ESSAYS ON STOCK RETURN FORECASTING, TREND-FOLLOWING TRADING STRATEGY AND EMPIRICAL ASSET PRICING

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CONTEXTUAL STATEMENT

The first two essays in this thesis discuss stock return forecast (prediction), a thrilling endeavor of both practitioners and academics of finance with a long history. The practitioners forecast the stock return in real-time to optimize asset allocation and seek an alpha return. In the meantime, recognizing the underlying reason of return predictability may help academic researchers identify what variables explain/drive the stock returns, and thus help them produce improved asset pricing theory.

Most of the existing literature on stock return prediction focus on the macroeconomic variables, including the dividend-price ratio, inflation rate, interest rate, volatility, et cetera (e.g., Campbell & Thompson 2008; Welch & Goyal 2008). However, little attention has been paid to the technical indicator (technical analysis) which is extensively used by practitioners (Burghardt & Walls 2011; Covel 2009; Lo & Hasanhodzic 2010, 2011; Menkhoff 2010; Park & Irwin 2007; Schwager 2012). Meanwhile, most of the literature on technical indicator exclusively investigate the profitability but do not investigate the ability of technical indicator in directly predicting the equity risk premium, while predicting equity premium is the focus of vast literature on macroeconomic variables. The only exception is Neely et al. (2014) and they find that technical indicator provides vast complementary information to macroeconomic variables in predicting equity risk premium in the U.S.

The first essay extends the playground to China, and investigates the predictability of technical indicator together with macroeconomic variables in China. We choose China for several reasons. Firstly, the Chinese stock market hase become increasingly relevant to not only the academics but also the investment industry. Since 2015, Shanghai and Shenzhen stock exchange together has become the second largest stock market by market capitalization (the largest is NYSE). Secondly, a high level of information friction due to non-transparency and short-sell restriction, and the prevalence of individual investors causing more server behaviour biases (underreaction and overreaction) can boost the predictive power of technical indicators. Lastly, no study has examined the predictability of technical analysis in China, so my first essay filled the gap. We find that technical indicators outperform macroeconomic variables in China and capture ample complementary information. We also find that weekly-level technical indicators outperform monthly-level ones, implying a short-term trending feature of the Chinese stock market.

The second essay shifts the focus to the U.S. and other international markets, and is the first study to investigate the predictability of technical indicator in a cross-sectional view. We find that the predictive power of *intermediate-term* technical indicator identified by Neely et al. (2014) is only useful in predicting the top 10% U.S. companies by market cap, it appears to be a calendar effect, and it does not work well in many other countries. In contrast, the *short-term* technical indicator can well predict much more U.S. companies, it is not a calendar phenomenon, and it can well predict Japan and other Asia-pacific markets. Finally, contradict to the vast literature on the profitability of technical analysis, we find no positive correlation between volatility and the performance of technical indicators.

On the foundation of the Fama and French (2015) five-factor asset pricing model, the third essay proposes three additional risk factors in China based on: 1.) substantial daily-level short-term reversal; 2.) state ownership; 3.) institutional ownership, all of which are unique features of the Chinese stock market. We identify vast useful information provided by our proposed factors and we suggest that the five-factor asset pricing model is not a complete description of expected return in the Chinese stock market.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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CHAPTER 1: CAN TECHNICAL INDICATORS PREDICT THE CHINESE EQUITY RISK PREMIUM?

Abstract

We examine how technical indicator can help predict the Chinese equity premium. In-sample tests show that technical indicators provide complementary information to macroeconomic variables in predicting the Chinese equity risk premium. Out-of-sample tests suggest that technical indicators perform more consistently in the weekly frequency than in the monthly frequency. The weekly-level predictive power of technical indicators also presents on the firm-level, exist in the cross-section and generates robust certainty equivalent return. Overall, the Chinese stock market return seems to have a shorter-term price trend than the US. The predictive power of technical indicator is associated to market capitalization but not to volatility.

1. Introduction

Numerous studies report evidence regarding the power of macroeconomic variables to predict the U.S. equity risk premium (e.g., Breen, Glosten & Jagannathan 1989; Campbell 1987; Cochrane 2007; Fama & French 1988, 1989; Fama & Schwert 1977; Ferson & Harvey 1991; Lettau & Ludvigson 2001; Pástor & Stambaugh 2009; Pettenuzzo, Timmermann & Valkanov 2014), while others report findings for international markets (e.g., Ang & Bekaert 2006; Bekaert & Hodrick 1992; Cutler, Poterba & Summers 1991; Ferson & Harvey 1993; Harvey 1991; Henkel, Martin & Nardari 2011; Hjalmarsson 2010; Solnik 1993), including China (e.g., Chen, J et al. 2016; Chen, X et al. 2010; Goh et al. 2013; Jiang, F et al. 2011). Contrary to macroeconomic variables, technical indicators have received less attention despite their extensive use among practitioners (Covel 2009; Lo & Hasanhodzic 2010, 2011; Menkhoff 2010; Menkhoff & Taylor 2007; Park & Irwin 2007; Schwager 2012).

Our study examines the ability of technical indicators to predict the Chinese equity premium. We add to the existing literature on equity premium predictability by investigating the power of technical indicators in conjunction with macroeconomic variables to predict the U.S. equity risk premium (for a recent example, see Neely et al. 2014). While a lot of the existing literature on technical analysis is focused for the most part on the profitability of technical indicators (e.g., Brock, Lakonishok & LeBaron 1992; Lo, Mamaysky & Wang 2000a), we examine the predictive power of technical indicator directly over the equity risk premium.

Theoretically, macroeconomic variables can predict the equity risk premium because they measure changing macroeconomic conditions which are the fundamental drivers of time-varying expected returns. This predictive ability is consistent with rational asset pricing and reflects fluctuations in aggregate risk exposure which produces time-varying discount rates (see, for example, Cochrane 2011; Rapach, D & Zhou 2013). In contrast, the predictive ability of trend-following technical indicators is still controversial and requires more discussion. Cespa and Vives (2012) show that, in the presence of heterogeneous information, asset prices can systematically diverge away from fundamental values and generate rational trends in the market. Alternatively, behavioral biases can lead to deviation from fundamental values. For example, Hong and Stein (1999) show that investors tend to underreact to new information at first and then overreact in the long run, pushing the price higher. Daniel, K, Hirshleifer and Subrahmanyam (1998) suggest that investors are overconfident about their private information and overreact to confirming news, therefore causing the price trend. Barberis, Shleifer and Vishny (1998) posit that investors underweight new information and therefore cause price continuation. Finally, investor sentiment seems to be related to technical indicator’s predictive power. Neely et al. (2014) find that technical indicator can significantly predict the investor sentiment index, while measures of investor sentiment are found to help explain U.S. and international equity returns (Baker & Wurgler 2006, 2007; Baker, Wurgler & Yuan 2012)

Investigating technical indicators in China is interesting for three reasons. Firstly, individual investors dominate the Chinese stock market. By March 2018, 99.73% of the total security accounts belong to individual investors (China Securities Depository and Clearing Co. Ltd, http://www.chinaclear.cn). The Chinese retail investors are not well-educated financially, gambling oriented, and prone to behavioral biases. Therefore, as discussed above, the prevalence of behavioral biases (e.g., underreaction and overreaction) in China may result in price trend and would boost the predictive power of technical indicators.

Secondly, short-sell is highly restricted in the Chinese stock market and is only open to the high-net-worth Chinese investor. As of December 5, 2016, there are 950 A-shares allowed to be borrowed and short, a number that is less than one-third of the total number of A-shares. Short-sell restriction can slow price discovery process (Bai, Y, Chang & Wang 2007; Chang, Cheng & Yu 2007; Miller 1977). Jiang, GJ, Lu and Zhu (2014) posit that short-sale restriction causes negative information not instantaneously incorporated into stock prices. As a result, a gradual market reaction to news indicates a price continuation and the predictive power of the trend-following technical indicators.

Thirdly, initiated in December 1990, the Chinese stock market has a short history. Its regulatory system is under development, and asymmetric information problem is still severe. Chinese listed companies have weaker corporate governance and weaker shareholder protection compared with the developed markets (Bai, C-E et al. 2004; Sun & Tong 2003; Wei, Xie & Zhang 2005). Overall, the Chinese market embeds considerable amount of uncertainty due to unstable policy and non-transparent information. Zhang (2006) show that investors tend to underreact more to new information under greater information uncertainty. Taylor (2014) finds that the excess return of technical analyses is higher when there are higher market illiquidity and macroeconomic uncertainty. Along this line, we believe the uncertainty within the Chinese stock market would benefit the performance of technical indicator.

We perform both in-sample and out-of-sample tests and use data spanning 1997:07 to 2016:12. Our methodology is similar to that of Neely et al. (2014). However, unlike their US result, we find that monthly-level technical indicators do not provide comparable predictive power to the macroeconomic variables. In contrast, we find that technical indicators perform more consistently in the *weekly* frequency in China. We highlight our contributions in the following:

- Monthly-level in sample tests show that technical indicators provide complementary information to the macroeconomic variables in predicting the Chinese equity premium and the R^2 are much higher than the US result reported in Neely et al. (2014). Weekly-level technical indicators also exhibit tremendous predictive power. However, traditional asset pricing models leave no room for technical analysis despite growing evidence of its predictive power.
- In the out-of-sample tests, macroeconomic variables outperform the benchmark while *monthly-level* technical indicators underperform. In contrast, *weekly-level* technical indicators can deliver more powerful and consistent predictive power both in-sample and out-of-sample, and generate considerable certainty equivalent return gain after transaction cost. Moreover, the predictive ability of the weekly-level technical indicators presents on the firm-level while monthly-level ones do

not. We argue the weekly-level predictive power is of great economic value given the scarcity of weekly-level predictor.

- The superior performance of weekly-level trend-following technical indicators reveals that the price trend mainly exists in the weekly frequency in the Chinese stock market. This finding suggests a short-term price trend in China, consistent with Pan, Tang and Xu (2013) who find that momentum only exists in the weekly frequency in China, as well as Han et al. (2014) who show that a short-term moving average delivers a substantial alpha return in this market. Moreover, our finding sheds light on why the previous studies fail to find momentum in China (e.g. Cakici, Chatterjee & Topyan 2015; Chui, Titman & Wei 2010; Griffin, Ji & Martin 2003; Li et al. 2017; Wang & Chin 2004). The reason is that they only exclusively examine the *monthly-level* data following the standard literature regarding momentum, while the price trend presents mainly in the weekly frequency.
- Compared to the US, the Chinese stock market seems to have a higher-frequency price trend. Our result poses a theoretical implication that any asset pricing theory addressing price trend (rational or behavioral) should be able to explain the difference in price trend across countries. The underlying reason for this international difference can be an interesting research topic.
- Finally, cross-sectional tests suggest that the *predictive ability* of technical indicators is sensitive to market cap but not to volatility, different from the existing literature of technical indicators which usually find volatility is a strongly correlated with the *profitability* of the technical indicators (e.g., Glabadanidis 2015b; Han, Yang & Zhou 2013). This puzzling discrepancy among the two measurements of technical indicator performance requires more discussion.

2. Predictive regression and the predictors

A conventional way to analyze the in-sample predictability is through the following model:

$$r_{t+1} = \alpha_i + \beta_{i,j} x_{j,t} + \varepsilon_{i,t+1}\,, \tag{1}$$

where the equity risk premium, r_{t+1}, is the return on the market portfolio in excess of the risk-free rate from period t to $t+1$; $x_{j,t}$ is the predictor at time t; $\varepsilon_{i,t+1}$ is the disturbance term with zero mean. $x_{j,t}$ can take the value of the level of a macroeconomic variable, or a trading signal $S_{i,t}$ generated by a technical indicator. Under the null hypothesis $\beta_{i,j} = 0$, $x_{j,t}$ cannot predict the equity risk premium of portfolio i. In this case, the model breaks down into a constant expected equity risk premium model. We test H_0: $\beta_{i,j} = 0$ against H_1: $\beta_{i,j} > 0$ using the heteroskedasticity-consistent t-statistic[1], based on an ordinary least square (OLS) procedure.

When the independent variable is highly persistent, the Stambaugh (1999) bias may inflate the t-statistic and distorts test size. Many of the conventional indicators are highly persistent. We address this issue by calculating p-value using a bootstrap procedure, and we base the statistical interpretation on the wild bootstrapping p-value.

The current study performs predictive regression (1) on both monthly return and weekly return of a value-weighted market portfolio[2], which is constructed using all A-shares' log return and rebalances at the end of every month (week). A-shares include

[1] We use the Newey and West (1987) robust t-statistic with 5 lags.

[2] Our results are qualitatively similar when use the Shanghai Composite index return as a proxy for the market portfolio return.

all stocks traded in Shanghai and Shenzhen stock exchange open to domestic investors and trade in RMB (Chinese yuan). The Chinese A-shares data is obtained from Datastream. Chinese risk-free rate is retrieved from the China Stock Market & Accounting Research database (CSMAR).

2.1. Macroeconomic variables

For the monthly-level analysis, we study 15 monthly macroeconomic predictors which are representative of the existing literature (Jiang, F et al. 2011; Neely et al. 2014; Welch & Goyal 2008), as well as considering data availability in China. They are book-to-market ratio (BM), cash-flow to price ratio (CFP), dividend-earnings ratio (DE), dividend-price ratio (DP), dividend yield (DY), earning-price ratio (EP), inflation (INFL), stock variance (SVAR), trading volume scaled by market value (VO/MV), volatility index (VIX), 7-days repo rate (R007), overnight interbank lending rate (IBO001), M0 growth (M0G), M1 growth shock (M1G), and M2 growth (M2G). A detailed description of the data construction and data source is in Table 1.1.

Our sample period starts in December 2002 and continues until November 2016[3] due to data availability. Money supply data (M0, M1 and M2) is available starting at the end of 1999 and the short-term interest rates (R007 and IBO001) are available from the end of 2002. Both short-term interest rate and money supply data are gauges of the monetary policy pursued by the People's Bank of China (the central bank). Monetary policy can affect the equity market return is through the credit channel of monetary

[3] Section 3.4 also reports the results based on an extended sample from July 1997.

policy described in Bernanke and Gertler (1995). Looser monetary policy leads to cheaper bank credit loan which is a major financing channel for the listed Chinese firms, and thus may affect the equity market return (Jiang et al. 2011). In Table 1.2 we report the descriptive statistics for the market portfolio monthly (weekly) excess return and the fifteen macroeconomic variables. The valuation ratios (BM, CFP, DE, DP, DY, and EP), INFL, VO/MV and SVAR are highly persistent with a high autocorrelation coefficient at lag 1.

2.2. Technical indicators

Following Neely et al. (2014), we compare the macroeconomic variables to three types of trend-following technical indicators. They are the Moving Average (MA), Momentum (MOM), and Volume-based indicator (VOL).

A MA indicator generates a trading signal by comparing two moving averages at the end of t:

$$S_{i,t} = \begin{cases} 1 \; if \; MA_{s,t} \geq MA_{l,t} \\ 0 \; if \; MA_{s,t} < MA_{l,t} \end{cases} \tag{2}$$

where

$$MA_{j,t} = (1/j) \sum_{i=0}^{j-1} P_{t-i} \; for \; j = s, l; \tag{3}$$

$S_{i,t} = 0$ and $S_{i,t} = 1$ suggests a sell and buy signal, respectively; j denotes the maximum lag of the MA length and can be either s or l (short or long); P_t is the level of a portfolio index at time t. Therefore, an MA indicator will generate a signal based on a comparison between the value of $MA_{s,t}$ and $MA_{l,t}$. When $MA_{s,t}$ exceeds (falls short of) $MA_{l,t}$, indicating an upward (downward) trend, a buy (sell) signal will be generated. We denote the cross-over MA indicator as $MA(s,l)$. We use a comprehensive range of cross-over MA indicators with $s = 1\ month(week)$ and $l = 3, 5, 7, 9, 11\ months(weeks)$.[4]

Our second technical indicator is based on the well-known momentum effect, and it generates a trading signal in the following way:

$$S_{i,t} = \begin{cases} 1\ if\ P_t \geq P_{t-m} \\ 0\ if\ P_t < P_{t-m} \end{cases} \tag{4}$$

For a $MOM(m)$ indicator, when the level of the portfolio index exceeds (falls short of) its past level m periods ago, a buy (sell) signal will be generated by this indicator. Again, we examine a comprehensive range of $MOM(m)$ indictors, with $m = 3, 5, 7, 9, 11\ months(weeks)$.

Another technical indicator is the volume-based (VOL) indicator, following Neely et al. (2014). This indicator incorporates information in both past prices and trading volume. It generates a trading signal based on the "on-balance" trading volume (OBV):

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k, \qquad D_k = \begin{cases} 1\ if\ P_t \geq P_{t-1} \\ -1\ if\ P_t < P_{t-1} \end{cases} \tag{5}$$

where VOL_k is the total trading volume of the portfolio (stock) during period k. D_k is a binary variable that takes a value of 1 if the current price is equal or higher than the price of the last timestep and equals −1 if the price is lower than that of the last timestep.

[4] We examine a more comprehensive set of technical indicators than Neely et al. (2014) who only focus on indicators with $l = 9, 12\ months$.

Based on the moving average of the on-balance trading volume (OBV_t), a VOL indicator generates trading signal in the following way:

$$S_{i,t} = \begin{cases} 1\ if\ MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0\ if\ MA_{s,t}^{OBV} < MA_{l,t}^{OBV} \end{cases} \tag{6}$$

where

$$MA_{j,t}^{OBV} = (1/j) \sum_{i=0}^{j-1} OBV_{t-i}\ for\ j = s, l; \tag{7}$$

A $VOL(s, l)$ indicator generates a buy (sell) signal when the movement in trading volume accompanies a continuation of recent price increases (decreases). Similarly to $MA(s, l)$ and $MOM(m)$, we examine $VOL(s, l)$ with $s = 1\ month(week)$ and $l = 3, 5, 7, 9, 11\ months(weeks)$.

