimize their portfolios.

More generally, MPT defines an asset's return as a normally distributed function. In the theory, the return on assets is a random variable. Since a portfolio is a weighted combination of various asset classes, the return of the portfolio should also be a random variable, thus the return of the portfolio has a mean and a variance. In the model, the risk is defined as the standard deviation of portfolio returns.

The basic concept of MPT is that the assets in the portfolio should not be selected solely based on their own merits, it is important to consider how each change in asset prices relative to other asset price changes. Therefore, MPT explains how to plan the best possible strategy of diversification.

2.2 Research on the Volatility Timing Skills

Sharpe (1966) evaluated 34 American mutual funds' performances from 1954 to 1963, during the research, he found that the main difference in the rate of return was caused by different fees of these mutual funds; and mutual funds performed poorer using Sharpe Index, compared to their performance using the Dow Jones Industrial Average (DJIA).

Treynor and Mazuy (1966) used the T-M model to evaluate the timing skills of the mutual fund managers for the first time. They argued that if fund managers can time the market, managers will adjust their holding portfolios based on the forecast of the stock market trend. Thus, they can buy and hold high volatile securities when stock market goes up, sell this kind of securities when stock market goes down. As a result, beta of stocks shows timing-varying characteristics, and the linear relationship between portfolios and market risks is no longer in existence. Thus they built the T-M model based on the Capital Asset Pricing Model (CAPM), and used parameters in the model to estimate whether fund managers have market timing skills or not. Then they did the research on 57 mutual funds. The result shows that there is only one fund which has significant performance in market timing ability. No material evidence to claim if mutual fund managers possess the market timing skills.

Jensen (1969) carries out a famous index for evaluation of mutual funds performance based on CAPM. The index is called “Jensen’s Alpha”. Jensen employs the data of 115 American mutual funds during 1958 to 1964, but found little evidence to support portfolio managers’ stock selection skills.

Fama (1972) divides the forecasting abilities of mutual fund managers into two categories:

(i) Macro-forecasting-compared with fixed income securities (usually choosing risk free rate), mutual fund managers forecast changes of market returns and accordingly change the risk of their holding portfolios;

(ii) Micro-forecasting-many studies on measuring stock selection skills of mutual funds managers, it means fund managers forecast changes in price of one stock, compared with other stocks' price changes.

Alexander and Stover (1980) use the T-M model and 49 mutual funds during 1966 to 1971 as the sample, Treasury yields as the risk free rate, monthly return of NYSE as the benchmark, to do the empirical study. The empirical study indicates that funds in the sample have stock selection abilities in some extent, but little market timing abilities.

Henriksson and Merton (1981) apply Option Pricing Theory (OPT) into the measuring model of mutual fund market timing ability, thus the H-M model. Then they use parametric and nonparametric models to do the empirical study on monthly return rate of 116 mutual funds during 1968 to 1980. The research finds that 62% of mutual funds have negative market timing abilities, although the significance level of the result does not meet the 5%, thus there is no strong evidence to support market timing abilities of fund managers.

Veit and Chenry (1982) use 74 mutual funds during 1944 to 1978 as the sample, the return of S&P 500 as the benchmark, to do the empirical study based on CAPM. The research finds that mutual funds have stock selection abilities in some extent, but no significant market timing abilities.

Chang and Lewellen (1985) carries out the research based on Arbitrage Pricing Theory (APT), in order to avoid conclusion deviation caused by the differences between assumptions in CAPM and situations in reality. They separate market operation status into bullish and bearish, then do regression analysis on the beta in the two status and judge whether mutual funds have market timing skills based on the differences of beta. The result shows there is little evidence on supporting significant stock selection skills and market timing abilities.

Bhattacharya and Pfliederer (1986) put forward a simple regression technique to evaluate stock selection skills and market timing skills of fund managers, and do research by employing monthly data from 1970 to 1980. The empirical study shows that there is little evidence on supporting market timing abilities.

Jeffrey A. Busse (1999) introduces volatility into the evaluation model of mutual fund timing skills. He thinks there are two reasons for introducing volatility into the measurement:

(i) Volatility is a major factor which influences the assets performance, and compared with market return, market volatility is easier to observe and predict;

(ii) If market return has no positive relationship with volatility, fund managers can improve asset return by reducing the exposure to market, when market fluctuations increases.

Busse employs 230 equity funds' daily returns during January 1985 to December 1995, and use one factor, three factors and four factors models to detect volatility timing skills. The research finds that fund managers will change the exposure to the market when market volatility increase, thus prove fund managers have volatility timing skills. But more scholars' research (French, Schwert and Stambaugh (1987); Campbell (1987); Glosten, Jagannathan and Runkle (1993); Whitelaw (2000)) indicates that there is no significant positive or negative relationship between conditional market return and conditional market volatility. If there is no significant relationship between conditional market return and conditional market volatility, fund managers can reduce the exposure to the market when conditional market volatility increases.

The research of Busse does not consider the influence of traditional return timing factors, but no matter volatility timing or return timing, the basis of market volatility changes and the market trends have close relationship.

Goetzmann, Ingersoll and Ivkovic (2000) introduce simulation method into the GII model and the H-M model, and use the CAPM and Fama-French three factors model as assets pricing model to construct four models for empirical studies. They employ one simulated market index and 558 returns of simulated funds as the sample. The research finds all funds in the sample have no significantly positive market timing abilities; the GII model observes market timing abilities in some extent, thus its ability of testing has been improved. Survivorship bias and differences of funds' types has a huge influence on the result.

Bollen and Busse (2001) employ the way that evaluation frequency follows decision frequency to deal with frequency synchronization problem. They introduce momentum effect into the three factors model to construct the four factors model.

The result shows that some funds have exactly real market timing abilities, and the coefficient of fund market timing abilities in the reality is three times higher than the simulated ones. After using the daily data, more market timing abilities of mutual funds showed significant positive.

Fleming, Kirby and Ostdiek (2001) do further research on the economic meaning of volatility timing skills. They think that although Busse finds the existence of volatility timing abilities, it can not explain volatility timing activity must be caused by market volatility. Their empirical study indicates that volatility timing has a significant economic value. In 2002, they conducte research on volatility timing ability using realized volatility, and the result indicates that volatility timing ability is more significant.

Jiang (2003) puts forward that managers who really have market timing skills should actively make the timing decisions. Based on the idea of Henriksson and Melton, he assumes that fund managers' forecast on the next market returns of funds are based on the information in this period; so he compares the probability of the right forecast with the probability of the wrong forecast. If this is positive, it states that fund managers have market timing abilities.