Finally, **t**o differentiate the weekly-level technical indicators from the monthly-level indicators, we denoted the weekly-level indicators as $MA(s, l)^w$, $MOM(m)^w$ and $VOL(s, l)^w$. Note that our choice of parameters suggest that the weekly technical indicators employ the prior price information of up to 11 weeks (approximate 2.53 months). This is complementary to the monthly-level technical indicators that captures price information between past 3 months to past 11 months. Thus, the weekly technical indicators we have examined use non-overlapping past price information relative to their monthly counterparts.

3. Empirical results

3.1. In-sample tests

We first investigate the monthly equity premium before we focus on our weekly-level results. Table 1.3 reports estimates of the slope coefficients for the predictive regression (1) and the left-hand-side variable is the market portfolio *monthly* excess return from December 2002 until November 2016. Panel A of Table 1.3 shows that 10 of the 15 Macroeconomic variables have significant predictive power. A monthly R^2 near 0.5% can represent an economically significant degree of equity risk premium predictability (Campbell & Thompson 2008; Kandel & Stambaugh 1996; Xu 2004). The macroeconomic variables with significant predictive power have R^2 statistics ranging from 1.29% to 8.17% and are well above the 0.5% threshold. INFL, VO/MV, and DY deliver the highest R^2 of 8.17%, 4.45%, and 4.38%, respectively. Our newly proposed short-term interest rates gauges, R007 and IBO001 can significantly predict the Chinese stock market risk premium, revealing a significant effect of monetary policy on Chinese equity premium. Overall, most of the R^2 statistics are larger than the US result reported in Neely et al. (2014).

Turning to the monthly-level technical indicators, the right-hand-side of Table 1.3 shows that 12 of the 15 monthly technical indicators have significant predictive power. The R^2 statistics hover around 2% for MA and a bit less than that for MOM and VOL, most of which are well above the 0.5 % threshold for economic significance. Overall, monthly-level technical indicators in China also provide higher in-sample R^2 than the

US technical indicators reported in Neely et al. (2014). The slope estimates imply that a buy signal suggests the equity risk premium next month will be 84 basis points to 330 basis points higher when compared to a sell signal.

As a next step, we examine the sensitivity of predictive power under different market conditions. Similar to Neely et al. (2014), to compare the predictability under different market condition, we compute the following sub-sample R^2 statistic:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \, \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c \, (r_t - \bar{r})^2} \; for \; c = STA, VOL; \tag{8}$$

where I_t^{STA} (I_t^{VOL}) is an indicator variable that equals 1 when month (week) t is in the stable (volatile) periods and equals 0 otherwise. Since there is no business cycle data available for the Chinese stock market, we define two volatile periods, from January 2007 until December 2009 and September 2014 until December 2016, during which the market are volatile and experienced two major market crashes. The rest of the sample period are defined as stable periods. $\hat{\varepsilon}_{i,t}^2$ is the fitted residual based on the full-sample estimates of the original predictive regression model; $\bar{r}$ is the full-sample mean of r_t; and T is the number of usable observations for the full sample. Therefore, the R_{VOL}^2 statistic measures the total variation explained in the volatile periods and the R_{STA}^2 statistic do the same for the stable periods.

R_{VOL}^2 and R_{STA}^2 reported in the left-hand-side of Table 1.3 suggest that a few macroeconomic variables perform consistently regardless of stock market volatility (BM, CFP, DP, DY, INFL, VO/MV), while some are effective exclusively in the volatile periods (SVAR, R007 and IBO001). In contrast, right-hand-side the of Table 1.3 shows that most of the technical indicators perform well only in the volatile periods given consistently high R^2_{VOL} and low R^2_{STA}, similar to the US result in Neely et al. (2014).

Now we turn to the weekly-level predictive regression results. To line up with the monthly sample, we based our weekly-level analysis on the weekly excess return of the market portfolio of the same period, 27 December 2002 until 2 December 2016. We do not report any results for macroeconomic variables for weekly-level analysis because very few macroeconomic variables are available on a weekly basis.

The weekly-level predictive regression result is in Table 1.4. Panel A shows that every single weekly-level technical indicator exhibits significant predictive power. 14 out of the 15 weekly technical indicators generate R^2 statistics exceeding the monthly threshold of 0.5%, ranging from 0.64% to 1.51%. A similar level of R^2 statistic in the weekly-level predictive regression to the monthly-level one should indicate a stronger predictive power since the weekly returns are noisier by definition. However, since there is little guidance in the literature regarding a threshold of R^2 statistics for a weekly predictive regression, we leave the inference to the reader. The slope estimates imply that buy signals predict the equity risk premium next week to be 46 basis points to 89 basis points higher compared to the sell signals.

3.2. In-sample tests based on principal component analysis

To simultaneously incorporate the information from multiple predictors, we use a principal component analysis following the literature (Ludvigson & Ng 2007, 2009; Neely et al. 2014). The advantage of using the principal component analysis is to capture the key co-movements in multiple variables, filter out the noise in individual predictors, and mitigate the in-sample overfitting problem. The principal component predictive regression model (PC-ECON, PC-TECH and PC-ALL model) is defined as:

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t}^{x} + \varepsilon_{t+1} \quad for\ x = ECON, TECH, ALL \tag{9}$$

where $\hat{F}_t^{ECON} = (\hat{F}_{1,t}^{ECON}, \dots, \hat{F}_{K,t}^{ECON})'$ denotes the vector containing the first K principal components estimated from the *N*-vector ($N = 15$) of all macroeconomic variables; $\hat{F}_t^{TECH} = (\hat{F}_{1,t}^{TECH}, \dots, \hat{F}_{K,t}^{TECH})'$ denotes for the vector containing the first K principal components estimated from the *N*-vector ($N = 15$) of all technical indicators; $\hat{F}_t^{ALL} = (\hat{F}_{1,t}^{ALL}, \dots, \hat{F}_{K,t}^{ALL})'$ denotes the vector containing the first K principal components extracted from the *N*-vector ($N = 30$) of all predictors taken together. The value of K is determined by the adjusted R^2 and we restrict K to be no larger than 3. We use OLS to estimate model (9) and base our inferences on the wild bootstrapped p-values.

To compare the technical indicators with different time horizon, we also consider $\hat{F}_t^{TECH(3,5)}$ which is first K principal component extracted from the *N*-vector ($N = 6$) of short-term technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ with $l = 3, 5$, and $\hat{F}_t^{TECH(9,11)}$ which is the first K principal component extracted from the *N*-

vector ($N = 6$) of relatively long-term technical indicators with $l = 9, 11$. Similarly, we examine these principal components based on model (9) and the corresponding models are denoted as PC-TECH[3,5] and PC-TECH[9,11].

Panel B of Table 1.3 shows that the PC-ECON model has a K=1 (chosen by adjusted R^2). The first principal component of macroeconomic variables ($\hat{F}_1^{ECON}$) has a slope coefficient that is significant at 1% significance level and the R^2 is 5.95%. Moreover, R_{STA}^2 is 4.42% and R_{VOL}^2 is 6.68%, suggesting that macroeconomic variables overall perform consistently under different market volatility and do slightly better in volatile periods.

Right-hand-side of Panel B shows that the PC-TECH model has a K=1 (chosen by adjusted R^2) and the first principal component of the technical indicators ($\hat{F}_1^{TECH}$) has significant predictive power with an R^2 of 2.60%, lower than that of the macroeconomic variables. Meanwhile, the first principal component of the technical indicators with relative short-term horizon ($\hat{F}_1^{TECH(3,5)}$) generates an R^2 of 3.21%. $\hat{F}_1^{TECH[9,11]}$, $\hat{F}_2^{TECH[9,11]}$ and $\hat{F}_3^{TECH[9,11]}$ together provide a similar R^2 of 3.39%, indicating that short-term and long-term horizon technical indicators have similar predictive power to the monthly equity premium. Finally, the high R_{VOL}^2 and poor R_{STA}^2 on the principal component models of technical indicators verify that the technical indicators' predictive power concentrate on the volatile periods, similar to the findings documented in the existing literature on technical indicator (e.g., Han, Yang & Zhou 2013; Neely et al. 2014).

Do technical indicators provide complementary information to the macroeconomic variables in predicting Chinese equity premium? In Panel C of Table 1.3 we report our findings for the PC-ALL model utilizing information from all the predictors. Both $\hat{F}_1^{ALL}$ and $\hat{F}_2^{ALL}$ show significant predictive power and the PC-ALL model delivers a R^2 of 9.29%, higher than that of PC-ECON model and PC-TECH model combined, also much higher than the US result reported by Neely et al. (2014). Therefore, in-sample tests suggest that macroeconomic variables and technical indicators seem to provide non-overlapping information and complement each other in predicting the equity risk premium.

Turning to the weekly-level principal component result reported in Table 1.4. In Panel B we show that the first principal component based on all weekly technical indicators ($\hat{F}_1^{TECH^w}$) has significant predictive power with an R^2 of 1.45%. The principal component based on short-term horizon weekly indicators ($\hat{F}_1^{TECH[3,5]^w}$) delivers significant predictive power and an R^2 of 1.05%. The relatively long-term ones ($\hat{F}_1^{TECH[9,11]^w}$ and $\hat{F}_2^{TECH[9,11]^w}$) together also provide significant predictive power and an R^2 of 1.81%. Finally, if we compare R_{STA}^2 to R_{VOL}^2, all the principal component models perform better in the volatile periods. Overall, in-sample test suggests that technical indicator do well in both monthly and weekly frequency.

3.3. Out-of-sample tests

Welch and Goyal (2008) show that many popular predictors fail to outperform a simple benchmark in the out-of-sample tests. Thus, to further verify the in-sample result, we perform an out-of-sample test on the predictors. Interestingly, we find that weekly-level technical indicators perform more consistently in the out-of-sample tests.

Consider the out-of-sample forecasting model:

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} x_{i,t} \, , \tag{10}$$

For each time step t, we obtain $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ by regressing the realized return series $\{r_s\}_{s=2}^{t}$ on a constant and the lagged predictor $\{x_{i,s}\}_{s=1}^{t-1}$, where $x_{i,s}$ can be the level of a macroeconomic variable, as well as the trading signal $S_{i,t}$ generated by a technical indicator. We also perform a similar forecasting model based on the principal components:

$$\hat{r}_{t+1}^{j} = \hat{\alpha}_t + \sum_{k}^{K} \hat{\beta}_{t,k} \hat{F}_{1:t,k,t}^{j} \text{ for } j = ECON, TECH, or\ ALL; \tag{11}$$

For each timestep t, $\hat{F}_{1:t,k,t}^{j}$ is the *k*th principal component extracted from the 15 macroeconomic variables $(j = ECON)$, 15 technical indicators $(j = TECH)$, or all 30 predictors taken together $(j = ALL)$ estimated using the data through t; the value of K is selected by the adjusted R^2 and we restrict K to be no larger than 3; and $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ $(k = 1, \dots, K)$ are the OLS estimates from continuously regressing the realized return $\{r_s\}_{s=2}^{t}$ on a constant and the lagged principal component(s) $\{\hat{F}_{1:t,k,t}^{j}\}_{s=1}^{t-1} (k = 1, \dots, K)$.

We use the historical average (HA) forecast as the benchmark forecast, following the existing studies (e.g., Campbell & Thompson 2008; Ferreira & Santa-Clara 2011; Jiang, F et al. 2011; Neely et al. 2014; Welch & Goyal 2008). This benchmark assumes a constant expected equity risk premium, $r_{t+1} = \alpha + \varepsilon_{t+1}$. Therefore, we compare the forecasts of our predictors, $\hat{r}_{t+1}$, to the historical average forecast:

$$\hat{r}_{t+1}^{HA} = (1/t)\sum_{s=1}^{t} r_s \qquad (12)$$

We analyze the forecasts based on Campbell and Thompson (2008) out-of-sample R^2 (R_{OS}^2) and Clark and West (2007) MSFE-adjusted statistics. The R_{OS}^2 statistic measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast compared with the historical average forecast. The null hypothesis is that the historical average MSFE is less than or equal to the predictive regression MSFE, and the alternative hypothesis is historical average MSFE is higher than the predictive regression MSFE.

For monthly-level analysis, December 2002 until December 2007 is the initial estimation period (60 months), and January 2008 until November 2016 is the forecast evaluation period (107 months). The length of the initial estimation period is close to Jiang, F et al. (2011) and Rapach, DE, Strauss and Zhou (2013). We obtain the initial estimates of $\hat{\alpha}$ and $\hat{\beta}$ using the initial estimation period. We then continuously update $\hat{\alpha}$ and $\hat{\beta}$ using an expanding window and evaluate the performance in the forecast evaluation period.

In Table 1.5 we report the out-of-sample forecasting results. Panel A shows that 7 of the 15 macroeconomic variables outperform the HA benchmark as they have significant MSFE-adjusted statistics with positive R_{OS}^2 ranges from 1.11% to 8.10%. Panel B reports that the PC-ECON model outperform the benchmark ($R_{OS}^2 = 4.31\%$). In contrast, right-hand-side reports that only two short-term horizon monthly-level technical indicators, MA(1,3) and MOM(3), outperform the benchmark. Most technical indicators have negative R_{OS}^2, including the PC-TECH model ($R_{OS}^2 = -2.89\%$), casting doubt on the reliability of monthly-level technical indicators in predicting the Chinese equity risk premium. In contrast, the US result reported in Neely et al. (2014) shows that ALL their monthly-level technical indicators have positive R_{OS}^2 and outperform the benchmark.

It is noteworthy that PC-TECH[3,5] model perform far better than PC-TECH[9,11] as in Table 1.5, suggesting technical indicator utilizing short-term horizon information can more consistently predict Chinese equity premium. The question arises whether our week-level technical indicators utilizing shorter-term past price information will perform better.

Out-of-sample performance of the weekly technical indicators reported in Table 1.6 supports this hypothesis. We use 200 weeks starting from 26 December 2002 until 20 October 2006 as the initial estimation period (200 weeks), leaving us with 27 October 2006 until 3 December 2016 as the forecast evaluation period (528 weeks). In contrast to the poor out-of-sample performance of the *monthly-level* technical indicators, we identify tremendous predictive power in the weekly-level out-of-sample tests. Panel A of Table 1.6 shows that 13 out of 15 *weekly-level* technical indicators outperform the benchmark historical average forecasting and most MSFE-adjusted statistics are significant, showing positive R_{OS}^2. In Panel B we find that the week-level versions of the principal component models significantly outperform the benchmark. The PC-TECH^w model, the PC-TECH[3,5]^w model, and the PC-TECH[9,11]^w model all significantly outperform the HA benchmark.

3.4. Extended sample

To further verify the difference between monthly-level and weekly-level technical indicators, we then examine them on an extended sample beginning at July 1997. This extended sample includes 4.5 years of additional data compared to our previous analysis. We align the forecast evaluation periods: 2003:01 until 2016:11 for the monthly-level analysis and 2003:01:03 until 2016:12:02 for the weekly-level one. The corresponding initial estimation periods are the same for both analyses, from July 1997 until the end of 2012.

In Table 1.7 we report the in-sample and out-of-sample performance of the monthly-level technical indicators on the extended sample. Although the left-hand-side of Table 1.7 shows that the 11 of 15 monthly-level technical indicators have significant in-sample predictive power, the right-hand-side indicates only two of them outperform the benchmark in the out-of-sample test with marginal significance. The significant indicators are still the short-term horizon indicator MA(1,3) and MOM(3). Moreover, Panel B of Table 1.7 suggests that short-term model (PC-TECH(3,5)) significant outperform HA benchmark while PC-TECH[9,11] does not, verifying our finding in the original sample that short-term past price information seems to help better predict Chinese equity premium.

Table 1.8 reveals that weekly-level technical indicators which utilize shorter-term past price information (within 11 weeks, or 2.53 months, complementary to our month-level indicators) generate substantial predictive power both in-sample and out-of-sample. Left-hand-side reports that ALL weekly-level technical indicators and their principal component models show significant in-sample predictive power. More importantly, right-hand-side of Table 1.8 suggests that every single weekly-level technical indicator significantly outperform the benchmark forecast in the out-of-sample tests. Overall, the test on the extended sample verified that technical indicator can predict the Chinese equity premium more consistently in the weekly frequency than in the monthly frequency.

In summary, macroeconomic variables can consistently predict monthly equity premium in-sample and out-of-sample. Although most *monthly-level* technical underperform the benchmark in the out-of-sample tests, *weekly-level* technical indicators have substantial predictive power in-sample and out-of-sample. This difference reveals that weekly-level technical indicators are better predictors of the Chinese equity risk premium. If these trend-following strategies are an indication of price trend, our results suggest that such price trend exists in China and concentrates on the weekly frequency but much weaker in the monthly frequency. Moreover, we argue that the predictive power at the weekly frequency is of great value given the scarcity of weekly-level predictors.

4. Robustness

4.1. Firm-level analysis

To see whether the predictors can predict individual firm excess return, we perform the predictive regression (1) for the individual listed company. We filter and choose the Chinese A-shares that have at least 36 months of prior stock return and 12 months of accounting data subsequent to December 2002, obtaining a sample size of 2506 firms. We then generate monthly (weekly) technical indicators based on the monthly (weekly) prices and trading volume of the individual stock and examine predictive regression (1) separately on each company's monthly (weekly) excess return.

In Table 1.9 we present the results of monthly and weekly bivariate predictive regression based on individual firm excess return. As shown in columns 4 and 5, there is no distinguishable difference between the number of companies with positive significance and negative significance when using monthly-level technical indicators. Thus, we corroborate our previous findings regarding the inability of monthly technical indicators to predict monthly stock returns in the case of individual stocks.

In the right-hand-side of Table 1.9, we present our findings for the firm-level weekly returns. For a non-trivial proportion of companies, we can positively identify their future stock returns while only very few companies future stock returns are wrongly predicted. This implies that there is a distinct pattern and further supports our prior evidence of the predictive power of weekly-level technical indicators. In Panel B of Table 1.9 we present evidence showing that the principal components of the weekly technical indicators have modest predictive power as well. PC-TECH^{W} model can positive significantly predict 6.30% of the companies while negative significantly predict only 0.66% of the companies. In summary, we find evidence that *weekly* technical indicators have significant predictive on the individual firm-level while the *monthly* technical indicators do not.

4.2. Asset allocation

How much economic value will these predictors provide in an asset allocation perspective? As in Campbell and Thompson (2008), Ferreira and Santa-Clara (2011) and Neely et al. (2014), we examine the certainty equivalent return (CER) gain for a mean-variance investor who allocates a fraction of her wealth to equities and the remainder to a risk-free asset based on forecasts of our predictors against the benchmark historical average forecast.

The expected utility of a mean-variance investor is the following:

$$U(R_p) = E(R_p) - \frac{1}{2}\gamma Var(R_p)\,, \tag{13}$$

where R_p is the return on the investor's portfolio, $E(R_p)$ is the expected portfolio return, $Var(R_p)$ is the variance of the portfolio return, and γ is the relative risk aversion coefficient for the investor. At the end of month (week) t, the investor allocates the following proportion of the portfolio to equities during month (week) t +1:

$$w_t = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{14}$$

where $\hat{r}_{t+1}$ is a forecast of the equity risk premium and $\hat{\sigma}^2_{t+1}$ is a forecast of its variance. Then we assume that the investor uses a 60-month (200-week) moving window of past monthly (weekly) returns to estimate the variance of the equity risk premium. We constrain w_t to stay between 0 and 1.5, allowing for leveraging up to 50%. The proportion $1 - w_t$ is invested to risk-free assets. Therefore, the portfolio return at $t + 1$ is:

$$R_{p,t+1} = w_t r_{t+1} + (1 - w_t)R_{f,t+1}\,, \tag{15}$$

where $R_{f,t+1}$ is the risk-free return.

Finally, the certainty equivalent return (CER) for the investor is given by:

$$CER_p = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}^2_p\,, \tag{16}$$

where $\hat{\mu}_p$ and $\hat{\sigma}^2_p$ are the portfolio mean and variance during the forecast evaluation period when the investor optimally allocates the equities and risk-free asset in the way described above. The relative risk aversion coefficient γ takes a value of 5 in the calculation of CER[5]. Then we compare the CER based on forecasts generated by technical indicators to the CER based on the historical average forecast by computing the incremental CER. This gain in CER is given by the difference between the CER for an investor who uses forecasts based on technical indicators and the CER for the same

[5] The results are similar when use other reasonable relative risk aversion coefficient values.

investor if she uses the historical average forecast instead. We multiply this difference by 1200 for monthly analysis, and by 5200 for weekly analysis, representing the annualized percentage management fee an investor would be willing to pay to have access to the forecasts from the predictive regressions over the historical average forecast.

In Table 1.10 and 1.11 we present the CER values (Δ) for an investor who uses the historical average forecast and CER gains (Δ) arising from predictive regressions. We also report Sharpe ratios of the optimal portfolio calculated as the portfolio excess return divided by the standard deviation of the portfolio excess return. Relative average turnover for the portfolio using historical average (HA) forecast is the average percentage of wealth traded each month (week). For other portfolios, relative average turnover is the average turnover divided by the average turnover of the portfolio using the historical average forecast. We also report CER gains for the stable periods and volatile periods separately (Δ, Stable; Δ, Volatile). CER gains after transaction costs of 50 basis points are also presented (Δ, 50 bps cost). The transaction costs are calculated based on the turnover measure. The initial estimation period and forecast evaluation period are identical to the previous out-of-sample analysis since the CER calculation is based on the out-of-sample forecasts.

Table 1.10 reports the monthly-level results. The annualized CER for the portfolio using historical average (HA) forecast is 2.20%. Panel A shows that the annualized CER gains are positive for 8 of the 15 portfolios using macroeconomic variable forecasts, indicating that these portfolios provide higher CER than the portfolio of the HA forecast. Among them, BM, DP, DY, IBO001 and M0G provide annualized CER gains exceeding 100 basis points (bps). 7 of the 15 macroeconomic variables generate a positive CER gain after a transaction cost of 50 bps. Finally, Panel B of Table 1.10 shows that the PC-ECON model provides a decent CER gain of 414 bps after transaction cost. Turning to the results using the *monthly* technical indicators, right-hand side of Table 1.10 shows that 14 of the 15 portfolios have negative CER gains, indicating a CER loss when using monthly technical indicator forecasts. This confirms our prior out-of-sample findings regarding the failure of monthly technical indicators to beat the historical average forecast.

Weekly-level CER gains are reported in Table 1.11. We verify that weekly-level technical indicators perform much better than their monthly counterparts as far as CER gains are concerned. The CER of the benchmark portfolio using the historical average forecast is 3.93%, which is considerably higher than the monthly result. Although this benchmark CER is now tougher to beat, 14 of the 15 portfolios using forecasts based on weekly-level technical indicators generate positive annualized CER gains, spanning from 86 bps to 497 bps. Since the weekly technical indicators trigger more frequent trading than their monthly counterparts, the CER gains decrease considerably after imposing a transaction cost of 50 bps. Nevertheless, 7 of the 15 technical indicators have positive CER gains after the transaction costs, still far better than the negative CER gain for the entire set of the monthly-level technical indicator. In Panel B of Table

1.11 we show that PC-TECH^{w} model can generate 610 bps CER gain before transaction cost and 113bps after transaction cost and PC-TECH[9,11]^{w} model performed even better, providing 291 bps CER gain after transaction cost.

In summary, at the monthly frequency, macroeconomic variables can generate CER gain after transaction cost, while the *monthly-level* technical indicators do not. In contrast, *weekly-level* technical indicators offer considerable CER gains even after the imposition of a substantial transaction cost, verifying that technical indicator can predict Chinese equity premium more consistently in weekly frequency.

4.3. Cross-sectional tests

In this section, we report the performance of weekly technical indicators in the cross-section. Our cross-sectional analysis is different from existing literature on technical indicator. Firstly, recent literature investigating technical indicators focus on the profitability while we use predictive ability as a measure of performance. Secondly, the existing literature usually uses single variable sorted portfolios to examine the cross-sectional performance (e.g., Glabadanidis 2015b; Han et al. 2014; Han, Yang & Zhou 2013). They found that the profitability of technical analysis is related to both volatility and market-value (size). However, we argue that single variable sorting cannot distinguish the impact of one variable from the impact of the other. For example, small firms tend to have higher volatility, and large firms generally have lower volatility. This interaction of size with volatility may affect the portfolio analysis result and interpretation.

To address this issue, we examine the predictability on 25 size-volatility double-sorted portfolios. We define volatility as the standard deviation of the weekly return in the prior 51 weeks. Market capitalization (Size) is the last week-end closing price multiplied by the number of shares outstanding for each company. The 25 double-sorted size-volatility portfolios are constructed using the weekly return data of all Chinese A-shares and the data comes from Datastream. From 1997:07 to 2016:12, we rebalance the portfolios at the end of every June using sorting data available and are held until the following June[6]. All portfolios are value-weighted. We end up with 25 portfolios that have a similar number of firms in every year[7].

For clarity, we only report the result for three type of principal component models. The first one is the principal component model using all the weekly technical indicators which we refer to as the PC-TECH^{w} model. The second one is PC-TECH[3,5]^{w} model which is based on $MA(1,l), MOM(1,l)$ and $VOL(1,l)$ with $\mathrm{l} = 3, 5$ $week$. The last one is PC-TECH[9,11]^{w} model based on longer-horizon weekly technical indicators with $\mathrm{l} = 9, 11$ $weeks$. In line with the previous principal component model, the up-limit for the number of principal components is K=3 and the number of K is determined by the adjusted R^2. A full set of technical indicators and their principal components models are generated separately for each double-sorted portfolio.

[6] For 2016 only, the portfolios are held to December 2016 due to data availability.

[7] The average number of firms in the 25 VW double-sorted portfolios is evenly distributed, ranging from 52.38 to 84.62.

Overall, Table 1.12 suggest the weekly technical indicators have substantial predictive power for all double-sorted portfolios in the in-sample tests (R^2 are reported in the left-hand-side) and can outperform the benchmark forecast for most portfolios in the out-of-sample tests (R_{OS}^2 are reported in the right-hand-side).

We find that there is little cross-sectional variation present by the PC-TECH^w model. In contrast, PC-TECH[3,5]^w and the PC-TECH[9,11]^w models exhibit apparent cross-sectional variation in both in-sample and out-of-sample results. Firstly, Table 1.12 shows that, in both in-sample (left-hand-side) and out-of-sample tests (right-hand-side), PC-TECH[3,5]^w model can better predict the smallest quintile (first column) than the largest quintile (fifth column), obtaining consistently high R^2 (R_{OS}^2). If trend-following strategies we examined are an indication of price trend, the small firms show stronger short-term price trend when compared to large firms, because PC-TECH[3,5]^w model which uses past price information in a shorter time horizon can better explain the smallest quintile. In contrast, PC-TECH[9,11]^w model seems to better predict the smallest and largest size quintile at the same time while do worse for the medium-size firms. Our result indicates smallest and largest firms show distinct price dynamics in the short-term time horizon which requires further investigation.

Secondly, the performance of technical indicators seems not to be sensitive to the volatility of the underlying asset, as we fail to identify any clear pattern along the rows of Table 1.12. However, Han et al. (2014) found that the excess returns generated by technical indicators are significantly higher for high volatility quintiles in the Chinese stock market. A similar association between technical indicator' profitability and underlying asset's volatility has been reported for the U.S. (e.g., Glabadanidis 2015b; Han, Yang & Zhou 2013). Therefore, an interesting discrepancy between the profitability and predictability of the technical indicators arises here. It seems that the increasing profitability of the technical indicator across volatility deciles is not necessarily associated with an increasing predictive power as suggested by our findings[8].

5. Conclusion

We find that monthly-level technical indicators provide complementary information to macroeconomic variables in predicting Chinese monthly equity premium. The proportion of variation explained is higher than that of the US result reported in Neely et al. (2014). Macroeconomic variables outperform the HA benchmark in the out-of-sample tests while most monthly-level technical indicators underperform the benchmark. In contrast, our newly proposed weekly-level technical indicator utilizing non-overlapping price information to the monthly counterparts show substantial predictive ability in-sample and out-of-sample, generating considerable certainty equivalent gain after 50 bps transaction cost. Moreover, weekly-level technical indicators significantly predict firm-level excess return while monthly-level one does not. Overall, the different performance between monthly-level and weekly-level trend-following technical indicator suggests that a short-term price trend exists in

[8] We find a similar result when examining the monthly-level technical indicators on double-sorted portfolio monthly returns.

China and concentrate on the weekly frequency rather than the monthly frequency. Our finding, if compared with the US result in Neely et al. (2014), suggests that the Chinese stock market has a different price dynamic to the US where the monthly-level technical indicators worked very well. Finally, we find that the predictive power of technical indicator is associated with market capitalization but not volatility in the cross-section.

The implication is threefold. Firstly, weekly-level technical indicators well predict Chinese equity premium and the predictive ability is of great economic value given the scarcity of weekly-level predictor. However, traditional asset pricing models leave no room for technical analysis despite growing evidence of its predictive power. Thus, it is important to bridge the gap between traditional asset pricing model and theoretical models of technical analysis.

Secondly, we find that technical indicator' predictive ability is not sensitive to volatility, contradicting to Han, Yang and Zhou (2013) who argue information uncertainty (proxied by volatility) is a major explanatory factor to technical indicators. Thus, the driving force of the technical indicator's predictive ability is still controversial and require further investigation.

Thirdly, the distinct price trend between China and US identified by the current study poses a challenge to the theoretical model of technical analysis and price trend. They should be able to explain the difference in the time horizon (i.e., length) of price trend across countries. Possible explanations may arise through the perspective of the market efficiency, the presence of behavioral biases, investor sentiment, information friction, and level of heterogeneous information (as reviewed in the introduction). Moreover, given the difference across countries, an extensive focus on US equity premium might be problematic, and it is critical to examine technical indicators' predictive ability on other international markets before we can obtain a more comprehensive picture about what drives international equity premium and cross-sectional stock returns. We leave these important issues to future research.

6. Tables

Table 1.1 Macroeconomic Variable Construction

Variable	Construction method	Data source
Book-to-market ratio, BM	For the months of July of year t to June of year t+1, BM is computed by dividing the sum of "common shareholders' equity" (WC03501[9]) of all A shares for fiscal year-end in year t-1 by the total market value (MV) of all A shares at the end of the current month.	Datastream
Cash-flow to price ratio, CFP	For the months of July of year t to June of year t+1, CFP is the ratio of the sum of "funds from operations" (WC04201) of all A shares at the fiscal year-end of year t-1, to the sum of the total market value (MV) of all A shares at the end of the current month.	Datastream
Dividend-Earnings ratio (log), DE	For the months of July of year t to June of year t+1, DE is the difference between the log of the sum of the "cash dividends paid" (WC04551) of all A shares at the fiscal year-end of year t-1, and the log of the sum of the "net income" (WC01706) of all A shares at the fiscal year-end of year t-1.	Datastream
*Dividend-Price ratio (log),*DP	For the months of July of year t to June of year t+1, DP is the difference between the log of the sum of the "cash dividends paid" (WC04551) of all A shares at the fiscal year-end of year t-1, and the log of the sum of the market value (MV) of all A shares at the current month end.	Datastream
Dividend Yield (log), DY	For the months of July of year t to June of year t+1, DY is the difference between the log of the sum of the "cash dividends paid" (WC04551) of all A shares at the fiscal year-end of year t-1, and the log of the sum of the market value (MV) of all A shares at the last month end.	Datastream
Earnings-price ratio (log), EP	For the months of July of year t to June of year t+1, EP is the difference between the log of the sum of the "net income" (WC01706) of all A shares at the fiscal year-end of year t-1, and the log of the sum of the market value (MV) of all A shares at the current month end.	Datastream
Inflation, INFL	It is a monthly annual inflation rate using monthly CPI data from the National Bureau of Statistics of the People's Republic of China[10]. We lagged the CPI for one month since there is a one-month delay for the announcement of CPI data.	National Bureau of Statistics of the People's Republic of China

[9] The symbols in the parentheses are Datastream codes if applicable.

[10] The CPI data is constructed by comparing the current price level with the price level of same month last year. Thus, the inflation used in this paper is the annual inflation compared with the same month last year, which can absorb some seasonal pattern in the inflation.

Stock variance, SVAR	It is the sum of squared daily returns of the Shanghai Composite index of the current month.	China Stock Market & Accounting Research (CSMAR)
Trading volume scaled by market value, VO/MV	It is the ratio of the total trading volume of Shanghai A and Shenzhen A market divided by the total market value of all A shares of the current month.	China Stock Market & Accounting Research (CSMAR)
Volatility index, VIX	It is the percentage change in the VIX index at the end of every month, which is downloaded from the Federal Reserve Bank of St. Louis.	Federal Reserve Bank of St. Louis.
7-days Repo, R007	It is the percentage change in the 7-days Repo rate at the current month end compared with that of the last month end.	China Stock Market & Accounting Research (CSMAR)
Overnight interbank lending rate, IBO001	It is the percentage change of the Overnight interbank lending rate at the current month end compared with that of the last month end.	China Stock Market & Accounting Research (CSMAR)
M0 growth, M0G	It is the percentage change of the currency in circulation (M0) of every month.	National Bureau of Statistics of the People's Republic of China
M1 growth shock, M1G	It is the difference between the percentage change of the money (M1) of the current month and the last month.	National Bureau of Statistics of the People's Republic of China
M2 growth, M2G	It is the percentage change of the money and quasi-money (M2) of every month.	National Bureau of Statistics of the People's Republic of China

Table 1.2 Descriptive Statistics, 2002:12 to 2016:11

Variable	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation	Skewness	Kurtosis
MKT	-0.237	8.519	-29.439	19.355	0.113	-0.766	4.375
MKT^w	-0.069	3.606	-16.079	13.378	0.095	-0.471	5.288
BM	0.470	0.153	0.147	0.822	0.955	0.149	2.530
CFP	0.129	0.060	0.040	0.315	0.971	1.237	4.256
DE	-1.283	0.405	-1.795	-0.556	0.952	0.517	1.823
DP	-4.183	0.499	-5.412	-3.208	0.962	-0.037	2.481
DY	-4.169	0.503	-5.412	-3.142	0.954	-0.020	2.511
EP	-2.900	0.430	-3.953	-2.026	0.958	-0.196	2.373
INFL	2.685	2.054	-1.800	8.700	0.947	0.606	3.483
SVAR	0.006	0.006	0.001	0.031	0.650	2.142	7.508
VO/MV	0.036	0.024	0.010	0.124	0.825	1.521	4.876
VIX	0.017	0.226	-0.385	1.346	-0.170	1.824	10.184
R007	0.030	0.243	-0.631	0.907	-0.170	0.822	4.513
IBO001	0.036	0.277	-0.574	1.111	-0.297	0.898	4.454
M0G	0.011	0.072	-0.186	0.306	-0.169	0.888	7.041
M1G	0.000	0.034	-0.105	0.099	-0.549	-0.170	3.461
M2G	0.013	0.011	-0.015	0.047	-0.062	0.370	3.587

Notes: MKT is log equity risk premium (in percent) of the monthly market portfolio. MKT^w is log equity risk premium (in percent) of the weekly market portfolio. BM is book-to-market ratio. CFP is cash flow-to-price ratio. DE is log dividend-to-price ratio. DY is log dividend yield. EP is log earning-to-price ratio. Inflation is lagged monthly inflation rate. SVAR is stock variance. VO/MV is trading volume scaled by market value. VIX is the percentage change in the VIX index. R007 is the percentage change in the 7-days Repo rate. IBO001 is the percentage change in the overnight interbank lending rate. M0G is the percentage change of the currency in circulation. M1G is the money (M1) growth shock. M2G is the percentage change of quasi-money (M2). See Table 1 for the detailed variable construction.