Keith Cuthbertson and Dirk Nitzsche (2006) do empirical study on the volatility timing skills of mutual funds by using nonparametric method, the study shows that small portion of mutual funds (about 1.5%) has positive timing abilities and significant in 5% confidence level; 10% to 20% of mutual funds have negative timing abilities, and the rest has not showed timing abilities.

ErasmoGiambona and Joseph Golec (2007) indicate that compensation drive partly on the volatility timing skills of mutual fund managers, and the more of the management fee, the less of using counter-cyclical or pro-cyclical volatility timing strategies. The active style of mutual funds would like choosing counter-cyclical operations, thus reduce the beta of portfolio when market volatility increases. In the result, fund managers would like employing active management style to outperform the market.

2.3 Research Undertaken By Chinese Scholars

Mutual fund market started recently in China, the research on market timing skills of mutual fund managers are mainly based on mature theories and models from abroad, using classic models such as the T-M model, the H-M model, the C-L model, to do empirical studies.

Shen and Huang (2001) evaluate performances of 70 funds from May 14, 1999 to March 23, 2001. They use three analysis methods, risk adjusted index, the T-M model and the H-M model, to do the research. They employ weighted average of 40% Shanghai composite index return rate, 40% Shenzhen component index return rate and 20% Treasury yields, as the benchmark. The result shows that the performance of mutual funds in China outperforms the market, but it is contributed by stock selection skills of fund managers, not timing skills of fund managers.

Wang (2002) employs the T-M, the H-M and the GII models which are based on the

CAPM and Fama-French three factors model to do the empirical study, and uses 33 funds which starte trading in the end of 2001. The study finds that funds have different timing skills in different time periods. In 1999, funds show weak security selection skills, but strong timing abilities; in 2000, funds in the sample perform well in both stock selection skills and market timing skills; in 2001, funds show strong security selection skills, but weak timing skills. Generally speaking, there is no material evidence to support market timing abilities of mutual funds, and security selection skills have little contribution to the funds' returns. The result also indicates that some differences in security selection skill and market timing ability are caused by differences in mutual funds. Only small parts of mutual funds perform persistent in timing skills, most of funds perform unstable.

Zhang and Du (2002) use 22 mutual funds from December 31, 1999 to September 28, 2001 as the sample, and 28 days treasury repurchase rate as the risk free rate. They employ the Sharpe index, the Treynor index and the Jensen index to evaluate these funds' performance after eliminating effect of new shares placement. The research indicates that mutual funds in China underperform the benchmark and no excellent stock selection skills and timing abilities.

Based on the modified volatility timing model, Ma, Fu and Yang (2005) introduce market volatility which has better effect on the forecast, instead of market return, to evaluate mutual funds in Chinese security market. During the research, they find that fund managers reduce market exposure of their holding assets when market risks increase; and compared to the closed-end funds, this behavior of open-ended funds are more obvious. However, there are no huge differences between different styles of funds, thus mutual funds in the Chinese market show significant volatility timing skills, and open-ended funds are better than closed-end funds.

Yang (2008) does empirical study on the security selection skills and market timing abilities of equity funds and mixed fund managers in China from January 2003 to April 2008. The research employs Jensen's Alpha, the T-M model and the H-M model, and divides the study period into bull market time and bear market time. The study finds that more than half of the funds in the sample outperform the market; funds perform strong market timing abilities in bear market and strong security selection skills in bull market.

Liu (2009) does empirical study on 57 different types of mutual funds in different time periods. The study finds:

(i) Slant model fund and balanced fund have positive market timing abilities, partial debt fund has negative timing abilities;

(ii) From market timing point, funds show stronger timing abilities, thus like "stop loss", funds have the characteristics of risk aversion;

(iii) Generally speaking, mutual funds obtain abnormal return through market timing abilities, it is a big challenge on Efficient Market Hypothesis (EMH), and it indicates Chinese market is still not efficient.

From all these studies, the empirical study on timing abilities of mutual fund manager employs parametric method, few by using nonparametric method; and most use the T-M model, the H-M model, or modified models based on these two models. A large percentage of the studies show that mutual fund managers have no timing abilities. When Busse employs volatility timing skills in 1999, scholars focus on volatility timing skills of mutual fund managers, and research before this idea is regarded as return timing abilities. Return timing abilities are based on forecast of market return rate; volatility timing skills are based on forecast of market volatility. Because of the cluster and persistence of market volatility, it is easier to forecast market volatility, compared with market return rate. Thus, this paper will do an empirical study on timing skills of mutual fund managers based on market volatility.

Data and Methodology

3.1 Data selection

In order to totally reflect the volatility timing abilities of Chinese mutual fund managers, this paper chooses 45 growth style funds which set up before January 1, 2007; and mutual fund investment is a long-term investment, investors pay more attention to long-term performance, so this paper sets the investigation period from January 1, 2007 to December 30, 2011. From the data selection aspect, most researches on volatility timing abilities from abroad choose daily data. The reasons are that volatility timing ability of mutual funds reflects the characteristics of high frequent time series, and these funds need to publish net asset value (NAV) every day, operation cycle is close to one day. So this paper also chooses daily data for reflecting fund managers' volatility timing abilities better; and after carefully investigation, there are six funds which do not provide sufficient daily data. So the paper used 39 growth style mutual funds. All data are picked from the Hexun mutual funds database.

3.2 Methodology

The research on market timing abilities of mutual funds starts earlier, but there are two defects in these researches:

(i) The concept of market timing abilities describes fully enough in the model, but there is no material evidence to support significant timing skills of fund managers in the empirical studies; mutual fund managers have certain timing skills is no doubt a fact. There is huge discrepancy between theory and reality;

(ii) Market timing abilities is a kind of dynamic behavior that mutual fund managers do based on historical data; but the model only includes historical return information; it does not reflect the information like forecast of market volatility.

The discrepancy between theory and reality causes continuously researches on timing skills, and a new research method came out at the same time, Busse put forward the idea of volatility timing in 1999. Busse (1999) thought the model of timing abilities should include market volatility factor, and firstly proved exist of volatility timing abilities in theory, thus if fund managers have timing skills, beta of fund should follow the downtrend with the increase of market volatility, when there is no significant positive relationship between conditional market return and volatility; this means $\partial\beta_{mp}/\partial\sigma_{mt} \leq 0$; certainly that not all fund managers will reduce systematic risk with increasing volatility, this assumption can be used to examine whether mutual fund managers have volatility timing abilities or not. So from this aspect, there is time- varying relationship between beta of mutual funds and volatility.