Table 1.3 Predictive Regression Estimation Results (monthly-level), 2002:12 to 2016:11

Macroeconomic variables					Technical indicators (monthly-level)				
Predictor	Slope coefficient	R^2	R^2_{STA}	R^2_{VOL}	Predictor	Slope coefficient	R^2	R^2_{STA}	R^2_{VOL}
Panel A: Bivariate Predictive Regressions									
BM	9.68 [2.16]*	3.03%	3.57%	2.77%	MA(1,3)	2.55 [1.96]**	2.25%	-2.81%	4.65%
CFP	17.41 [1.77]	1.51%	1.28%	1.62%	MA(1,5)	2.44 [1.85]**	2.04%	-1.51%	3.73%
DE	1.17 [0.77]	0.30%	0.58%	0.17%	MA(1,7)	2.05 [1.52]*	1.43%	-0.38%	2.29%
DP	3.24 [2.38]**	3.57%	4.67%	3.05%	MA(1,9)	2.88 [2.12]**	2.75%	-1.94%	4.98%
DY	3.56 [2.69]***	4.38%	5.37%	3.91%	MA(1,11)	2.68 [1.94]**	2.35%	-2.16%	4.49%
EP	3.31 [2.10]*	2.80%	0.99%	3.65%	MOM(3)	3.30 [2.52]***	3.73%	2.25%	4.43%
INFL	1.17 [3.18]***	8.17%	5.90%	9.24%	MOM(5)	2.47 [1.88]**	2.09%	-2.59%	4.32%
SVAR	241.12 [1.92]**	2.82%	-1.35%	4.80%	MOM(7)	1.89 [1.40]*	1.21%	-2.00%	2.74%
VO/MV	74.38 [2.97]***	4.45%	2.41%	5.42%	MOM(9)	2.36 [1.61]*	1.76%	0.22%	2.50%
R007	4.80 [1.95]**	1.88%	-2.00%	3.72%	MOM(11)	0.84 [0.54]	0.22%	0.91%	-0.10%
IBO001	5.06 [2.50]***	2.71%	-3.08%	5.46%	VOL(1,3)	1.81 [1.39]*	1.13%	0.49%	1.43%
M0G	13.42 [1.76]**	1.29%	5.92%	-0.90%	VOL(1,5)	2.31 [1.79]**	1.83%	0.76%	2.33%
M1G	5.63 [0.33]	0.05%	0.75%	-0.28%	VOL(1,7)	2.34 [1.81]**	1.89%	-1.65%	3.58%
M2G	54.59 [1.24]	0.46%	-0.39%	0.87%	VOL(1,9)	1.19 [0.92]	0.49%	0.07%	0.69%
VIX	4.33 [1.25]	1.31%	1.83%	1.06%	VOL(1,11)	0.98 [0.75]	0.33%	0.16%	0.41%
Panel B: Principal Component Predictive Regressions									
$\hat{F}_1^{ECON}$	1.00 [3.04]***	5.95%	4.42%	6.68%	$\hat{F}_1^{TECH}$	0.46 [1.94]**	2.60%	-0.67%	4.16%
					$\hat{F}_1^{TECH[3,5]}$	0.77 [2.23]**	3.21%	-0.69%	5.06%
					$\hat{F}_1^{TECH[9,11]}$	0.54 [1.54]*	3.39%	0.07%	2.36%
					$\hat{F}_2^{TECH[9,11]}$	-0.74 [-1.10]			
					$\hat{F}_3^{TECH[9,11]}$	-1.23 [-1.45]*			
Panel C: Principal Component Predictive Regression, All Predictors Taken Together									
$\hat{F}_1^{ALL}$	0.44 [1.97]*	9.29%	3.04%	12.26%					
$\hat{F}_2^{ALL}$	1.06 [3.23]***								

Notes: Panel A reports estimation results for the in-sample predictive regression model (1) and the dependent variable is the market portfolio monthly excess return. *, ** and *** indicate significance at the 10%, 5% and 1% levels, based on the one-side wild bootstrapped *p*-value. R^2_{STA} (R^2_{STA}) is a sub-sample R^2 statistic for the stable (volatile) periods, as given by (8) in the text.

Panel B and C report estimation results for the principal component predictive regression model (9) and the dependent variable is also the market portfolio monthly excess return. $\hat{F}_k^j$ is the *k*th principal component extracted from the 15 macroeconomic variables ($j = ECON$), 15 monthly-level technical indicators ($j = TECH$), or all 30 predictors taken together ($j = ALL$). $\hat{F}_k^{TECH[3,5]}$ is the *k*th principal component extracted from six short-term monthly-level technical indicators $MA(1,l), MOM(1,l)$ and $VOL(1,l)$ given $l = 3,5$ $month$s. Similarly, $\hat{F}_k^{TECH[9,11]}$ is the *k*th principal component extracted from six longer-term technical indicators given $l = 9,11$ $months$.

Table 1.4 Predictive Regression Estimation Results (weekly-level), 2002:12:27 to 2016:12:02

Technical indicators (weekly-level)				
Predictor	Slope coefficient	R^2	R^2_{STA}	R^2_{VOL}
Panel A: Bivariate Predictive Regressions				
$MA(1,3)^w$	0.66 [2.47]***	0.84%	0.98%	0.77%
$MA(1,5)^w$	0.64 [2.41]**	0.80%	0.59%	0.91%
$MA(1,7)^w$	0.83 [3.12]***	1.32%	0.94%	1.53%
$MA(1,9)^w$	0.87 [3.30]***	1.46%	0.42%	2.02%
$MA(1,11)^w$	0.89 [3.34]***	1.51%	-0.29%	2.47%
$MOM(3)^w$	0.71 [2.64]***	0.96%	0.65%	1.12%
$MOM(5)^w$	0.58 [2.17]**	0.64%	0.34%	0.81%
$MOM(7)^w$	0.74 [2.77]***	1.05%	-0.70%	1.98%
$MOM(9)^w$	0.83 [3.14]***	1.33%	-0.70%	2.41%
$MOM(11)^w$	0.88 [3.30]***	1.47%	-0.18%	2.35%
$VOL(1,3)^w$	0.48 [1.79]**	0.44%	-0.41%	0.90%
$VOL(1,5)^w$	0.64 [2.38]***	0.78%	0.73%	0.80%
$VOL(1,7)^w$	0.68 [2.53]***	0.88%	1.52%	0.54%
$VOL(1,9)^w$	0.63 [2.35]***	0.76%	1.12%	0.57%
$VOL(1,11)^w$	0.46 [1.70]**	0.39%	1.17%	-0.02%
Panel B: Principal Component Predictive Regressions				
$\hat{F}_1^{TECH^w}$	0.14 [3.33]***	1.45%	0.80%	1.80%
$\hat{F}_1^{TECH[3,5]^w}$	0.18 [2.84]***	1.05%	0.65%	1.27%
$\hat{F}_1^{TECH[9,11]^w}$	0.21 [3.31]***	1.81%	0.64%	1.92%
$\hat{F}_2^{TECH[9,11]^w}$	0.25 [1.60]*			

Notes: Panel A reports estimation results for the in-sample predictive regression model (1) and the dependent variable is the market portfolio weekly excess return. *, ** and *** indicate significance at the 10%, 5% and 1% levels, based on the one-side wild bootstrapped *p*-value. R^2_{STA} (R^2_{STA}) is a sub-sample R^2 statistic for the stable (volatile) periods, as given by (8) in the text.

Panel B and C report estimation results for the principal component predictive regression model (9) and the dependent variable is the market portfolio weekly excess return. $\hat{F}_1^{TECH^w}$ is the 1st principal component extracted from the 15 weekly technical indicators. $\hat{F}_1^{TECH[3,5]^w}$ is the first principal component extracted from six short-term weekly technical indicators $MA(1,l), MOM(1,l)$ and $VOL(1,l)$ given $l = 3, 5$ $weeks$. $\hat{F}_k^{TECH[9,11]^w}$ is the kth principal component of six longer-term weekly technical indicators given $l = 9, 11$ $weeks$.

Table 1.5 Out-of-Sample Forecasting Results (monthly-level), 2002:12 to 2016:11

Macroeconomic variables	MSFE	R^2_{OS}	*MSFE-adjusted*	R^2_{OS}, Stable	R^2_{OS}, Volatile	$(\bar{\hat{e}})^2$	$Var(\hat{e})$
HA	82.41					0.39	82.02
Panel A: Bivariate Predictive Regression Forecasts							
BM	80.03	2.88%	2.12**	2.67%	2.91%	0.48	79.56
CFP	81.55	1.04%	1.16	3.22%	0.49%	0.15	81.40
DE	83.12	-0.86%	-0.17	-0.62%	-1.00%	0.99	82.13
DP	79.92	3.02%	2.42***	-3.48%	4.68%	2.40	77.52
DY	79.34	3.72%	2.62***	-5.63%	6.16%	2.26	77.09
EP	80.12	2.78%	2.06**	-0.45%	3.71%	0.79	79.33
INFL	75.73	8.10%	2.38***	2.24%	9.66%	0.62	75.12
SVAR	82.87	-0.56%	0.62	-3.92%	0.27%	0.67	82.20
VO/MV	81.21	1.45%	1.68**	-9.00%	4.56%	0.84	80.37
R007	82.32	0.11%	1.26	-7.92%	2.42%	0.35	81.97
IBO001*	81.50	1.11%	1.89**	-13.87%	5.25%	0.28	81.22
M0G	82.69	-0.35%	0.78	6.71%	-2.28%	0.42	82.27
M1G	83.52	-1.35%	-0.39	-12.64%	1.80%	0.44	83.08
M2G	83.65	-1.51%	1.07	-12.21%	1.53%	0.33	83.32
VIX	86.91	-5.46%	-0.46	1.42%	-7.25%	0.59	86.32
Panel B: Principal Component Predictive Forecasts							
PC-ECON	78.85	4.31%	2.83***	-17.90%	10.39%	0.86	78.00
Panel C: Principal Component Predictive Forecasts, All Predictors Taken Together							
PC-ALL	79.16	3.95%	2.87***	-32.50%	13.91%	0.62	78.53

Technical indicators (monthly−level)	MSFE	R^2_{OS}	*MSFE-adjusted*	R^2_{OS}, Stable	R^2_{OS}, Volatile	$(\bar{\hat{e}})^2$	$Var(\hat{e})$
MA(1,3)	81.28	1.37%	1.33*	-15.09%	5.84%	0.54	80.74
MA(1,5)	82.40	0.01%	1.02	-15.35%	4.17%	0.34	82.06
MA(1,7)	84.96	-3.09%	0.28	-22.59%	2.23%	0.32	84.64
MA(1,9)	82.83	-0.51%	0.87	-19.64%	4.68%	0.25	82.58
MA(1,11)	84.03	-1.96%	0.53	-24.08%	4.05%	0.23	83.79
MOM(3)	81.08	1.61%	1.53*	-8.14%	4.18%	0.45	80.63
MOM(5)	82.49	-0.10%	0.95	-13.02%	3.38%	0.35	82.14
MOM(7)	83.97	-1.89%	0.27	-18.45%	2.61%	0.30	83.67
MOM(9)	83.49	-1.31%	0.46	-10.45%	1.11%	0.36	83.13
MOM(11)	86.58	-5.06%	-1.18	-5.88%	-4.81%	0.53	86.05
VOL(1,3)	82.65	-0.29%	0.48	-4.07%	0.68%	0.44	82.21
VOL(1,5)	82.80	-0.47%	0.93	-10.20%	2.14%	0.29	82.51
VOL(1,7)	82.29	0.15%	1.01	-13.15%	3.75%	0.41	81.88
VOL(1,9)	84.16	-2.13%	0.07	-11.07%	0.30%	0.47	83.69
VOL(1,11)	84.63	-2.69%	-0.21	-11.38%	-0.22%	0.46	84.17
PC-TECH	84.79	-2.89%	0.50	-20.14%	1.78%	0.26	84.53
PC-TECH[3,5]	82.09	0.39%	1.20	-15.36%	4.62%	0.29	81.80
PC-TECH[9,11]	86.74	-5.25%	-0.07	-23.30%	-0.43%	0.29	86.45

Notes: This table reports the monthly-level out-of-sample forecasting result as given by (10) and (11) in the text. The dependent variable is the market portfolio monthly excess return. MSFE is the mean squared forecast error. R^2_{OS} measures the reduction in MSFE for the predictive regression forecast relative to the benchmark historical average (HA) forecast. *MSFE-adjusted* is the Clark and West (2007) statistic, testing a null hypothesis that the MSFE of HA forecast is smaller than the MSFE of the predictive regression forecasts. R^2_{OS} for the stable and volatile periods are reported separately. $(\bar{\hat{e}})^2$ and $Var(\hat{e})$ are the squared forecast bias and forecast error variance, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels. PC-ECON denotes the principal component forecasting model (11) based on the 15 macroeconomic variables. PC-TECH denotes the principal component forecasting model (11) based on the 15 monthly-level technical indicators. PC-TECH[3,5] is the principal component model (11) based on six short-term monthly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 3, 5\ months.$ PC-TECH[9,11] is the principal component model (11) based on six longer-term monthly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 9, 11\ months.$ PC-ALL is the principal component model (11) based on all the 30 predictors taken together. December 2002 until December 2007 is the initial estimation period (60 months), and January 2008 until November 2016 is the forecast evaluation period (107 months).

Table 1.6 Out-of-Sample Forecasting Results (weekly-level), 2002:12:27 to 2016:12:02

Technical indicators (weekly-level)							
Predictor	MSFE	R^2_{OS}	*MSFE-adjusted*	R^2_{OS}, Stable	R^2_{OS}, Volatile	$(\bar{\hat{e}})^2$	$Var(\hat{e})$
HA	15.15					0.00	15.15
Panel A: Bivariate Predictive Regression Forecasts							
MA(1,3)^w	15.08	0.52%	1.59*	-0.48%	0.77%	0.00	15.08
MA(1,5)^w	15.07	0.58%	1.72**	-1.05%	0.98%	0.00	15.07
MA(1,7)^w	14.99	1.07%	2.28**	-1.33%	1.67%	0.00	14.99
MA(1,9)^w	14.96	1.25%	2.60***	-3.10%	2.33%	0.00	14.96
MA(1,11)^w	14.95	1.34%	2.69***	-4.42%	2.77%	0.00	14.95
MOM(3)^w	15.03	0.82%	1.95**	0.05%	1.02%	0.00	15.03
MOM(5)^w	15.08	0.47%	1.60*	-0.98%	0.83%	0.00	15.08
MOM(7)^w	15.03	0.84%	2.07**	-4.24%	2.10%	0.00	15.03
MOM(9)^w	14.97	1.25%	2.56***	-3.37%	2.39%	0.00	14.96
MOM(11)^w	14.96	1.28%	2.63***	-4.83%	2.80%	0.00	14.96
VOL(1,3)^w	15.12	0.23%	1.18	-1.61%	0.69%	0.00	15.12
VOL(1,5)^w	15.07	0.57%	1.66**	-0.42%	0.82%	0.00	15.07
VOL(1,7)^w	15.06	0.60%	1.73**	0.81%	0.55%	0.00	15.06
VOL(1,9)^w	15.10	0.38%	1.53*	-0.70%	0.65%	0.00	15.10
VOL(1,11)^w	15.17	-0.12%	1.20	-1.19%	0.14%	0.00	15.17
Panel B: Principal Component Predictive Forecasts							
PC-TECH^w	15.03	0.83%	2.24**	-2.94%	1.76%	0.00	15.03
PC-TECH[9,11]^w	15.02	0.89%	2.13**	-0.88%	1.33%	0.00	15.02
PC-TECH[9,11]^w	14.99	1.10%	2.49***	-3.93%	2.35%	0.00	14.99

Notes: This table reports the weekly-level out-of-sample forecasting result as given by (10) and (11) in the text. The dependent variable is the market portfolio weekly excess return. MSFE is the mean squared forecast error. R^2_{OS} measures the reduction in MSFE for the predictive regression forecast relative to the benchmark historical average (HA) forecast. *MSFE-adjusted* is the Clark and West (2007) statistic, testing a null hypothesis that the MSFE of HA forecast is smaller than the MSFE of the predictive regression forecasts. R^2_{OS} for the stable and volatile periods are reported separately. $(\bar{\hat{e}})^2$ and $Var(\hat{e})$ are the squared forecast bias and forecast error variance, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels. PC-TECH^w denotes the principal component forecasting model (11) based on the weekly-level 15 technical indicators. PC-TECH[3,5]^w is the principal component model (11) based on six short-term weekly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 3, 5\ weeks$. PC-TECH[9,11]^w is the principal component model (11) based on six longer-term weekly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 9, 11\ weeks$. 26 December 2002 until 20 October 2006 is the initial estimation period (200 weeks), and 27 October 2006 until 3 December 2016 is the forecast evaluation period (528 weeks).