Busse viewed market volatility as information factor, and built relationship between beta coefficient and market volatility:

$\beta_{mp} = \beta_{1p} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma_m})$ (1)

Where:

σ_{mt}: Standard deviation of market return at the period t;

$\overline{\sigma_m}$: Average standard deviation of market return at the period t;

β_{1p}: Constant term in the formula;

γ_{mp}: Reflect volatility timing skills of mutual fund managers, thus time- varying relationship between beta of mutual funds and volatility, $\gamma_{mp}=\partial\beta_{mp}/\partial\sigma_{mt}$; when γ_{mp} is negative, it indicates fund managers have volatility timing skills, the smaller the value, the stronger the volatility timing skills of fund managers.

Introducing formula (1) into T-M model, we can get the single factor model:

$r_{pt} - r_f = \alpha_p + \beta_{1p}(r_{mt} - r_f) + \gamma_{mp}(r_{mt} - r_f)(\sigma_{mt} - \overline{\sigma_m}) + \beta_{tp}(r_{mt} - r_f)^2 + \varepsilon_{pt}$(2)

Where:

r_{pt}: Return of fund p at the period t;

$r_{pt} - r_f$: Abnormal return of fund p at the period t;

r_{mt}: Return of market portfolio at the period t;

$r_{mt} - r_f$: Abnormal return of market portfolio at the period t;

α_p: Constant term in the formula, presenting security selection skills of fund managers, α_p>0 indicates that fund managers have security selection skills;

β_{tp}: Indicator of fund manager's timing ability, when β_{tp}>0, no matter $(r_{mt} - r_f)$ is positive or negative, the contribution of $\beta_{tp}(r_{mt} - r_f)^2$ on the abnormal return of fund is positive, thus β_{tp}>0 indicates that fund manager succeeds in forecasting changes of market, and allocate assets reasonably between market portfolio and risk free asset; the larger the β_{tp}, the stronger the fund manager's market timing ability.

This paper will employ the model above to do empirical study on Chinese growth style mutual funds, and investigate whether fund managers have volatility timing skills or not.

3.3 How to Determine the Parameters In the Model

From the single factor model above, we can see that parameters which need to be determined are: risk free rate r_f, return of fund p r_{pt}, return of market portfolio r_{mt} and market volatility σ_{mt}.

3.3.1 The Selection of Risk Free Rate

Researched from abroad usually use treasury bills yields as the risk free rate, for example, return rate of 30 days treasury bills. But in China, bond market is mainly constitute by long-term treasury bonds, even if there are bonds which maturity are in one year, their market price can not present the lowest standard return in the investment. In theory, interbank market treasury bonds' repurchase rates can be used as the risk free rate, but its trade is influenced by demand and supply of the market, so it is also not the lowest standard return of the investment. So both rates can not be used as the risk free rate.

This paper will use the practice in China that is choosing the one-year deposit interest rate as the risk free rate, and convert it into daily risk free rate according to 365 trading days.

Date	One-year deposit interest rate	Daily risk free rate
2006.08.19-2007.03.17	0.0252	0.000069041095890411
2007.03.18-2007.05.18	0.0279	0.0000764383561643836
2007.05.19-2007.07.20	0.0306	0.0000838356164383562
2007.07.21-2007.08.21	0.0333	0.0000912328767123288
2007.08.22-2007.09.14	0.036	0.0000986301369863014
2007.09.15-2007.12.20	0.0387	0.000106027397260274
2007.12.21-2008.10.08	0.0414	0.000113424657534247
2008.10.09-2008.10.29	0.0387	0.000106027397260274
2008.10.30-2008.11.26	0.036	0.0000986301369863014

2008.11.27-2008.12.22	0.0252	0.000069041095890411
2008.12.23-2010.10.19	0.0225	0.0000616438356164384
2010.10.20-2010.12.25	0.025	0.0000684931506849315
2010.12.26-2011.02.08	0.0275	0.0000753424657534247
2011.02.09-2011.04.05	0.03	0.0000821917808219178
2011.04.06-2011.07.06	0.0325	0.000089041095890411
2011.07.07-2012.06.07	0.035	0.0000958904109589041

Table 3.1 Risk Free Rate

3.3.2 Calculation of Fund's Return Rate

The arithmetic daily rate of return is calculated as follow:

$$r_{pt} = \frac{NAV_{end} - NAV_{beg}}{NAV_{beg}} \qquad (3)$$

Where:

r_{pt}: Arithmetic daily rate of return;

NAV_{beg}: Net asset value at the beginning of the trading day;

NAV_{end}: Net asset value at the end of the trading day.

3.3.3 The Selection of Market Portfolio Return

In the selection of market portfolio return, market index can generally represent market portfolio. This paper focuses on Chinese growth style mutual funds and time interval is from January 4, 2007 to December 30, 2011, so the paper chooses Shanghai-Shenzhen 300 index as the market portfolio return. Shanghai-Shenzhen 300 index was established on April 8, 2005 by SSE and SZSE, it reflects the overall trend of A-share market. The establishment objective of Shanghai-Shenzhen 300 index is to reflect the overview of Chinese securities' price changes and operation status, and is able to be the benchmark of investment performance. It provides basic conditions for indexing investment and innovation of index derivatives. Shanghai-Shenzhen 300 index covers around 60% value of A-share market, it has good market representative.

Market portfolio return = Shanghai-Shenzhen 300 index return

Calculation formula: $r_{mt} = (INDEX_t - INDEX_{t-1})/INDEX_{t-1}$ (4)

3.3.4 Daily Market Return Volatility

The research on volatility is starting nearly 20 years in the financial area. There are mainly two kinds of models:

(i) One is using historical information to forecast future volatility, referred to historical information method, such as the ARCH model, Stochastic Volatility model (SV model);

(ii) The other one is deducing expectation of future volatility, according to option price, thus implied volatility.

Because the option market in Chinese mainland is a new market, the trading price deviate seriously from the theoretical price, it can not be used for implied volatility research. So the researches on volatility are mainly using historical information method. This paper chooses daily market return volatility directly from Bloomberg database.

The Result and Analysis of Empirical Study on Volatility Timing Abilities

4.1 The Empirical Result

According to the single factor model, γ_{mp} represents the volatility timing abilities of mutual fund managers. If fund managers have volatility timing abilities, they would reduce the systematic risk of funds when market volatility is high, and increase systematic risk of funds when market volatility is low. γ_{mp} reflects time-varying relationship between systematic risk of funds and market volatility, if γ_{mp} is negative, it represents fund managers have volatility timing skills, and the lower the value of γ_{mp}, the stronger the volatility timing skills of mutual fund managers.