Table 1.7 Technical indicator performance on the extended sample (monthly-level), 1997:07 to 2016:11

In-sample results, technical indicators (monthly-level)			Out-of-sample results, technical indicators (monthly-level)					
Predictor	Slope coefficient	R^2	Predictor	MSFE	R_{OS}^2	*MSFE -adjusted*	$(\bar{\hat{e}})^2$	$Var(\hat{e})$
			HA	72.97			0.05	72.91
Panel A: Bivariate Predictive Model								
MA(1,3)	2.03 [1.92]**	1.56%	MA(1,3)	72.06	1.24%	1.34*	0.01	72.05
MA(1,5)	1.75 [1.62]*	1.15%	MA(1,5)	72.41	0.76%	1.03	0.02	72.39
MA(1,7)	1.55 [1.43]*	0.90%	MA(1,7)	72.66	0.43%	0.85	0.02	72.64
MA(1,9)	1.92 [1.75]**	1.35%	MA(1,9)	72.24	0.99%	1.16	0.03	72.22
MA(1,11)	1.79 [1.61]*	1.17%	MA(1,11)	72.42	0.76%	0.99	0.03	72.39
MOM(3)	2.29 [2.12]**	1.95%	MOM(3)	71.68	1.77%	1.57*	0.01	71.67
MOM(5)	1.47 [1.37]*	0.81%	MOM(5)	72.85	0.16%	0.69	0.02	72.83
MOM(7)	0.25 [0.23]	0.02%	MOM(7)	74.96	-2.74%	-1.30	0.01	74.95
MOM(9)	1.91 [1.65]**	1.30%	MOM(9)	72.41	0.77%	0.99	0.04	72.37
MOM(11)	0.11 [0.10]	0.00%	MOM(11)	73.75	-1.07%	-0.96	0.00	73.75
VOL(1,3)	1.46 [1.37]*	0.80%	VOL(1,3)	72.75	0.29%	0.68	0.01	72.74
VOL(1,5)	1.82 [1.73]**	1.25%	VOL(1,5)	72.32	0.88%	1.18	0.01	72.31
VOL(1,7)	1.50 [1.42]*	0.85%	VOL(1,7)	72.73	0.33%	0.81	0.02	72.71
VOL(1,9)	0.64 [0.61]	0.16%	VOL(1,9)	73.39	-0.58%	-0.05	0.01	73.38
VOL(1,11)	0.54 [0.51]	0.11%	VOL(1,11)	73.40	-0.60%	-0.09	0.01	73.39
Panel B: Principal Component Predictive Model								
PC-TECH	0.31 [1.60]**	1.69%	PC-TECH	72.99	-0.03	0.73	0.00	72.99
	0.40 [1.00]							
PC-TECH[3,5]	0.56 [1.98]**	1.88%	PC-TECH[3,5]	72.01	1.32	1.31*	0.01	72.00
PC-TECH[9,11]	0.35 [1.26]	2.14%	PC-TECH[9,11]	72.90	0.08	0.76	0.01	72.89
	-0.45 [-0.86]							
	-1.18 [-1.54]*							

Notes: Left-hand side reports the estimation results based on weekly-level predictive regression model (1) and principal component model (9). *, ** and *** indicate significance at the 10%, 5% and 1% levels, based on the one-side wild bootstrapped *p*-value. Right-hand side reports the out-of-sample forecasting results as given by (10) and (11) in the text. MSFE is the mean squared forecast error. R_{OS}^2 measures the reduction in MSFE for the predictive regression forecasts relative to the benchmark historical average (HA) forecast. *MSFE-adjusted* is the Clark and West (2007) statistic that tests a null hypothesis that the MSFE of HA forecast is smaller than the MSFE of the predictive regression forecasts. R_{OS}^2 for the stable and volatile periods are reported separately. $(\bar{\hat{e}})^2$ and $Var(\hat{e})$ are the squared forecast bias and forecast error variance, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels. 0.00 represents less than 0.005 in absolute value. Initial estimation period is 1997:07 until 2012:12 and forecast evaluation period is 2003:01 until 2016:11.

PC-TECH denotes the principal component model of the 15 monthly-level technical indicators, as given by (9) and (11) in the text. PC-TECH[3,5] is the principal component model of the six short-term monthly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 3, 5\ months$. PC-TECH[9,11] is the principal component model of the six longer-term monthly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 9, 11\ months$.

Table 1.8 Technical indicator performance on the extended sample (weekly-level), 1997.07.04 to 2016:12:02

In-sample results, technical indicators (weekly-level)			Out-of-sample results, technical indicators (weekly-level)					
Predictor	Slope coefficient	R^2	Predictor	MSFE	R^2_{OS}	*MSFE-adjusted*	$(\bar{e})^2$	$Var(\hat{e})$
			HA	13.08			0.00	13.08
Panel A: Bivariate Predictive Model								
MA(1,3)^w	0.61 [2.83]***	0.79%	MA(1,3)^w	12.99	0.67%	2.07**	0.00	12.99
MA(1,5)^w	0.63 [2.91]***	0.83%	MA(1,5)^w	13.00	0.64%	2.06**	0.00	12.99
MA(1,7)^w	0.80 [3.72]***	1.35%	MA(1,7)^w	12.93	1.17%	2.75***	0.00	12.93
MA(1,9)^w	0.77 [3.56]***	1.23%	MA(1,9)^w	12.92	1.23%	2.90***	0.00	12.92
MA(1,11)^w	0.72 [3.34]***	1.08%	MA(1,11)^w	12.93	1.16%	2.85***	0.00	12.93
MOM(3)^w	0.75 [3.47]***	1.17%	MOM(3)^w	12.98	0.79%	2.32**	0.00	12.98
MOM(5)^w	0.52 [2.39]***	0.56%	MOM(5)^w	13.02	0.46%	1.73**	0.00	13.02
MOM(7)^w	0.59 [2.74]***	0.73%	MOM(7)^w	12.98	0.74%	2.22**	0.00	12.98
MOM(9)^w	0.65 [3.02]***	0.88%	MOM(9)^w	12.96	0.94%	2.56***	0.00	12.96
MOM(11)^w	0.59 [2.73]***	0.72%	MOM(11)^w	12.98	0.75%	2.23**	0.00	12.98
VOL(1,3)^w	0.55 [2.52]***	0.63%	VOL(1,3)^w	13.05	0.26%	1.50*	0.00	13.05
VOL(1,5)^w	0.66 [3.05]***	0.92%	VOL(1,5)^w	13.00	0.62%	2.06**	0.00	13.00
VOL(1,7)^w	0.62 [2.86]***	0.81%	VOL(1,7)^w	12.99	0.71%	2.14**	0.00	12.99
VOL(1,9)^w	0.50 [2.29]**	0.52%	VOL(1,9)^w	13.02	0.49%	1.71**	0.00	13.02
VOL(1,11)^w	0.42 [1.90]**	0.36%	VOL(1,11)^w	13.05	0.23%	1.40*	0.00	13.05
Panel B: Principal Component Predictive Model								
PC-TECH^w	0.13 [3.66]***	1.27%	PC-TECH^w	12.96	0.94%	2.61***	0.00	12.96
PC-TECH[3,5]^w	0.18 [3.53]***	1.17%	PC-TECH[3,5]^w	12.96	0.89%	2.51***	0.00	12.96
PC-TECH[9,11]^w	0.17 [3.24]***	1.28%	PC-TECH[9,11]^w	12.95	1.01%	2.63***	0.00	12.95
	-0.13 [-1.10]							
	0.19 [1.19]							

Notes: Left-hand side reports the estimation results based on weekly-level predictive regression model (1) and principal component model (9). *, ** and *** indicate significance at the 10%, 5% and 1% levels, based on the one-side wild bootstrapped *p*-value. Right-hand side reports the out-of-sample forecasting results as given by (10) and (11) in the text. MSFE is the mean squared forecast error. R^2_{OS} measures the reduction in MSFE for the predictive regression forecasts relative to the benchmark historical average (HA) forecast. *MSFE-adjusted* is the Clark and West (2007) statistic that tests a null hypothesis that the MSFE of HA forecast is smaller than the MSFE of the predictive regression forecasts. R^2_{OS} for the stable and volatile periods are reported separately. $(\bar{e})^2$ and $Var(\hat{e})$ are the squared forecast bias and forecast error variance, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels. 0.00 represents less than 0.005 in absolute value. Initial estimation period is 1997:07:04 until 2012:12:28 and forecast evaluation period is 2003:01:03 until 2016:12:02.

PC-TECH^w denotes the principal component model of the 15 weekly-level technical indicators, as given by (9) and (11) in the text. PC-TECH[3,5]^w is the principal component model of the six short-term weekly-level technical indicators $MA(1,l), MOM(1,l)$ and $VOL(1,l)$ given $l = 3, 5$ $weeks$. PC-TECH[9,11]^w is the principal component model of the six longer-term weekly-level technical indicators $MA(1,l), MOM(1,l)$ and $VOL(1,l)$ given $l = 9, 11$ $weeks$.

Table 1.9 Firm-level predictive regression estimation results, 2002:12 to 2016:11

Technical indicators (monthly-level)							Technical indicators (weekly-level)						
Predictor	Loading (Mean)	Loading (+)	Loading (−)	Sig. (+)	Sig. (-)	R^2 (Mean)	Predictor	Loading (Mean)	Loading (+)	Loading (+)	Sig. (+)	Sig. (-)	R^2 (Mean)
Panel A: Bivariate Predictive Regressions													
MA(1,3)	0.16	54.91%	45.09%	2.04%	0.92%	0.82%	MA(1,3)^{w}	0.25	69.24%	30.76%	6.03%	0.45%	0.32%
MA(1,5)	-0.35	48.48%	51.52%	2.08%	2.00%	1.00%	MA(1,5)^{w}	0.34	76.91%	23.09%	8.39%	0.07%	0.34%
MA(1,7)	-0.63	47.05%	52.95%	1.92%	3.27%	1.23%	MA(1,7)^{w}	0.26	74.02%	25.98%	5.61%	0.17%	0.31%
MA(1,9)	-0.36	52.19%	47.77%	2.39%	3.07%	1.16%	MA(1,9)^{w}	0.24	72.31%	27.69%	6.48%	0.31%	0.31%
MA(1,11)	-0.24	53.07%	46.85%	1.80%	2.47%	1.03%	MA(1,11)^{w}	0.22	72.94%	27.06%	6.44%	0.42%	0.31%
MOM(3)	-0.66	44.89%	55.11%	1.60%	3.03%	1.09%	MOM(3)^{w}	0.36	77.92%	22.08%	10.62%	0.24%	0.37%
MOM(5)	-0.38	54.35%	45.65%	2.67%	4.39%	1.39%	MOM(5)^{w}	0.16	69.31%	30.69%	3.76%	0.21%	0.28%
MOM(7)	0.52	61.77%	38.23%	1.92%	1.12%	0.87%	MOM(7)^{w}	-0.07	57.68%	42.32%	3.03%	1.01%	0.32%
MOM(9)	0.64	65.84%	34.00%	1.80%	1.12%	0.79%	MOM(9)^{w}	-0.02	62.94%	37.06%	4.28%	0.94%	0.34%
MOM(11)	0.33	60.10%	39.55%	0.84%	1.04%	0.77%	MOM(11)^{w}	-0.19	54.79%	45.21%	2.33%	1.53%	0.36%
VOL(1,3)	0.33	54.07%	45.93%	1.92%	1.40%	0.91%	VOL(1,3)^{w}	-0.06	52.28%	47.72%	1.74%	1.39%	0.28%
VOL(1,5)	-0.75	40.34%	59.66%	1.32%	3.23%	0.99%	VOL(1,5)^{w}	0.15	66.56%	33.44%	6.58%	0.56%	0.35%
VOL(1,7)	-0.38	45.01%	54.99%	1.96%	2.59%	0.97%	VOL(1,7)^{w}	-0.05	57.96%	42.04%	3.87%	1.18%	0.35%
VOL(1,9)	-0.56	43.66%	56.30%	2.19%	3.31%	1.04%	VOL(1,9)^{w}	-0.16	55.17%	44.83%	3.20%	2.12%	0.38%
VOL(1,11	-0.43	46.37%	53.59%	1.56%	3.15%	0.97%	VOL(1,11)^{w}	-0.15	56.08%	43.85%	3.24%	1.92%	0.40%
Panel B: Principal Component Predictive Regressions													
PC-TECH	0.00	52.91%	47.09%	1.88%	2.08%	2.27%	PC-TECH^{W}	0.03	72.20%	27.80%	6.30%	0.66%	0.78%
PC-TECH[3,5]	-0.03	51.84%	48.16%	2.04%	1.76%	2.56%	PC-TECH[3,5]^{W}	0.07	74.89%	25.11%	6.76%	0.35%	0.68%
PC-TECH[9,11]	0.01	54.23%	45.77%	1.52%	1.52%	2.32%	PC-TECH[9,11]^{W}	0.01	67.19%	32.81%	4.91%	0.98%	0.82%

Notes: The table reports the in-sample predictive regression estimation results on the firm-level, based on individual firm monthly(weekly) excess return. Left-hand-side is the monthly-level result the right-hand-side is the weekly-level result. Loading (Mean) is the average slope coefficients of the predictive regressions for all firm-level regressions. Loading(+) and loading (–) are the proportion of companies that have positive slope coefficient and negative slope coefficient. Sig.(+) and Sig.(–) are the proportion of companies that have *significant* positive and negative slope coefficients on the predictors. R^2 (Mean) is the average R^2 statistics for a given predictor for all firm-level regressions. The principal component models are defined in Table 7 and 8.

Table 1.10 Portfolio Performance Measures (monthly), 2002:12 to 2016:11

Macroeconomic variables

Predictor	Δ	Sharpe ratio	Relative average turnover	Δ, Stable	Δ, Volatile	Δ, 50bps cost
HA	2.20%	-0.13	0.36%			2.18%
Panel A: Bivariate Predictive Regression Forecasts						
BM	1.50%	0.02	9.33	0.74%	2.34%	1.32%
CFP	-0.36%	-0.09	2.54	0.13%	-0.91%	-0.40%
DE	-4.35%	-0.05	9.23	-0.20%	-9.20%	-4.54%
DP	1.23%	0.11	17.75	0.72%	1.34%	0.88%
DY	2.71%	0.14	19.20	0.35%	4.96%	2.31%
EP	0.95%	-0.03	6.05	-0.71%	2.80%	0.85%
INFL	-3.44%	0.07	25.88	-0.37%	-7.10%	-3.97%
SVAR	-5.49%	-0.10	20.54	-1.24%	-10.55%	-5.93%
VO/MV	0.90%	0.02	17.36	0.01%	1.88%	0.56%
R007*	-1.51%	-0.06	47.37	-1.49%	-1.60%	-2.51%
IBO001*	1.54%	0.06	69.92	-3.11%	6.78%	0.06%
M0G	1.67%	0.06	39.95	1.50%	1.86%	0.89%
M1G	-1.08%	-0.15	16.28	-2.53%	0.51%	-1.40%
M2G	0.88%	0.02	60.97	-2.87%	5.06%	-0.37%
VIX	-9.77%	-0.09	43.21	-0.60%	-20.10%	-10.73%
Panel B: Principal Component Predictive Forecasts						
PC-ECON	5.53%	0.18	66.75	-2.94%	15.04%	4.14%
Panel C: Principal Component Predictive Forecasts, All Predictors Taken Together						
PC-ALL	1.44%	0.14	69.80	-6.42%	10.34%	-0.14%

Technical indicators (monthly-level)

Predictor	Δ	Sharpe ratio	Relative average turnover	Δ, Stable	Δ, Volatile	Δ, 50bps cost
MA(1,3)	0.29%	0.06	33.21	-3.75%	4.58%	-0.48%
MA(1,5)	-1.88%	0.03	27.69	-3.82%	-0.01%	-2.53%
MA(1,7)	-6.36%	-0.04	35.30	-5.47%	-7.75%	-7.21%
MA(1,9)	-3.13%	0.02	24.35	-5.16%	-1.25%	-3.73%
MA(1,11)	-4.47%	0.00	25.52	-5.95%	-3.23%	-5.10%
MOM(3)	-2.73%	0.06	34.82	-1.57%	-4.48%	-3.58%
MOM(5)	-2.68%	0.00	22.69	-3.74%	-1.86%	-3.21%
MOM(7)	-3.84%	-0.03	18.19	-4.75%	-3.15%	-4.24%
MOM(9)	-5.29%	0.00	22.72	-3.17%	-8.13%	-5.80%
MOM(11)	-10.76%	-0.12	12.21	-1.83%	-20.83%	-11.07%
VOL(1,3)	-1.62%	-0.06	27.07	-1.44%	-2.05%	-2.22%
VOL(1,5)	-3.45%	-0.02	31.08	-2.51%	-4.82%	-4.16%
VOL(1,7)	-2.47%	0.00	23.99	-3.21%	-1.96%	-3.00%
VOL(1,9)	-5.05%	-0.07	17.09	-2.85%	-7.71%	-5.42%
VOL(1,11)	-5.59%	-0.09	16.06	-2.89%	-8.74%	-5.95%
PC-TECH	-7.79%	0.00	39.77	-5.68%	-10.61%	-8.75%
PC-TECH[3,5]	-4.68%	0.03	43.54	-3.41%	-6.62%	-5.71%
PC-TECH[9,11]	-6.23%	-0.01	33.20	-5.96%	-7.36%	-7.00%

Notes: The table presents portfolio performance measures for a mean-variance investor with relative risk aversion coefficient of five who use an historical average (HA) forecast or predictive regression forecast to allocate *monthly* between equities and risk-free asset. Δ is the annualized certainty equivalent return (CER) gain for an investor who use the monthly-level predictive regression forecast instead of the HA forecast; we report the absolute level of CER for the HA forecast only. Δ are also reported for the stable and volatile periods separately. The definition of certainty equivalent return is given in (16). Relative average turnover is the average monthly turnover divided by the average monthly turnover for the portfolio based on the HA forecast; for HA forecast only, we report the average turnover level. Δ, 50bps cost is the CER gain after a transaction cost of 50 basis points per trade. The principal component models are defined in Table 7 and 8.

Table 1.11 Portfolio Performance Measures (weekly), 2002:12:27 to 2016:12:02

Technical indicators (weekly-level)						
Predictor	Δ	Sharpe ratio	Relative average turnover	Δ, Stable	Δ, Volatile	Δ, 50bps cost
HA	3.93%	-0.01	0.35%			3.84%
Panel A: Bivariate Predictive Regression Forecasts						
$MA(1,3)^w$	2.93%	0.07	48.79	-2.42%	7.59%	-1.66%
$MA(1,5)^w$	2.90%	0.07	40.24	-2.61%	7.70%	-0.92%
$MA(1,7)^w$	4.97%	0.10	43.42	-3.49%	12.43%	0.77%
$MA(1,9)^w$	4.48%	0.10	41.03	-5.57%	13.34%	0.50%
$MA(1,11)^w$	4.15%	0.09	35.40	-6.78%	13.80%	0.72%
$MOM(3)^w$	3.51%	0.08	34.23	-1.23%	7.63%	0.30%
$MOM(5)^w$	1.63%	0.06	31.01	-2.64%	5.35%	-1.26%
$MOM(7)^w$	2.55%	0.07	26.22	-5.64%	9.75%	0.10%
$MOM(9)^w$	4.25%	0.09	25.10	-5.07%	12.46%	1.89%
$MOM(11)^w$	3.64%	0.10	30.18	-7.10%	13.17%	0.78%
$VOL(1,3)^w$	0.86%	0.04	45.05	-2.36%	3.65%	-3.27%
$VOL(1,5)^w$	2.45%	0.07	42.36	-0.70%	5.20%	-1.48%
$VOL(1,7)^w$	2.19%	0.07	34.58	0.04%	4.07%	-1.03%
$VOL(1,9)^w$	1.91%	0.07	31.55	-1.83%	5.20%	-1.03%
$VOL(1,11)^w$	-0.80%	0.05	29.37	-2.47%	0.68%	-3.54%
Panel B: Principal Component Predictive Forecasts						
$PC\text{-}TECH^W$	6.10%	0.11	52.43	-2.97%	14.10%	1.13%
$PC\text{-}TECH[3,5]^W$	4.61%	0.09	61.25	-0.01%	8.64%	-1.16%
$PC\text{-}TECH[9,11]^W$	6.50%	0.11	37.79	-2.68%	14.63%	2.91%

Notes: The table presents portfolio performance measures for a mean-variance investor with relative risk aversion coefficient of five who use an historical average (HA) forecast or weekly-level predictive regression forecast to allocate weekly between equities and risk-free asset. Δ is the annualized certainty equivalent return (CER) gain for an investor who use the predictive regression forecast instead of the HA forecast; we report the absolute level of CER for the HA forecast only. Δ are also reported for the stable and volatile periods separately. The definition of certainty equivalent return is given in (16). Relative average turnover is the average weekly turnover divided by the average monthly turnover for the portfolio based on the HA forecast; for HA forecast only, we report the average turnover level. Δ, 50bps cost is the CER gain after a transaction cost of 50 basis points per trade. The principal component models are defined in Table 7 and 8.

Table 1.12 Cross-Sectional Performance of the Weekly-level Technical Indicators, 1997.07.04 to 2016:12:02

SIZE / VOL	Small	2	3	4	Big	Small	2	3	4	Big
	In-sample R^2					Out-of-sample R_{OS}^2				
Panel A: PC-TECH^w model										
Low	1.70%***	1.48%***	1.67%***	1.99%***	1.36%***	1.01%***	1.35%***	0.96%***	1.52%***	0.85%***
2	1.85%***	1.57%***	1.29%***	1.38%***	1.46%***	1.49%***	0.83%***	0.42%**	0.33%**	0.83%***
3	1.75%***	1.70%***	1.53%***	1.60%***	1.24%***	1.23%***	0.34%**	0.65%**	1.13%***	0.84%***
4	1.97%***	1.26%***	1.56%***	1.46%***	1.28%***	1.22%***	0.59%**	0.57%**	0.68%**	0.91%***
High	2.07%***	1.64%***	1.29%***	1.70%***	0.88%***	1.21%***	1.05%***	0.34%**	0.99%***	0.66%**
Panel B: PC-TECH[3,5]^w model										
Low	2.01%***	1.54%***	1.38%***	1.79%***	1.20%***	1.26%***	1.02%***	1.25%***	1.47%***	0.99%***
2	1.92%***	1.57%***	1.21%***	1.35%***	0.80%**	1.83%***	1.04%***	1.03%***	0.87%***	0.30%*
3	1.84%***	1.62%***	1.72%***	1.56%***	0.83%***	1.59%***	0.76%***	1.03%***	1.51%***	0.79%**
4	1.98%***	1.38%***	1.58%***	1.34%***	1.10%***	1.59%***	1.11%***	1.18%***	0.76%***	0.66%**
High	2.34%***	1.49%***	1.48%***	1.76%***	0.76%***	1.35%***	0.70%***	0.65%***	0.98%***	0.57%**
Panel C: PC-TECH[9,11]^w model										
Low	0.89%***	1.15%***	1.41%***	1.45%***	1.16%***	0.55%**	0.81%***	0.60%**	1.10%***	0.95%***
2	1.07%***	0.83%***	0.46%**	0.66%***	1.73%***	0.83%***	0.59%**	0.13%	0.18%*	1.21%***
3	1.24%***	0.96%***	0.72%***	0.50%**	1.53%***	0.87%***	-0.09%	0.46%**	0.00%	1.13%***
4	1.29%***	0.87%***	0.44%**	0.74%**	1.42%***	0.28%**	0.35%**	0.19%*	0.28%*	0.99%***
High	0.97%***	0.46%**	0.71%**	1.18%***	0.79%***	0.34%**	0.27%*	0.36%*	0.61%***	0.42%**

Notes: This table reports the in-sample and out-of-sample performance of the principal component models based on weekly-level technical indicators for the 25 size-volatility double-sorted portfolios. In-sample R2 statistic and out-of-sample R_{OS}^2 statistic are reported in the left-hand-side and right-hand-side, respectively. For in-sample R2, *, ** and *** indicate the slope coefficient is significant at the 10%, 5% and 1% levels, based on the one-side wild bootstrapped p-value. For out-of-sample R_{OS}^2, *, ** and *** represent the MSFE-adjusted statistic is significant at 10%, 5% and 1% levels. Initial estimation period is 1997:07:04 until 2012:12:28 and forecast evaluation period is 2003:01:03 until 2016:12:02 for the out-of-sample tests.

PC-TECHw denotes the principal component model (as given by (9) and (11) in the text) based on the 15 weekly-level technical indicators. PC-TECH[3,5]w is the principal component model of the six short-term weekly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 3, 5\ weeks$. PC-TECH[9,11]w is the principal component model of the six longer-term weekly-level technical indicators $MA(1,l), MOM(1,l)\ and\ VOL(1,l)$ given $l = 9, 11\ weeks$.

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Principal Author

Name of Principal Author (Candidate)	Mingwei Sun		
Contribution to the Paper	Conducted the data collection and empirical data analysis, wrote manuscript.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Supervised development of work, helped in data interpretation, evaluated and revised the manuscript.		
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Contribution to the Paper			
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CHAPTER 2: TWO DISTINCT PHENOMENA? — THE PREDICTIVE POWER OF THE SHORT-TERM AND INTERMEDIATE-TERM MOVING AVERAGES

Abstract

We find that moving average indicators over *intermediate-horizons* (roughly 7 to 15 months) generate strong predictive power for US market indices, which is solely driven by the top 10% companies by market capitalization. The significant predictive power of intermediate-horizon technical indicator in Neely et al. (2014) appears to be a unique phenomenon for the largest companies as they examined only the S&P 500 index. In contrast, companies with small-to-medium market capitalization exhibit future price predictability using *short-horizon* moving average indicators. A weekly-level analysis reveals that moving average indicators provide strong and long-lasting *short-horizon* predictive power for over 50% of the cross-section. This short-horizon predictive power is strongly correlated with market capitalization but not with other sorting criteria including volatility. A qualitatively similar result holds in out-of-sample test. Sub-period tests show that the intermediate-horizon predictive power is likely due to a calendar effect. Overall, the *intermediate-horizon* and *short-horizon* predictive power of technical indicators appear to capture two distinct phenomena of US stock returns. The former resembles the "echo" effect described in Novy-Marx (2012) and Goyal and Wahal (2015). The use of momentum indicators yields a similar result and suggests momentum indicators capture similar information as moving average indicators. Nevertheless, momentum indicators exhibit weaker and shorter-lasting predictive power compared to moving average indicators. International evidence suggests that the predictive power of moving average indicators at intermediate horizons is strong only in the US market. In contrast, that predictive power of short-horizon moving average indicators is very strong in stock markets in Japan as well as other countries in the Asia-Pacific region.

1. Introduction

Technical analysis attempts to forecast future prices by relying on past price and volume information. Examples of the most commonly used technical indicators include momentum and moving averages, both of which are trend-following trading strategies. The profitability of technical indicators has been investigated and documented in numerous studies (e.g., Brock, Lakonishok & LeBaron 1992; Chan, Jegadeesh & Lakonishok 1996; Lo, Mamaysky & Wang 2000b). More recently, several researchers have shown that applying technical analysis to the cross-section can generate substantial excess returns which are greater for small capitalization stocks and more volatile stocks (e.g., Glabadanidis 2015a, 2015b, 2016; Han et al. 2014; Han, Yang & Zhou 2013; Shynkevich 2012). Technical analysis has also been used to predict future values of the equity risk premium. Neely et al. (2014) show that technical indicators can predict the monthly excess return of the S&P 500 index and that they provide complementary information to that supplied by conventional macroeconomic predictors. We intend to fill the gap in this literature by examining the predictive power of technical indicators (moving average and momentum indicators) in multiple indices, in the cross-section, as well as using higher frequency data, i.e., weekly in addition to monthly stock returns.

Neely et al.(2014) find that trend-following technical indicators with the horizon of 9-to-12 months can significantly predict the excess return of the S&P 500 index. We replicate their approach using both the S&P 500 index and CSRP value-weighted index. Our first finding is that the predictive power of moving averages is strong exclusively at intermediate horizons (around 7 to 15 months). Our second major finding is that the predictive power is much weaker for the CRSP value-weighted return, which contains a much larger number of companies with small-to-medium market capitalization compared to the S&P 500 index. Therefore, it is possible that the finding in Neely et al. (2014) is driven by the concentration of extra-large companies in the S&P 500 index. This possibility motivates us to examine the power of predictive regressions in the cross-section. Our third finding is that the predictive power of moving average (and momentum) indicators at intermediate horizons is significant only for the top/bottom size decile portfolios. Therefore, since Neely et al. (2014) examine only the largest 500 companies in the U.S. stock market, their result is mainly driven by the superior predictive power of intermediate-horizon moving averages for the companies with the largest market capitalization. In contrast, the predictive power of intermediate-horizon moving averages in the rest of the cross-section is much lower.

Our fourth finding is that short-horizon moving averages have substantial predictive power over future stock returns of firms with small market capitalization. Short-horizon (3-7 months) moving average indicators can significantly predict the returns of the smallest size decile. For all other size sorted deciles (except the largest decile), we also observe a greater predictive power at very short horizons. As a result, small-to-medium size companies seem to have very “sluggish” returns in the short-term, while the largest decile exclusively exhibits intermediate-term predictive power. This cross-sectional difference implies that short-horizon and intermediate-horizon moving averages may be capturing two distinct phenomena.

We repeat our analysis using weekly returns. We find that the predictive power of short-horizon moving average indicators is quite prominent. Based on the weekly return, we find that there is a persistent and substantial predictive power of short-horizon moving average for most of the cross-section which is also relatively long-lasting for more than 30 weeks. The absence of this predictability in monthly level returns suggests that there is a prominent short-term trend at the weekly frequency, indicating that a price trend may last for a week but not necessarily for a month. We show that the predictive power of short-term technical indicators is strongly and monotonically correlated with market capitalization, suggesting that smaller firms have stronger and more "sluggish" returns while larger firms have weaker and shorter-lasting price trends. The largest firms even exhibit negative predictive power. We do not find the same cross-sectional result when using other sorting characteristics. Our result is consistent with Gutierrez and Kelley (2008), who report a long-lasting weekly momentum return after a short-lasting reversal effect.

Subperiod analysis shows that the predictive power of the intermediate-horizon moving average appears to be due to a calendar effect. We examined the sub-sample R^2 statistic regarding calendar months and business cycles. We find that the monthly-level predictability at intermediate horizons is due to the June and October monthly returns while the predictive power of short-horizon moving average indicators is not sensitive to any calendar month. Thus, the predictive power of the intermediate-horizon moving average indicators appears to be a distinct phenomenon to that captured by short-term moving average indicators. In terms of the effect of business cycles, the predictive power of both short-horizon and intermediate-horizon moving averages is greater during recessions, which is consistent with the predictability literature.

The implications of our findings are fourfold. First, we provide an alternative way to examine and compare the performance of technical indicators, while the existing empirical literature exclusively uses profitability as the measurement of performance. For example, Han, Yang and Zhou (2013) examine the excess return generated by moving average in the cross-section of the US stock market. They found that high stock volatility, small market capitalization and other "information uncertainty" proxies are related to the profitability of short-horizon technical indicators in the cross-section. However, due to large cross-sectional differences in volatility, comparing average return may not help us get much insight into predictability mechanism of technical indicators. Glabadanidis (2015b, 2016) suggest that the timing ability of technical indicators creates a payoff resembling an at-the-money put option combined with regards to a buy-and-hold position in the underlying risky asset. Technical indicators may capture some of the upside volatility while avoiding some of the downside volatility and, hence, the average historical return may be highly correlated with past volatility. Therefore, technical indicators will generate a greater average excess return for an underlying asset with high volatility due to the convexity of the payoff. This could mean that it is possible that the excess return may be due to the influence of volatility differences rather than a genuinely greater predictive power. Rather than focus on comparing average return we focus on studying the predictive power of the moving average technical indicators. This provides an alternative angle to investigate the performance of technical indicators.

Second, the differences in the predictive power of intermediate-horizon and short-horizon moving average indicators may be capturing two distinct phenomena. The high predictive power of intermediate-horizon moving averages with monthly stock returns coincides with that in Novy-Marx (2012), who find that momentum profits are concentrated on portfolios sorted by the past performance at intermediate-horizons (7 to 12 months) rather than short-horizons. If the predictive power of trend-following technical indicators is indeed driven by a strong price trend[11], this greater predictive

[11] There is not an ideal way to measure price continuation. Momentum strategies which sort stocks by past winners/losers provides only indirect evidence of a price trend as well. Similarly, simulating trend-following technical trading strategies and measuring their average

power that is concentrated at intermediate horizons is in conflict with the intuition about price trends that "price increases are followed by further price increases and price declines are followed by further price declines." Goyal and Wahal (2015) call this an "echo" effect rather than price continuation. We contribute to the literature by showing that this monthly level "echo" effect is a distinct phenomenon present only in the largest 10% companies. In sharp contrast, our weekly analysis shows that the short-horizon predictive power is strong at first and decays at greater lags, which is consistent with the notion of a price trend. Moreover, this short-term predictive power of trend-following technical indicators is found to be monotonic in market capitalization, where the companies with the smallest market capitalization exhibit the strongest and longest-lasting price trends. Yao (2012) argues that the January effect has been the driver of the "echo" effect found in Novy-Marx (2012) and Goyal and Wahal (2015). In contrast, our findings suggest that the predictive power of intermediate-horizon moving average indicators relies highly on the months of June and October.

Third, in contrast with the literature measuring the investment performance of technical analysis (e.g., Glabadanidis 2015b, 2016; Han et al. 2014; Han, Yang & Zhou 2013), we find that the predictive power of short-term technical indicators is highly associated with market capitalization, not volatility. This finding supports several theoretical explanations regarding the links between the investment performance of technical analysis and market capitalization. For example, information frictions[12] may be one of the factors closely related to the market capitalization of the underlying asset. Also, if the magnitude of the predictive power of the trend-following technical indicator

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return is also an indirect measurement of a price trend. We believe that examining the predictive power of trend-following technical indicators provides an alternative angle in examining price trends.

[12] Neely et al. (2014) reviewed four types of theoretical model on information friction that may explain to the success of the trend-following technical.

is representative of the strength of the price trend, then the predictive power of the short-horizon indicators and, especially with weekly returns, is indicative of a price continuation. This predictive power of short-term moving average indicators makes intuitive sense especially for firms with smaller market capitalization. Any theory attempting to explain price trends will have to address specifically the relationship between market capitalization and price trends.

Lastly, in the cross-section, we can observe high predictive power when using weekly returns but not monthly returns. Thus, it seems that the price trend is strong at the weekly frequency but is much weaker at the monthly frequency. One possible interpretation of this finding is the gradual decay of the price trend.

2. Methodology and data

We retrieve S&P 500 return data from Wharton Research Data Services. Value-weighted, equal-weighted market return and daily variance sorted decile portfolio are obtained from Centre for Research in Security Prices (CRSP). All data on other decile portfolios is retrieved from Kenneth R. French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Monthly risk-free return is retrieved from Amit Goyal's website (http://www.hec.unil.ch/agoyal/). Lastly, we obtain the daily risk-free return from Kenneth R. French's website. Our sample is from July 1963 until December 2016.

Consider the following predictive regression model:

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1} , \tag{1}$$

where the equity risk premium, r_{t+1}, is the return on the market portfolio in excess of the risk-free rate from period t to $t+1$; $\varepsilon_{i,t+1}$ is the disturbance term with zero mean. The signal $S_{i,t}$ is the trading signal generated by technical indicator i at time t. Under the null hypothesis $\beta_{i,j} = 0$, $S_{i,t}$ cannot predict the equity risk premium of the underlying asset. In this case, the model breaks down into a constant expected equity risk premium model. Inoue and Kilian (2005) recommend a one-sided attest to increase the statistical power of in-sample predictability test. We thus test $H_0: \beta_{i,j} = 0$ against $H_1: \beta_{i,j} > 0$ using the heteroskedasticity-consistent t-statistic[13], based on an ordinary least square (OLS) procedure.