In order to explain the volatility timing abilities of growth style mutual funds in China, substituting funds return rate, daily risk free rate, daily market return volatility into the single factor model, use ordinary least squares (OLS) method to do the regression and get volatility timing coefficient γ_{mp}. Regression result is shown in table 4.1.

Fundid	γ_{mp}	R-squared
000001	-0.270**	0.443
000021	-0.330***	0.595
020001	-0.455**	0.31

020003	-0.000924	0.307
020005	0.147	0.389
040001	-0.106	0.246
070002	-0.0441	0.808
070006	-0.0974**	0.872
100026	-0.144	0.472
110005	-0.350**	0.385
121005	0.0375	0.556
160106	-0.0511	0.839
161606	-0.201	0.521
161609	-0.0529	0.783
162102	0.00875	0.555
162703	-0.123**	0.89
163803	0.0133	0.422
202003	-0.211***	0.745
206001	-0.236	0.331

233001	-0.131	0.338
240001	0.24	0.375
240009	-0.0766*	0.926
253010	-0.398***	0.29
260108	-0.432***	0.491
310318	0.0118	0.274
310328	-0.234**	0.606
320005	0.115	0.556
360006	0.175	0.579
378010	-0.0098	0.724
400001	0.316***	0.515
400003	0.262*	0.451
450002	-0.266**	0.58
460001	0.11	0.342
519692	-0.268***	0.882
530003	-0.138	0.574

540002	0.00058	0.674
550002	-0.133	0.474
560002	0.0539	0.563
580001	-0.0806	0.488

Table 4.1 OLS Result

(*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

4.2 The Analysis of the Result

From the result of empirical study using single factor model, 26 mutual funds' volatility timing coefficients are negative in the sample of 39 funds, thus they have volatility timing abilities in some extent; but only 13 funds pass the significance test, 33.33% of the sample; there are 13 mutual funds which volatility timing coefficients are positive, 33.33% of the sample, 400001 and 400003 pass the significance test. The result shows that some mutual fund managers take positive reactions when facing market volatility, reduce the systematic risk of funds timely when market volatility is high, and increase systematic risk in time of lower market volatility.

Moreover, the value of γ_{mp} reflects the strength of mutual fund volatility timing abilities, the negative coefficient represents fund managers have volatility timing skills; the smaller the coefficient indicates the stronger the volatility timing abilities. From the empirical study result, most of the volatility timing coefficient values are small; 020001 has the optimal performance on volatility timing ability in the sample, its volatility timing coefficient is -0.455, the second is 260108 which volatility timing coefficient is -0.432. Thus, Chinese growth style mutual funds show minor volatility timing behavior.

Conclusions and Recommendations

5.1 Conclusions

This paper chooses 39 growth style funds which set up before January 1, 2007 as the sample, using parametric method to do empirical study on volatility timing abilities of these funds from January 1, 2007 to December 30, 2011. This paper employs daily data and modified Busse volatility timing model, thus introduced return timing factor into the volatility timing model to remove such effect.

The empirical result indicats that, most volatility timing coefficients of growth style mutual funds are negative, but only 33.33% passed t test. This means small part of the sample shows volatility timing abilities in some extent, thus mutual fund manages reduce the exposure to market timely for reducing systematic risk of funds when market volatility is high, and increase the exposure to market in time of lower market volatility with the result of higher systematic risk; but values of volatility timing coefficient are small, fund managers perform weak in volatility timing abilities.

There are several reasons for this result:

(i) Unpredictability of the policy: Chinese securities market is more susceptible to be influenced by the policy, the frequent changes in policy leads to the volatility of Chinese stock market is relatively high, predictability is low; this prejudices asset management of fund managers and has negative impact on volatility timing abilities of mutual fund managers. Market imperfection and the prevalence of short-term trading also cause high volatility in the market, thus not good for long-term trading of mutual funds. Mutual funds focus on long-term investments and value investing, the sizes of mutual funds are generally large, so that fund managers usually need some time to adjust the allocation of the holding assets after publishing announcements. So fund managers can only passively accept various kinds of implications from the policy side, unable to play their volatility timing abilities more powerful.

(ii) Lack of Short-Mechanism leads to limitations on volatility timing abilities of mutual fund managers. Mutual fund managers in China has limited kinds of hedging tools and re-investment vehicles; this restricts on volatility timing skills of fund managers, because it causes difficulties for fund managers to make appropriate adjustments on their assets, even if they have right forecast on market volatility.

5.2 Recommendations

Researches on volatility timing abilities of mutual funds mainly employed parametric method, using volatility timing model which is introduced by Busse and incorporating some factors to do the empirical study. From the building of the model, considering realities in Chinese mutual fund market, whether there are other factors that could impact on excess return of mutual funds or not, is still worth for further exploration. On the other hand, although Busse described the volatility timing abilities of mutual funds, the relationship between volatility timing abilities of fund managers and the performance of funds has no reasonable analysis; so how to study the relationship and apply into the model has great meanings in both theory and reality aspects.

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Appendix A: Summary of the Empirical Study Data

Variable	Obs	Mean	Std. Dev.	Min	Max
id	47502	20	11.25475	1	39
fundid	47502	252449.1	175589.5	1	580001
date	0				
fr	47463	-.0000796	.0223283	-.7666278	.4155272
mr	47463	.0003403	.0216918	-.0923981	.0934198
hisvol	47502	.3174298	.1450463	.06477	.78669
avervol	47502	.3174298	0	.3174298	.3174298
rf	47502	.0000821	.0000198	.0000616	.0001134
r1	47501	-.0001617	.0223208	-.7667338	.4154508
rm	47501	.0002579	.021685	-.0924671	.0933064
vol	47501	1.53e-06	.1450474	-.2526598	.4692602
rmvol	47501	-.0000835	.0044503	-.0303708	.0408649
rm2	47501	.0004703	.0009152	3.41e-10	.0087061

Appendix B:

-> id = 1

Source	SS	df	MS
Model	.269235718	3	.089745239
Residual	.339059236	1213	.000279521
Total	.608294954	1216	.000500243

Number of obs	=	1217
F(3, 1213)	=	321.07
Prob > F	=	0.0000
R-squared	=	0.4426
Adj R-squared	=	0.4412
Root MSE	=	.01672

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7160142	.0278721	25.69	0.000	.6613313	.7706972
rmvol	-.2697839	.1347507	-2.00	0.045	-.5341543	-.0054135
rm2	-.2387024	.528675	-0.45	0.652	-1.275921	.7985165
_cons	-.000429	.000541	-0.79	0.428	-.0014904	.0006323

-> id = 2

Source	SS	df	MS
Model	.324372066	3	.108124022
Residual	.22120791	1214	.000182214
Total	.545579976	1217	.000448299

Number of obs	=	1218
F(3, 1214)	=	593.39
Prob > F	=	0.0000
R-squared	=	0.5945
Adj R-squared	=	0.5935
Root MSE	=	.0135

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7911119	.0225036	35.15	0.000	.7469617	.8352622
rmvol	-.329571	.1087963	-3.03	0.003	-.5430206	-.1161214
rm2	-.0191034	.4267992	-0.04	0.964	-.8564493	.8182425
_cons	-.0000964	.0004365	-0.22	0.825	-.0009528	.0007601

-> id = 3

Source	SS	df	MS
Model	.278841286	3	.092947095
Residual	.620729914	1214	.00051131
Total	.8995712	1217	.000739171

Number of obs	=	1218
F(3, 1214)	=	181.78
Prob > F	=	0.0000
R-squared	=	0.3100
Adj R-squared	=	0.3083
Root MSE	=	.02261

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7383264	.0376967	19.59	0.000	.6643685	.8122842
rmvol	-.4551566	.182249	-2.50	0.013	-.8127145	-.0975987
rm2	-1.504205	.7149483	-2.10	0.036	-2.906876	-.1015337
_cons	.0000878	.0007313	0.12	0.904	-.0013468	.0015225

-> id = 4

Source	SS	df	MS
Model	.312057267	3	.104019089
Residual	.705169944	1214	.000580865
Total	1.01722721	1217	.000835848

Number of obs	=	1218
F(3, 1214)	=	179.08
Prob > F	=	0.0000
R-squared	=	0.3068
Adj R-squared	=	0.3051
Root MSE	=	.0241

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7326596	.0401789	18.23	0.000	.6538317	.8114875
rmvol	-.0009245	.1942498	-0.00	0.996	-.3820271	.3801782
rm2	-.8584678	.7620267	-1.13	0.260	-2.353503	.6365675
_cons	-.0003559	.0007794	-0.46	0.648	-.001885	.0011732

-> id = 5

Source	SS	df	MS
Model	.380431517	3	.126810506
Residual	.597399251	1214	.000492092
Total	.977830768	1217	.000803476

Number of obs	=	1218
F(3, 1214)	=	257.70
Prob > F	=	0.0000
R-squared	=	0.3891
Adj R-squared	=	0.3875
Root MSE	=	.02218

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7964002	.0369815	21.54	0.000	.7238455	.8689548
rmvol	.1473109	.1787912	0.82	0.410	-.2034631	.4980849
rm2	-.0199388	.7013836	-0.03	0.977	-1.395997	1.35612
_cons	-.0004402	.0007174	-0.61	0.540	-.0018476	.0009673

-> id = 6

Source	SS	df	MS
Model	.208969109	3	.06965637
Residual	.639135947	1214	.000526471
Total	.848105056	1217	.000696882

Number of obs	=	1218
F(3, 1214)	=	132.31
Prob > F	=	0.0000
R-squared	=	0.2464
Adj R-squared	=	0.2445
Root MSE	=	.02294

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.6164114	.0382515	16.11	0.000	.541365	.6914577
rmvol	-.1063142	.1849313	-0.57	0.565	-.4691346	.2565061
rm2	-.0833806	.7254707	-0.11	0.909	-1.506696	1.339935
_cons	-.0005606	.000742	-0.76	0.450	-.0020164	.0008952

-> id = 7

Source	SS	df	MS
Model	.199588211	3	.066529404
Residual	.047334218	1214	.00003899
Total	.246922429	1217	.000202894

Number of obs	= 1218
F(3, 1214)	= 1706.31
Prob > F	= 0.0000
R-squared	= 0.8083
Adj R-squared	= 0.8078
Root MSE	= .00624

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.5932163	.0104097	56.99	0.000	.5727932	.6136393
rmvol	-.0440545	.050327	-0.88	0.382	-.1427922	.0546831
rm2	-.4065647	.197429	-2.06	0.040	-.7939046	-.0192249
_cons	.000595	.0002019	2.95	0.003	.0001988	.0009911

-> id = 8

Source	SS	df	MS
Model	.309125639	3	.10304188
Residual	.045494355	1214	.000037475
Total	.354619994	1217	.000291389

Number of obs	= 1218
F(3, 1214)	= 2749.63
Prob > F	= 0.0000
R-squared	= 0.8717
Adj R-squared	= 0.8714
Root MSE	= .00612

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7444199	.0102054	72.94	0.000	.7243977	.7644421
rmvol	-.0974399	.0493392	-1.97	0.049	-.1942395	-.0006402
rm2	-.3486849	.1935539	-1.80	0.072	-.7284222	.0310525
_cons	.0005159	.000198	2.61	0.009	.0001275	.0009043

-> id = 9

Source	SS	df	MS
Model	.319815651	3	.106605217
Residual	.357071869	1214	.000294128
Total	.67688752	1217	.000556194

Number of obs	= 1218
F(3, 1214)	= 362.44
Prob > F	= 0.0000
R-squared	= 0.4725
Adj R-squared	= 0.4712
Root MSE	= .01715

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7643214	.028591	26.73	0.000	.7082282	.8204147
rmvol	-.1440253	.1382266	-1.04	0.298	-.4152148	.1271642
rm2	-.0554715	.5422519	-0.10	0.919	-1.119326	1.008383
_cons	-.0002615	.0005546	-0.47	0.637	-.0013496	.0008266

-> id = 10

Source	SS	df	MS
Model	.274939272	3	.091646424
Residual	.438409852	1214	.000361128
Total	.713349124	1217	.000586154

Number of obs	=	1218
F(3, 1214)	=	253.78
Prob > F	=	0.0000
R-squared	=	0.3854
Adj R-squared	=	0.3839
Root MSE	=	.019

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7303575	.0316805	23.05	0.000	.6682029	.7925121
rmvol	-.3499954	.153163	-2.29	0.022	-.650489	-.0495018
rm2	-.5099063	.6008463	-0.85	0.396	-1.688719	.6689062
_cons	-.0005284	.0006146	-0.86	0.390	-.0017341	.0006773

-> id = 11

Source	SS	df	MS
Model	.351115543	3	.117038514
Residual	.280609858	1214	.000231145
Total	.631725401	1217	.000519084