The moving average of past prices is a widely used technical trading indicator. We use the trading signal generated by a cross-over moving average (MA) rule as the predictor in the regression in (1) above. The MA rule generates a trading signal by comparing two moving averages at the end of t:

$$S_{i,t} = \begin{cases} 1 \ if \ MA_{s,t} \geq MA_{l,t} \\ 0 \ if \ MA_{s,t} < MA_{l,t} \end{cases} \tag{2}$$

where

$$MA_{j,t} = (1/j) \sum_{i=0}^{j-1} P_{t-i} \ for \ j = s, l; \tag{3}$$

$S_{i,t} = 0$ and $S_{i,t} = 1$ suggests a sell and buy signal, respectively; j denotes the maximum lag of the MA length and can be either s or l (short or long); P_t is the level of a portfolio index at time t. Therefore, an MA indicator will generate a signal based on a comparison between the value of $MA_{s,t}$ and $MA_{l,t}$. When $MA_{s,t}$ exceeds (falls short of) $MA_{l,t}$, indicating an upward (downward) trend, a buy (sell) signal will be generated. For our monthly (weekly) analysis, we use 2-year horizon of cross-over MA indicators with $s = 1 \ month \ (week)$ and $l = 3 \ to \ 24 \ months \ (3 \ to \ 104 \ weeks)$. Since we only use moving average with $s = 1$ with varying l, we drop s and denote a

[13] We use the Newey and West (1987) robust t-statistic.

MA indicator as $MA(l)^{month}$ for indicator which is based on monthly return, and as $MA(l)^{week}$ for one generated from weekly return.

3. Predicting market indices

We use the moving average indicators described in (2) and (3) to estimate the predictive regression model in (1). For ease of presentation, we provide a novel way to visualize the predictive power of moving average indicators. We plot the t-statistics and R^2 along the lag horizon (l) of the moving average indicators, as in Figure 2.1. We present our findings throughout the paper in figures rather than in tabular format.[14] This presentation of our findings makes it easier to compare the performance of moving average indicators for various values of the lag parameter l. We can also easily compare the performance of technical indicators in the cross-section.

In Figure 2.1 we plot the in-sample predictive power of the moving average indicators $MA(l)^{month}$ with $l = 3, 4, 5, \ldots, 23, 24$. In Section A of Figure 2.1 we present the predictive power of the regression for excess return of the S&P 500 index starting in July 1963 until December 2016. The findings indicate that the predictive power is weak[15] for the moving average indicator $MA(l)^{month}$ with l in the short-term (3, 4 or 5 month), but increases and reaches a peak at intermediate lags (around 10 months to 17 months) with a t-statistic of around two[16]. The R^2 statistics reach 0.8% to 1% around the same lag windows. The predictive power is statistically significant around the peak and the in-sample R^2 statistic is well above the 0.5% threshold which provides substantial economic significance as suggested in Campbell and Thompson

[14] All estimation data is available upon request and will be published online.

[15] Note that the t-statistics are negative in the first two months. We do not use bootstrapped p-value because the computation cost is too high when examine multiple underlying assets.

[16] For a one-sided test, $t = 1.645$ indicates significant at 5% significance level. We mark $t = 2$ as benchmark for conventional reason. At the same time, this provides a more rigorous threshold.

(2008). This significant predictive power of moving average indicators at intermediate horizons is consistent with the findings reported in Neely et al. (2014) for the S&P 500 index using moving average indicators with $l = 9$ and 12 months.

We extend our analysis to other market indices. In Section B of Figure 2.1 we report our findings for the value-weighted CRSP index during the same sample period. The predictive power of moving average indicators over future monthly returns of the value-weighted CRSP index is similar though weaker than that reported for S&P 500. The predictive power of moving averages is very weak for lags of between 3 and 8 months, but increases for lags of between 10 and 17 months and reaches a peak at lag of 15 months with a t-statistic of over 1.6 and an R-squared of 0.7%. At greater horizons the predictive power gradually decays. Overall, the hump-shaped term-structure of the predictive power of moving average indicators is similar though weaker than the one for the S&P 500 index.

The hump-shaped curve implies that the moving average indicators using more recent past price information does not predict the nearest future month return well. However, using a longer history of past price does a better job at explaining well future stock index returns. Since the moving average indicator is a typical "trend-following" technical indicator the hump-shared predictability pattern indicates that there is a strong price trend at intermediate lags which is not present for the first 3 to 6 months of past prices. Price continuation, or momentum, is perceived as higher prices following a rising price as well as lower future prices following a price drop. It is puzzling why price continuation is weak and insignificant at shorter horizons, but is stronger afterward, contradicting our intuition about "price continuation." Our result is similar to the finding of Novy-Marx (2012), who report that the momentum strategy based on the past returns of between 7 and 12 month outperforms the strategy based on past returns of between 2 and 6 months. He argues that momentum profitability is mainly driven by the past performance in the intermediate term. Goyal and Wahal (2015) describe this vividly as an "echo" effect. We observe a similar phenomenon in a different experimental setup.

The difference between the performance of moving average indicators for the S&P 500 index and the CRSP value-weighted index reveals an important cross-sectional pattern of the predictive power of moving averages. The plots in Sections A and B of Figure 2.1 we demonstrate that moving average indicator can better predict the S&P 500 index than the CRSP value-weighted index, especially in the intermediate term. The main difference between the CRSP value-weighted index and S&P 500 is their composition. S&P 500 includes the largest 500 companies while the CRSP value-weighted index is a more comprehensive representation of the market. The fact that the result is stronger for S&P 500 raises the question whether it is the largest companies that drive the predictive power of the intermediate-term moving average indicator.

To address this possibility, we repeat our analysis using an equal-weighted CRSP index, which puts much greater weight on the small-to-medium companies. We report our findings in Section C of Figure 2.1. In addition to the significant predictive power in the intermediate term, we also observe strong predictive power using the short-term moving average ($MA(l)^{month}$ with $l = 3, 4, 5, 6$,7) with t-statistics ranging from 2 to 3.5 and R^2 well above 1 percent, which is unobservable in the prior result based on the value-weighted index. This difference between the value-weighted and the equal-weighted findings implies that it is small-to-medium size companies that have different short-term price patterns compared to large companies. The predictive power at short-term horizons is strong and gradually decays at longer lags with a "bump" in the intermediate term. Next, we turn to the examination of the cross-sectional differences in the predictive power of moving average indicators.

4. Cross-sectional Predictability

Since value-weighted and equal-weighted indices have a distinct pattern of price-continuation, using portfolios sorted by market capitalization may help us gain some insights about the differential predictive power in the cross-section. We perform the predictive regression (1) using value-weighted portfolios sorted by market capitalization (size) with monthly returns retrieved from Kenneth French's online Data Library. We simulate the moving average trading signal for each of the size decile portfolios and use the signals to predict future portfolio monthly returns.

In Figure 2.2 we present our findings for the power of the predictive regression size-sorted decile portfolios. In the cross-section, the predictive power varies substantially using the moving averages at different horizons. Firstly, Figure 2.2 suggests that the largest-cap decile indeed has the greatest and most significant predictive power (black curve) at intermediate horizons (around 10 to 17 months), while most of the other size deciles have much weaker results. This cross-sectional difference explains why we find significant intermediate-term predictive power in S&P 500 but weaker result in CRSP value-weighted return since the predictive power in the intermediate term is mostly an effect mostly due to the largest companies. It is worthwhile noting that the rest of the size-sorted portfolio do exhibit an increasing though insignificant predictive power at intermediate horizons. We show that the largest-cap companies play a substantial role in driving the greater predictive power at intermediate horizons. Overall, this unique behavior of the stock returns of the largest companies reveals that the predictive power of technical indicators described in Neely et al. (2014) appears to be driven by the companies with the largest market capitalizations which constitutes the majority of the composition of the S&P 500. Also, the evidence we present is consistent with the view that the largest companies may contribute exclusively to the "echo" effect documented in Novy-Marx (2012) Goyal and Wahal (2015).

Secondly, Figure 2.2 shows that the decile with the smallest market capitalization (micro caps) exhibits the greatest predictive power over and above that of all the other deciles and it is slowly decreasing at larger horizons. The predictive power for the smallest decile is very strong initially, indicating a very "sluggish" return in the short-term. Except for the largest decile, all the other deciles appear to have relatively high predictive power in the short-term (using $MA(3)^{\ month}$ and $MA(4)^{\ month}$), indicating that there is a price-continuation in the very short-term (higher frequency), which is not covered by our monthly analysis. Thus, it would be interesting to investigate the predictive power at a higher frequency, which we address in the next session.

So far, market capitalization seems to be an important cross-sectional factor associated with the predictive power of moving average indicators. As a comparison, we repeat our analysis using five additional sets of decile portfolios retrieved from French Kenneth's website, namely, portfolios sorted by variance, beta, book-to-market, industry, and momentum. We present our findings for these portfolio in Sections A through E of Figure 2.3. For comparison purpose, we hold the scale of the graphs as same as in Figure 2.2. Regarding the t-statistics and R^2 statistics, none of these portfolios show the same cross-sectional variation as the one with portfolios sorted by market capitalization in Figure 2.2. For example, Section A of Figure 2.3 shows that short-term moving average indicators can predict the future monthly return of the high variance decile while longer horizon indicators predict the future returns of the low variance decile. Nevertheless, the cross-sectional difference in predictive power is not of nearly as large as the one reported for size sorted decile portfolios. In other words, portfolios sorted by market capitalization have the largest cross-sectional variation in predictive power, especially for the largest and smallest decile. As a result, this finding indicates that market capitalization may better explain the differential predictive power of the moving average indicator than other sorting criteria or characteristics. Nevertheless, short-term moving average indicators, $MA(3)^{month}$ and $MA(4)^{month}$, can still predict well future returns of the highest variance decile, the highest beta decile, and the highest B/M decile. For momentum-sorted portfolios, future returns of past winners (8^{th}, 9^{th} and 10^{th} deciles) can be significantly predicted by moving averages at intermediate horizons. Overall, we can document greater predictive power using short-term and intermediate-term moving averages, with a "dip" in between these two horizons.

5. Weekly-level cross-section

The existing literature pays little attention to weekly returns, except Gutierrez and Kelley (2008), among others, who have documented a long-lasting *weekly* momentum of up to 52 weeks in US stock returns. In the previous section, we show that monthly technical indicators with the shortest horizon ($MA(3)^{month}$ and $MA(4)^{month}$) have relatively high predictive power compared with the longer horizons in most decile portfolios. This suggests the possible existence of price continuation at a higher frequency, within the minimum formation period of $MA(l)^{month}, l = 3\ months$.

We explore this possibility by running the predictive regression with *weekly* returns[17]. Using daily decile portfolio return data retrieved from Kenneth French's online Data Library website, we compute Wednesday to Wednesday weekly return

[17] We do not examine daily return to avoid criticism regarding market microstructure issues.

series[18]. In case of a missing Wednesday return, we replace it with the Thursday data of the same week. For the week starting on 10th September 2001, there is no Wednesday or Thursday data due to the 9/11 terrorist attack. We use Monday data for that week. We generate the moving average indicators on each portfolio and run the predictive regression in (1). To be consistent with our monthly level analysis using $MA(l)^{\,month}$ with $l = 3, 4, 5, \dots, 23, 24$, in our weekly level analysis we use $MA(l)^{\,week}$ with $l = 3, 4, 5, \dots, 103, 104$, covering a same 2-year post-formation period.

There are three differences between the weekly and monthly findings: Firstly, the weekly moving average indicator utilizes additional information which is within the horizon of 3 to 13 weeks (< 3 months). Secondly, the weekly predictive regression predicts future stock returns only one week forward, capturing predictive power at a higher frequency. Meanwhile, our monthly level predictive regression predicts future stock returns one month forward. Thirdly, weekly price movement contains inherently more (noisy) information than the monthly price, which may affect the predictive power. Since the monthly return is nosier than the yearly return, the weekly return may also be noisier than the monthly return. We believe the threshold for economic significance for weekly predictive regression should be lower than 0.5%, the threshold for monthly level predictive regression. However, there is no commonly accepted threshold for the R^2 statistic using predictive regression with weekly return data. We leave the inference to the reader.

Our findings for weekly returns are distinct from our findings with monthly returns in two ways: Firstly, as shown in Figure 2.4, within horizons of up to $l = 30$ weeks the magnitude of t-statistics/R-squared are *monotonically* lower across deciles as

[18] We do this in order to avoid potential contamination of weekly returns arising from beginning-of-the-week and end-of-the-week trading issues.

market capitalization increases. This indicates that market capitalization is a very strong coincidental factor for the predictive power of short-term moving averages in the cross-section.

Secondly, Figure 2.4 shows that, apart from the three largest deciles, the other seven size deciles have positively significant short-term price predictive power within horizons of up to $l = 30$ weeks. This suggest a very "sluggish" stock return for 70% of the cross-section in the weekly level. In contrast, our results for monthly returns reported in Figure 2.2 shows that only the smallest two size deciles have significant short-term predictive power. In Figure 2.4 we see that the smallest decile portfolio allows the strongest level of predictive power with R^2 of around 5% at horizons of just a few weeks. On the contrary, the largest size decile has a negatively significant (at 5% significance level for a one-sided test) t-statistic at the shortest horizons, which increases at longer lags but remains negative for lags of up to 15 weeks. This negative predictive power suggests a "negative trend", capturing the short-term reversal effect. In the bottom panel of Figure 2.4 we see that the six smallest deciles have R-squared reaching the 0.5% using $MA(l)^{week}$ with $l < 10\, weeks$.

This regularity of cross-sectional pattern across market capitalization and the strong predictive power using weekly returns is not observable at the monthly frequency with size-sorted deciles plotted in Figure 2.2. Considering the difference in findings between weekly and monthly predictive regressions, we provide the following interpretations:

The predictive power of the moving average indicator is stronger for next week stock returns than for next month stock returns. Alternatively, this may indicate that the rising (falling) price keeps rising (falling) for one extra week but does not last long enough for one additional month. Therefore, using weekly return may be better in capturing short-term price dynamics than using monthly returns.

The downward sloping of predictive power as a function of the weekly horizon is consistent with our understanding of the price trend getting weaker over time. In contrast, with monthly stock returns, the concentration of predictive power in the intermediate term driven by the largest capitalization companies is not consistent with the usual intuition about a price trend. As a result, the predictive power of short-term and intermediate moving average indicators appears to capture two distinct phenomena.

Market capitalization is negatively correlated with the cross-sectional variation in the weekly return predictive power, which is not the case for monthly returns.

Furthermore, the weekly price trend cannot be subsumed by the conventional momentum strategy based on monthly returns, and our result is consistent with the finding of Gutierrez and Kelley (2008), who report a long-lasting weekly momentum effect following a brief reversal in the nearest weeks. Our findings indicate that the initial short-term reversal is stronger for large-caps while most the other companies have longer-lasting "sluggish" stock returns in the short-term.

We find that market capitalization can explain well the "sluggish" cross-sectional weekly returns. However, it is also possible that other firm characteristics have a bearing on this cross-sectional phenomenon. To address this possibility, we present our findings for volatility-sorted, book-to-market, momentum-sorted and industry-sorted decile portfolios in Figure 2.5 and 2.6.[19] The portfolios sorted by prior variance are equally weighted while the other three sets of portfolios are value-weighted.[20]

[19] Our choice of these four sets of decile portfolios is largely driven by data availability.

[20] We use equal-weighted return because value-weighted daily volatility sorted deciles are not available from CRSP. These deciles are sorted based on prior 1 year's daily standard deviation.

As presented in Figure 2.5, the predictive power of weekly moving average indicators volatility-sorted deciles is quite strong at horizons of up to $\mathrm{l} = 30$ weeks across all deciles. However, unlike the size-sorted deciles, the volatility-sorted deciles largely overlap with each other. The exception is the decile portfolio with the highest historical volatility which shows the strongest predictive power with a very high t-statistic. Compared with our findings for size-sorted deciles, there is not much cross-sectional variation (except for the highest volatility decile) in the predictive power of $MA(l)^{week}$ with $l < 30\, weeks$, indicating volatility may be not be a good characteristic to capture the cross-sectional variation of the predictive power of weekly moving average indicators. However, the existing literature shows that the *short-term* trend-following technical trading rules can generate higher excess returns in deciles with higher volatility (e.g., Han et al. 2014; Han, Yang & Zhou 2013; Han, Zhou & Zhu 2015). If the predictive power of moving averages is similar across volatility-sorted deciles, then what is the possible mechanism for this result? Glabadanidis (2015b, 2016) suggest that the payoffs of moving average rules resemble that of an at-the-money put option with a long time-varying position in the underlying asset. Therefore, even though the predictive power of moving averages is similar across the volatility deciles, high volatility itself will lead to higher excess return using the moving average trading rule due to its greater convexity in the underlying buy-and-hold return. Because of the timing ability of moving averages[21], they can successfully capture more upside volatility while avoiding some of the downside volatility, resulting in higher excess returns even when the predictive power is the same across portfolios. Therefore, it is quite plausible that the similar level of predictability and the differences in profitability

[21] See Han, Yang and Zhou (2013) and Glabadanidis (2015b, 2016) for the evidence of market timing ability of moving averages using methodology described in Treynor and Mazuy (1966) and Henriksson and Merton (1981)

of moving averages indicators across volatility-sorted deciles can manifest at the same time.