Number of obs	=	1218
F(3, 1214)	=	506.34
Prob > F	=	0.0000
R-squared	=	0.5558
Adj R-squared	=	0.5547
Root MSE	=	.0152

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7775872	.0253456	30.68	0.000	.7278611	.8273133
rmvol	.037512	.1225364	0.31	0.760	-.2028947	.2779187
rm2	-.132883	.4807007	-0.28	0.782	-1.075979	.8102133
_cons	-.0004961	.0004917	-1.01	0.313	-.0014607	.0004685

-> id = 12

Source	SS	df	MS
Model	.356589943	3	.118863314
Residual	.068186997	1214	.000056167
Total	.42477694	1217	.000349036

Number of obs	=	1218
F(3, 1214)	=	2116.24
Prob > F	=	0.0000
R-squared	=	0.8395
Adj R-squared	=	0.8391
Root MSE	=	.00749

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7941753	.012494	63.56	0.000	.769663	.8186876
rmvol	-.0510749	.0604038	-0.85	0.398	-.1695824	.0674326
rm2	-.1971253	.2369595	-0.83	0.406	-.6620208	.2677702
_cons	-.0000397	.0002424	-0.16	0.870	-.0005152	.0004358

-> id = 13

Source	SS	df	MS
Model	.463655935	3	.154551978
Residual	.425477514	1214	.000350476
Total	.889133449	1217	.000730594

Number of obs	=	1218
F(3, 1214)	=	440.98
Prob > F	=	0.0000
R-squared	=	0.5215
Adj R-squared	=	0.5203
Root MSE	=	.01872

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.9246382	.0312097	29.63	0.000	.8634072	.9858692
rmvol	-.2006627	.1508871	-1.33	0.184	-.4966911	.0953657
rm2	.1412728	.591918	0.24	0.811	-1.020023	1.302569
_cons	-.0008051	.0006054	-1.33	0.184	-.0019929	.0003827

-> id = 14

Source	SS	df	MS
Model	.337358939	3	.11245298
Residual	.093285989	1214	.000076842
Total	.430644928	1217	.000353858

Number of obs	=	1218
F(3, 1214)	=	1463.43
Prob > F	=	0.0000
R-squared	=	0.7834
Adj R-squared	=	0.7828
Root MSE	=	.00877

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7718137	.0146137	52.81	0.000	.7431428	.8004845
rmvol	-.0528623	.0706516	-0.75	0.454	-.1914751	.0857505
rm2	-.3599125	.2771606	-1.30	0.194	-.9036794	.1838544
_cons	-.0001909	.0002835	-0.67	0.501	-.0007471	.0003653

-> id = 15

Source	SS	df	MS
Model	.271570497	3	.090523499
Residual	.217996459	1214	.000179569
Total	.489566955	1217	.000402274

Number of obs	=	1218
F(3, 1214)	=	504.12
Prob > F	=	0.0000
R-squared	=	0.5547
Adj R-squared	=	0.5536
Root MSE	=	.0134

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.6833597	.0223396	30.59	0.000	.6395311	.7271884
rmvol	.0087455	.1080037	0.08	0.935	-.203149	.2206401
rm2	-.6567788	.4236898	-1.55	0.121	-1.488024	.1744666
_cons	-.0000618	.0004334	-0.14	0.887	-.000912	.0007884

-> id = 16

Source	SS	df	MS
Model	.484810693	3	.161603564
Residual	.0601533	1214	.00004955
Total	.544963993	1217	.000447793

Number of obs =	1218
F(3, 1214) =	3261.45
Prob > F =	0.0000
R-squared =	0.8896
Adj R-squared =	0.8893
Root MSE =	.00704

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.9322601	.011735	79.44	0.000	.9092371	.9552832
rmvol	-.1228821	.056734	-2.17	0.031	-.2341897	-.0115745
rm2	-.4524431	.222563	-2.03	0.042	-.8890939	-.0157923
_cons	.0002823	.0002276	1.24	0.215	-.0001644	.0007289

-> id = 17

Source	SS	df	MS
Model	.31896898	3	.106322993
Residual	.436194204	1214	.000359303
Total	.755163184	1217	.000620512

Number of obs =	1218
F(3, 1214) =	295.91
Prob > F =	0.0000
R-squared =	0.4224
Adj R-squared =	0.4210
Root MSE =	.01896

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7433067	.0316003	23.52	0.000	.6813094	.8053041
rmvol	.0132618	.1527755	0.09	0.931	-.2864715	.3129951
rm2	-.2312024	.5993261	-0.39	0.700	-1.407032	.9446276
_cons	-.0003959	.000613	-0.65	0.518	-.0015986	.0008067

-> id = 18

Source	SS	df	MS
Model	.316776826	3	.105592275
Residual	.108661124	1214	.000089507
Total	.42543795	1217	.000349579

Number of obs =	1218
F(3, 1214) =	1179.71
Prob > F =	0.0000
R-squared =	0.7446
Adj R-squared =	0.7440
Root MSE =	.00946

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7686874	.0157721	48.74	0.000	.7377438	.7996309
rmvol	-.2112172	.0762519	-2.77	0.006	-.3608174	-.061617
rm2	-.0407012	.2991303	-0.14	0.892	-.6275708	.5461685
_cons	-.0002329	.000306	-0.76	0.447	-.0008331	.0003674

-> id = 19

Source	SS	df	MS
Model	.26343162	3	.08781054
Residual	.532676784	1214	.000438778
Total	.796108405	1217	.000654156

Number of obs	=	1218
F(3, 1214)	=	200.13
Prob > F	=	0.0000
R-squared	=	0.3309
Adj R-squared	=	0.3292
Root MSE	=	.02095

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.6971443	.0349207	19.96	0.000	.6286325	.765656
rmvol	-.2358047	.1688285	-1.40	0.163	-.5670326	.0954232
rm2	-1.243584	.6623006	-1.88	0.061	-2.542965	.0557963
_cons	.000207	.0006774	0.31	0.760	-.001122	.001536

-> id = 20

Source	SS	df	MS
Model	.321048419	3	.10701614
Residual	.62962727	1214	.000518639
Total	.950675689	1217	.000781163

Number of obs	=	1218
F(3, 1214)	=	206.34
Prob > F	=	0.0000
R-squared	=	0.3377
Adj R-squared	=	0.3361
Root MSE	=	.02277

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7585881	.0379659	19.98	0.000	.6841021	.8330741
rmvol	-.1305331	.1835505	-0.71	0.477	-.4906445	.2295782
rm2	-.8911543	.720054	-1.24	0.216	-2.303843	.5215339
_cons	-.0002789	.0007365	-0.38	0.705	-.0017239	.001166

-> id = 21

Source	SS	df	MS
Model	.240352491	3	.080117497
Residual	.401154692	1214	.00033044
Total	.641507183	1217	.000527122

Number of obs	=	1218
F(3, 1214)	=	242.46
Prob > F	=	0.0000
R-squared	=	0.3747
Adj R-squared	=	0.3731
Root MSE	=	.01818

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.6170137	.0303045	20.36	0.000	.5575587	.6764688
rmvol	.239953	.1465108	1.64	0.102	-.0474895	.5273955
rm2	-.0084791	.5747503	-0.01	0.988	-1.136093	1.119135
_cons	-.0002989	.0005879	-0.51	0.611	-.0014522	.0008545

-> id = 22

Source	SS	df	MS
Model	.372368417	3	.124122806
Residual	.029823529	1214	.000024566
Total	.402191946	1217	.000330478

Number of obs	=	1218
F(3, 1214)	=	5052.56
Prob > F	=	0.0000
R-squared	=	0.9258
Adj R-squared	=	0.9257
Root MSE	=	.00496

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.8149601	.0082629	98.63	0.000	.798749	.8311712
rmvol	-.0765712	.0399478	-1.92	0.056	-.1549456	.0018033
rm2	-.1240084	.1567122	-0.79	0.429	-.4314652	.1834484
_cons	.0000999	.0001603	0.62	0.533	-.0002146	.0004144

-> id = 23

Source	SS	df	MS
Model	.097839509	3	.03261317
Residual	.239382907	1214	.000197185
Total	.337222416	1217	.000277093

Number of obs	=	1218
F(3, 1214)	=	165.39
Prob > F	=	0.0000
R-squared	=	0.2901
Adj R-squared	=	0.2884
Root MSE	=	.01404

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.4496045	.0234098	19.21	0.000	.4036763	.4955327
rmvol	-.3982912	.1131776	-3.52	0.000	-.6203365	-.1762458
rm2	-.9577535	.4439866	-2.16	0.031	-1.82882	-.0866874
_cons	8.82e-06	.0004541	0.02	0.985	-.0008821	.0008998

-> id = 24

Source	SS	df	MS
Model	.315052614	3	.105017538
Residual	.326319171	1214	.000268797
Total	.641371785	1217	.000527011

Number of obs	=	1218
F(3, 1214)	=	390.70
Prob > F	=	0.0000
R-squared	=	0.4912
Adj R-squared	=	0.4900
Root MSE	=	.0164

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.789028	.0273321	28.87	0.000	.7354046	.8426514
rmvol	-.4321615	.1321402	-3.27	0.001	-.69141	-.1729129
rm2	-.4019778	.5183756	-0.78	0.438	-1.418989	.6150337
_cons	-.0005175	.0005302	-0.98	0.329	-.0015577	.0005227

-> id = 25

Source	SS	df	MS
Model	.02566972	3	.008556573
Residual	.068123519	1214	.000056115
Total	.093793239	1217	.000077069

Number of obs	=	1218
F(3, 1214)	=	152.48
Prob > F	=	0.0000
R-squared	=	0.2737
Adj R-squared	=	0.2719
Root MSE	=	.00749

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.2001087	.0124882	16.02	0.000	.1756078	.2246095
rmvol	.0118417	.0603757	0.20	0.845	-.1066106	.130294
rm2	-1.033238	.2368491	-4.36	0.000	-1.497918	-.5685594
_cons	.0002925	.0002423	1.21	0.227	-.0001827	.0007678

-> id = 26

Source	SS	df	MS
Model	.411228061	3	.13707602
Residual	.266813919	1214	.000219781
Total	.67804198	1217	.000557142

Number of obs	=	1218
F(3, 1214)	=	623.69
Prob > F	=	0.0000
R-squared	=	0.6065
Adj R-squared	=	0.6055
Root MSE	=	.01483

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.8731447	.0247147	35.33	0.000	.8246563	.921633
rmvol	-.2344524	.1194863	-1.96	0.050	-.4688749	-.0000299
rm2	-.3708193	.4687351	-0.79	0.429	-1.29044	.5488015
_cons	-.0005381	.0004794	-1.12	0.262	-.0014787	.0004025

-> id = 27

Source	SS	df	MS
Model	.320989755	3	.106996585
Residual	.25654475	1214	.000211322
Total	.577534506	1217	.000474556

Number of obs	=	1218
F(3, 1214)	=	506.32
Prob > F	=	0.0000
R-squared	=	0.5558
Adj R-squared	=	0.5547
Root MSE	=	.01454

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7268863	.0242345	29.99	0.000	.6793402	.7744323
rmvol	.1150389	.1171643	0.98	0.326	-.1148281	.3449059
rm2	-1.090948	.4596263	-2.37	0.018	-1.992698	-.1891977
_cons	.0001656	.0004701	0.35	0.725	-.0007567	.0010879

-> id = 28

Source	SS	df	MS
Model	.386254232	3	.128751411
Residual	.280413477	1214	.000230983
Total	.666667709	1217	.000547796

Number of obs	=	1218
F(3, 1214)	=	557.41
Prob > F	=	0.0000
R-squared	=	0.5794
Adj R-squared	=	0.5783
Root MSE	=	.0152

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7902222	.0253368	31.19	0.000	.7405135	.8399309
rmvol	.1753934	.1224935	1.43	0.152	-.0649292	.4157159
rm2	-1.303293	.4805324	-2.71	0.007	-2.246059	-.360527
_cons	.0003908	.0004915	0.80	0.427	-.0005734	.0013551

-> id = 29

Source	SS	df	MS
Model	.326985441	3	.108995147
Residual	.124374533	1214	.00010245
Total	.451359974	1217	.000370879

Number of obs	=	1218
F(3, 1214)	=	1063.88
Prob > F	=	0.0000
R-squared	=	0.7244
Adj R-squared	=	0.7238
Root MSE	=	.01012

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7572223	.016874	44.88	0.000	.7241169	.7903277
rmvol	-.0097983	.0815792	-0.12	0.904	-.1698502	.1502536
rm2	.0773593	.3200288	0.24	0.809	-.5505115	.7052301
_cons	-.000181	.0003273	-0.55	0.580	-.0008232	.0004612

-> id = 30

Source	SS	df	MS
Model	.262794423	3	.087598141
Residual	.247593097	1214	.000203948
Total	.51038752	1217	.000419382

Number of obs	=	1218
F(3, 1214)	=	429.51
Prob > F	=	0.0000
R-squared	=	0.5149
Adj R-squared	=	0.5137
Root MSE	=	.01428

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.6314223	.0238079	26.52	0.000	.5847131	.6781314
rmvol	.3161386	.115102	2.75	0.006	.0903176	.5419596
rm2	-.7895284	.4515362	-1.75	0.081	-1.675406	.0963494
_cons	-.0002435	.0004618	-0.53	0.598	-.0011496	.0006626

-> id = 31

Source	SS	df	MS
Model	.366492107	3	.122164036
Residual	.445906862	1214	.000367304
Total	.812398969	1217	.000667542

Number of obs =	1218
F(3, 1214) =	332.60
Prob > F =	0.0000
R-squared =	0.4511
Adj R-squared =	0.4498
Root MSE =	.01917

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.765473	.0319502	23.96	0.000	.7027893	.8281568
rmvol	.2616982	.154467	1.69	0.090	-.0413538	.5647502
rm2	-.1926679	.6059619	-0.32	0.751	-1.381517	.9961809
_cons	.0000417	.0006198	0.07	0.946	-.0011742	.0012577

-> id = 32

Source	SS	df	MS
Model	.282451363	3	.094150454
Residual	.204644365	1214	.00016857
Total	.487095727	1217	.000400243

Number of obs =	1218
F(3, 1214) =	558.52
Prob > F =	0.0000
R-squared =	0.5799
Adj R-squared =	0.5788
Root MSE =	.01298

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7317062	.0216447	33.81	0.000	.689241	.7741713
rmvol	-.2661765	.1046438	-2.54	0.011	-.4714794	-.0608737
rm2	-.3275394	.4105095	-0.80	0.425	-1.132926	.4778473
_cons	-.0002094	.0004199	-0.50	0.618	-.0010332	.0006143

-> id = 33

Source	SS	df	MS
Model	.284461149	3	.094820383
Residual	.546978245	1214	.000450559
Total	.831439394	1217	.000683188

Number of obs =	1218
F(3, 1214) =	210.45
Prob > F =	0.0000
R-squared =	0.3421
Adj R-squared =	0.3405
Root MSE =	.02123

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.688101	.0353864	19.45	0.000	.6186757	.7575263
rmvol	.1096839	.1710798	0.64	0.522	-.225961	.4453288
rm2	-.481355	.6711325	-0.72	0.473	-1.798063	.8353534
_cons	-.0004943	.0006864	-0.72	0.472	-.001841	.0008524

-> id = 34

Source	SS	df	MS
Model	.330472231	3	.11015741
Residual	.044128845	1214	.00003635
Total	.374601076	1217	.000307807

Number of obs	=	1218
F(3, 1214)	=	3030.47
Prob > F	=	0.0000
R-squared	=	0.8822
Adj R-squared	=	0.8819
Root MSE	=	.00603

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7903964	.0100511	78.64	0.000	.770677	.8101158
rmvol	-.2681926	.0485931	-5.52	0.000	-.3635285	-.1728567
rm2	-.1678808	.1906271	-0.88	0.379	-.5418758	.2061143
_cons	.0003636	.000195	1.86	0.062	-.0000189	.0007461

-> id = 35

Source	SS	df	MS
Model	.367345686	3	.122448562
Residual	.272220165	1214	.000224234
Total	.639565851	1217	.000525527

Number of obs	=	1218
F(3, 1214)	=	546.07
Prob > F	=	0.0000
R-squared	=	0.5744
Adj R-squared	=	0.5733
Root MSE	=	.01497

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.8159028	.0249639	32.68	0.000	.7669257	.8648799
rmvol	-.137861	.1206907	-1.14	0.254	-.3746465	.0989246
rm2	-.2780279	.4734601	-0.59	0.557	-1.206919	.6508631
_cons	-.0003363	.0004843	-0.69	0.488	-.0012864	.0006138

-> id = 36

Source	SS	df	MS
Model	.318953427	3	.106317809
Residual	.154493581	1214	.00012726
Total	.473447007	1217	.000389028

Number of obs	=	1218
F(3, 1214)	=	835.44
Prob > F	=	0.0000
R-squared	=	0.6737
Adj R-squared	=	0.6729
Root MSE	=	.01128

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7443018	.0188065	39.58	0.000	.707405	.7811985
rmvol	.0005804	.090922	0.01	0.995	-.1778013	.1789621
rm2	-.3206788	.3566798	-0.90	0.369	-1.020456	.3790984
_cons	-.0000327	.0003648	-0.09	0.929	-.0007484	.0006831

-> id = 37

Source	SS	df	MS
Model	.329316434	3	.109772145
Residual	.365655495	1214	.000301199
Total	.694971929	1217	.000571053

Number of obs =	1218
F(3, 1214) =	364.45
Prob > F =	0.0000
R-squared =	0.4739
Adj R-squared =	0.4726
Root MSE =	.01736

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7749038	.0289326	26.78	0.000	.7181403	.8316673
rmvol	-.1328905	.1398781	-0.95	0.342	-.4073202	.1415392
rm2	.1032689	.5487308	0.19	0.851	-.973297	1.179835
_cons	-.0003433	.0005612	-0.61	0.541	-.0014444	.0007578

-> id = 38

Source	SS	df	MS
Model	.343487484	3	.114495828
Residual	.266430067	1214	.000219465
Total	.609917551	1217	.000501165

Number of obs =	1218
F(3, 1214) =	521.71
Prob > F =	0.0000
R-squared =	0.5632
Adj R-squared =	0.5621
Root MSE =	.01481

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.7591974	.0246969	30.74	0.000	.710744	.8076509
rmvol	.0538687	.1194003	0.45	0.652	-.1803852	.2881225
rm2	-1.240846	.4683978	-2.65	0.008	-2.159805	-.3218867
_cons	-.0001274	.0004791	-0.27	0.790	-.0010673	.0008125

-> id = 39

Source	SS	df	MS
Model	.249182915	3	.083060972
Residual	.261740294	1214	.000215602
Total	.51092321	1217	.000419822

Number of obs =	1218
F(3, 1214) =	385.25
Prob > F =	0.0000
R-squared =	0.4877
Adj R-squared =	0.4864
Root MSE =	.01468

r1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rm	.6664093	.0244786	27.22	0.000	.6183842	.7144344
rmvol	-.0806416	.1183448	-0.68	0.496	-.3128246	.1515413
rm2	-.4842456	.4642571	-1.04	0.297	-1.395081	.4265898
_cons	-.0002499	.0004748	-0.53	0.599	-.0011815	.0006817