Despite the conventional wisdom based on the profitability of moving averages, our results indicate that the performance of moving average indicators is more closely related to market capitalization than historical volatility. Except for the decile with the highest volatility, volatility does not appear to be positively associated with the predictive power of short-term moving average indicators. Moreover, we know from our previous findings that the predictive power of moving average indicators over small-cap stock returns is greater. As a result, using the equal-weighted volatility deciles amplified the significance of predictive power in Figure 2.5. If value-weighted volatility-sorted deciles were available, we would expect lower statistical significance making the slope in Figure 2.5 much flatter. Overall, it appears that market capitalization is more strongly associated with the cross-sectional differences in the predictive power of moving average indicators compared to historical volatility.

In Figure 2.6 we plot the predictive regression findings for book-to-market, momentum, and industry sorted portfolios. We hold the same scale along the vertical axis as in Figure 2.4. In Figure 2.6 we show that the cross-sectional variation is much smaller for book-to-market, momentum and industry sorted portfolios relative to that of size-sorted portfolios. This finding is consistent with the view that the predictive power of moving average indicators is better associated with differences in market capitalization.

Overall, we report very strong predictive power of moving average indicators using weekly returns in the cross-section, which is strong at short horizons and declines with lag length. This predictive power of short-term moving average indicators is consistent with the view that there is a strong price trend. We also show that market capitalization is monotonically associated with the predictive power of the weekly moving average indicator in the cross-section. Weekly stock returns of small-cap companies are more easily predicted and, thus, may have more 'sluggish' stock returns when compared with the weekly stock returns of large-cap companies. The largest 10% companies by market capitalization exhibit a "negative trend," implying that the largest-cap size decile is subject to the well-known short-term reversal effect.

6. Calendar effects and business cycles

Comparing the predictive power at the weekly frequency which behaves like price trend with the predictive power of intermediate-term moving averages at the monthly frequency does not appear to behave like price continuation. Yao (2012) argues that the January effect drives the intermediate-term "echo" effect discussed in Novy-Marx (2012). Indeed, a calendar effect may be behind the monthly return predictability at intermediate horizons. Therefore, using predictive regressions, we examine this possibility by revisiting our monthly frequency findings. Based on the sub-sample R-squared statistic in Neely et al. (2014), we calculate the following sub-sample R-squared statistic:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \, \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c \, (r_t - \bar{r})^2}, \qquad for\ c = 1,2 \ldots 12; \tag{4}$$

where I_t^c is an indicator variable that equals 0 when month t is the c^{th} calendar month[22] and equals 1 otherwise; $\hat{\varepsilon}_{i,t}^2$ is the fitted residual based on the full-sample estimates of the original predictive regression model; $\bar{r}$ is the full-sample mean of r_t; and T is the number of usable observations for the full sample. Note that R_c^2 can be negative.

[22] c can also be a subset of 1,2 … 12, in order to exclude multiple month from the sample at the same time.

R_c^2 is a sub-sample R-squared statistic that measures the goodness of fit by excluding a calendar month c from the calculation. We first consider monthly returns of the CRSP value-weighted index. In Section A of Figure 2.7 we plot the values of R_c^2. Note that the subsample goodness-of-fit for most subsamples are equal to or greater than that the full sample R^2 (black curve). In other word, removing these calendar months from the sample does not weaken the predictive regression result. The exceptions are February, June and October. Removing them separately from the sample causes a sizable reduction in the R-squared statistic. This indicates that the predictability of the moving average indicator is highly reliant on these three calendar months. To examine their overall effect on the predictive power, we remove the three months altogether and compute the sub-sample R^2. Section B of Figure 2.7 shows that removing them all together completely eliminates the predictive power and leads to negative R_c^2 at intermediate horizons.

We repeat this exercise using monthly returns of the equal-weighted CRSP index and report our findings in Sections C and D of Figure 2.7. Similar to the case of the value-weighted CRSP index, the predictive power at intermediate horizons relies heavily on the index returns in March, June, and October. In Section D we show what happens when we remove all three months from the sample. Generally, the predictive power of moving average indicators disappears entirely at intermediate-term horizons once we remove the March, June and October returns. Note that both the value-weighted and equal-weighted findings indicate strongly that June and October play a crucial role in boosting the predictive power of the moving average technical indicators. Furthermore, it is worthwhile noting that the predictive power at short horizons (using $MA(3)^{month}$, $MA(4)^{month}$, $MA(5)^{month}$) remains largely intact after removing these three calendar months, as shown in Section D. This finding indicates that the predictive power at short horizons does not rely entirely on the returns during these three calendar months.

Next, we investigate whether there is any calendar effect at the weekly return frequency. We report our findings using weekly value-weighted CRSP returns in Section E. The plots provide additional evidence suggesting that the predictive power of short-term technical indicators is not sensitive to any calendar month. In Section E we show that the value-weighted CRSP weekly return has a relatively low predictive power (< 0.5%) regardless of the sub-sample under consideration. Note that the composition of this index is dominated by large-cap companies and, hence, the predictive power of short-term moving average indicators over their future stock returns at short horizons is very low, if any. In contrast, as presented in Section F, the weekly *equal-weighted* CRSP returns exhibit long-lasting predictive power regardless of which calendar month is omitted. Overall, our findings suggest that the predictive power of moving average indicators at intermediate horizons appears to be a calendar effect, while the predictive power of moving average indicators at short horizons is not due to any calendar effects.

Based on model (4), we also examine the effect of business cycles on the predictive power of moving averages. We compute the sub-sample R^2 using the National Bureau of Economic Research (NBER) dated expansions and recessions. Section A of Figure 2.8 reports the results for the CRSP *value-weighted* monthly return. During economic recessions (yellow curve), R^2 is ranging between 2 and 3 percent at intermediate lags, while in economic expansions (orange curve) the R^2 is negative for most moving averages. This difference implies that the predictive power of intermediate-term moving averages over the value-weighted index is mostly due to its predictive power during recessionary periods.

In Section B of Figure 2.8 we report the sub-sample R^2 based on the CRSP *equal-weighted* monthly return. Moving averages can predict the equal-weighted index very well during recessions (yellow curve) at both short-horizon and intermediate-horizon lags, as represented by the large values of the R^2 statistics. In contrast, during recessionary periods (orange curve), moving averages still show some predictive power at short-horizon lags. However, there is no longer any predictive power in the intermediate term. This difference suggests that the predictive power over monthly returns of the equal-weighted index at intermediate lags is concentrated on recessionary periods, while the predictive power of short-term moving averages is less sensitive to the general economic conditions.

For the sake of completeness, we also investigate the differential predictive power of moving average indicators across both stages of the business cycle using portfolios sorted on market capitalization. In Section C of Figure 2.8 we show that most of the deciles have no predictive power during economic expansions, with the exception of the smallest three deciles which show economically significant R^2 using $MA(3)^{month}$, while the smallest decile show long-lasting predictive power using $MA(3)^{month}$ to $MA(8)^{month}$. This suggests that the "sluggish" *monthly* return of the smallest three deciles do appear to have an effect during economic expansions. In Section D we show that, during recessions, most of the size deciles have economically significant R-squared (above 0.5%) in the very short-term (using $MA(3)^{month}$ and $MA(4)^{month}$) and in the intermediate term. Among those, the largest and the smallest decile show the most extreme R-squared which are above 3% at intermediate lags, with the smallest decile also having a very high R-squared at short horizons, a similar pattern to what we reported previously.

In Figure 2.9 we report similar results using weekly returns. As the plots indicate, most of the predictive ability is concentrated during economic recessionary periods (yellow curve). As shown in Section C of Figure 2.9, the *smallest two* deciles exhibit substantial and economically significant predictive power using $MA(3)^{\ week}\ to\ MA(20)^{\ week}$ even during economic expansionary periods. The results we report in Section D of Figure 2.9 suggest that 80% of the cross-sectional variation in future returns of size decile portfolios can be well-predicted during economic recessions. Both the level of significance and lag of predictive power are much stronger than those we reported at the monthly frequency. This suggest further that moving averages provide better predictive ability for weekly returns rather than monthly returns.

7. Out-of-sample tests

To verify the robustness of our findings, we apply an out-of-sample test in this session. Consider the following out-of-sample forecasting model:

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} S_{i,t}\ , \tag{5}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{S_{i,s}\}_{s=1}^{t-1}$, where $S_{i,s}$ is the trading signal generated by a technical indicator i.

We use the historical average (HA) forecast as the benchmark forecast, following the literature (e.g., Campbell & Thompson 2008; Ferreira & Santa-Clara 2011; Jiang, F et al. 2011; Neely et al. 2014; Welch & Goyal 2008). This benchmark assumes a constant expected equity risk premium, $r_{t+1} = \alpha + \varepsilon_{t+1}$. Therefore, we compare the forecasts of our predictors, $\hat{r}_{t+1}$, to the historical average forecast computed using an expanding window:

$$\hat{r}_{t+1}^{HA} = \left(\frac{1}{t}\right)\sum_{s=1}^{t} r_s\,, \tag{6}$$

We analyze forecasts based on Campbell and Thompson (2008) out-of-sample R^2 (R_{OS}^2) and Clark and West (2007) MSFE-adjusted statistics. The R_{OS}^2 statistic measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast compared with the historical average forecast. The null hypothesis for MSFE-adjusted statistic is that the historical average MSFE is less than or equal to the predictive regression MSFE, and the alternative hypothesis is that the historical average MSFE is higher than the predictive regression MSFE.

Figure 2.10 presents the out-of-sample results on the size sorted decile portfolios using monthly returns. Both the MSFE-adjusted statistics[23] and R_{OS}^2 statistics confirm a similar cross-sectional and lag pattern as our in-sample findings. Firstly, for intermediate lags the largest decile has the highest predictive power using moving average indicators, while all other deciles have negative R_{OS}^2, failing to outperform the benchmark forecast. The largest decile has a R_{OS}^2 approaching 0.5% at intermediate lags, indicating the key role large-cap stocks play in the intermediate term. Secondly, at short-term horizons, the smallest two deciles have the strongest out-of-sample predictive power using $MA(3)^{\,month}$ with R_{OS}^2 exceeding 0.5% and 1.5% respectively, suggesting a short-term predictive power for small-cap stocks.

We repeat the same analysis using *weekly* decile portfolio returns sorted on market capitalization and report our findings in Figure 2.11. Unlike the out-of-sample result for monthly returns, Figure 2.11 shows more significant predictive power over future weekly returns using $MA(l)^{\,week}$ with $l = 3$ through 20 weeks. Section A shows that

[23] Note that the horizontal line in Section A of Figure 10 represents the MSFE-adjusted statistic equal to 1.3, which is around the threshold of significance at a 10% significance level.

the MSFE-adjusted statistics are significant for more than 50% of the cross-section, with the MSFE-adjusted statistics exceeding 2. Section B of Figure 2.11 shows that the smallest three deciles have the highest R^2_{OS} using $MA(l)^{week}$ with $l = 3 \text{ through } 20 \text{ weeks}$. Overall, these findings suggest that the predictive power of moving averages is stronger for weekly return than monthly returns, revealing that the price trend is stronger at the higher frequency. Moreover, it is worthwhile noting that MSFE-adjusted statistics are monotonically decreasing across size deciles, confirming that market capitalization is an important explanatory factor for the cross-sectional variation of the predictive power of short-term moving averages.

8. Random switching

The predictive power of short-term moving average indicators exhibits the most substantial variation across portfolios sorted on market capitalization. However, since small-cap and large-cap companies may contain different level of predictable component in their return, it is possible that the cross-sectional pattern is driven by the return differences across the size dimension itself rather than the performance of predictor. To test out this possibility, we check on and report the predictive power of random switching based on randomly generated trading signals in the cross-section.

The random trading signals generate a 1 or 0 signal randomly with 50%-50% probability at each time t. We generate 102 sets of such random signals to match the number of weekly moving average indicators. Then we use the random signal to run the predictive regression in (1) on each of the weekly size sorted decile portfolio. Figure 2.12 plots the t-statistics and R^2 of all the deciles. The evidence seems to suggest that the cross-sectional variation of the predictive power is not due to the different level of the predictable component among the weekly return of size-sorted deciles.

9. Momentum indicators

Regarding price continuation, the existing literature focuses more on momentum rather than on moving averages, even though they are both trend-following strategies based on technical indicators. The momentum strategy should capture similar information and, thus, be able to generate a similar result to the one produced by using moving averages. To compare the predictive power of moving averages with the predictive power of momentum, we test the performance of a momentum indicator based on the well-known momentum effect. Following Neely et al. (2014), this strategy generates a trading signal as follows:

$$S_{i,t} = \begin{cases} 1 \; if \; P_t \geq P_{t-m} \\ 0 \; if \; P_t < P_{t-m} \end{cases} \quad (7)$$

When the level of the portfolio index exceeds (falls short of) its past level m periods ago, a buy (sell) signal is generated. We denote this momentum indicator as $MOM(m)$. Similar to our moving average indicators, we examine a comprehensive range of $MOM(m)$ indictors, with $m = 3 \; to \; 24 \; months \; or \; 3 \; to \; 104 \; weeks$. $MOM(m)^{month}$ denotes a momentum indicator generated at the monthly frequency while $MOM(m)^{week}$ denotes a momentum indicator based on a weekly frequency.

We simulate trading signals based on each of our return indices and perform the predictive regression in (1) in order to predict their excess return. In Section A of Figure 2.13, we report our findings for the predictive regression results based on the S&P 500 monthly returns. The hump-shaped term-structure across various lags is similar to that found for moving average indicators, where the predictive power is weak at short-term lags (using $MOM(3)^{month}$ and $MOM(4)^{month}$) and strong at intermediate-term lags. However, the t-statistic and R^2 peak at $MOM(5)^{month}$ which is earlier than the case for moving average indicators, suggesting that there is perhaps a different dynamic at work for the momentum indicator. It can be easily observed from Section A of Figure 2.12 that the t-statistics are barely significant at lags between 5 to 12 months with the t-statistics approaching 2 using $MOM(5)^{month}$. Only $MOM(5)^{\mathrm{month}}$ and $MOM(10)^{month}$ generate in-sample R^2 larger than 0.5%. Moreover, the magnitude of t-statistic and R^2 decays much "faster" starting with $MOM(10)^{month}$, while the result for moving average indicators on S&P 500 suggests a higher level of predictive power that persists from $MA(10)^{month}$ until $MA(20)^{month}$, lasting much longer than the one using momentum indicators. Overall, momentum indicators have weaker predictive power than moving average indicators in predicting the S&P 500 excess return.

In Section B of Figure 2.13, we present our findings for how well the momentum indicators predict the CRSP value-weighted monthly return. Compared the results on S&P 500, momentum indicators exhibit a similar though weaker predictive power over the CRSP value-weighted monthly return. The t-statistics are in the range of 1 to 1.5 at the peak of the curve. Again, due to the different composition of S&P 500 and CRSP value-weighted index, this finding implies there is a major role played by companies with very large market capitalization in sustaining the predictive power of intermediate-term momentum indicator. Moreover, this strong predictive power at intermediate-term horizons bears a striking resemblance to the "echo" effect described in Goyal and Wahal (2015) and Novy-Marx (2012).

In Section C of Figure 2.13, we present our findings for the monthly returns of the equal-weighted CRSP index. In line with our findings regarding the predictive power of moving average technical indicators, the predictive power of short-term momentum indicators is much higher for the *equal-weighted* return than the *value-weighted* return. This indicates that momentum indicators have stronger predictive power at short horizons mostly for companies with smaller-to-medium market capitalization.

Our cross-sectional findings are based on monthly size sorted decile portfolios is presented in Section D of Figure 2.13. The predictive power of momentum indicators has a very similar cross-sectional pattern to the one obtained when using moving average indicator. First, the largest decile (black curve) exhibits the highest predictive power at intermediate-term lags. The largest capitalization companies appear to be the driving force behind the predictive power of technical indicators in the intermediate term, for both momentum and moving average indicators. Secondly, the smallest decile shows distinctly stronger predictive power in the short-term. In contrast, most of the other size decile portfolios largely overlap with each other with very similar predictive powers when using momentum indicators.

Next, we turn to our findings for the weekly frequency. Using weekly returns on size sorted decile portfolios leads to a much stronger predictive power of the momentum indicators as presented in Section E of Figure 2.13. Over 70% of the cross-section can be significantly predicted in the short-term, as suggested by the t-statistics in the top panel of Section E. Note that the predictive power is weaker and shorter-lasting than the moving average result presented in Figure 2.4. Secondly, the predictive power of the weekly momentum indicators monotonically increases as size decreases. We can summarize that market capitalization plays a critical role in explaining the cross-sectional variation in the predictive power of both *trend-following technical indicators* – momentum as well as moving averages.

In summary, momentum indicators appear to capture very similar information to moving average indicators. Our findings indicate that momentum indicators have weaker and shorter-lasting predictive power when compared to that offered by moving average indicators. Both sets of technical indicators suggest predictive power is high at short horizons and gradually decays as lags increase. Furthermore, the power to predict future returns with both technical indicators increases with market capitalization. The short-term predictive power agrees with the intuition regarding price continuation meaning price increases are followed by further price increases and vice versa. Furthermore, the predictive power of weekly momentum also decays over longer horizons in a manner similar to physical momentum encountering friction. In contrast, the monthly level analysis reveals that intermediate-term predictive power is driven by the largest decile only, and thus appears to be a distinct phenomenon.

10. International markets

Goyal and Wahal (2015) find the "echo" effect is not present outside the US market. So far we have only focused our analysis on the US equity market. It would be interesting to investigate whether moving average indicators have any predictive power over international stock market returns. We use the international value-weighted market excess return data obtained from the online Data Library of Kenneth French's website. The value-weighted market excess return data include Global, Global (exclude the US), European, North America, Japanese, and the Asia-Pacific (exclude Japan). Both monthly and daily returns are available. We use the daily data to construct Wednesday-to-Wednesday weekly return series. Thus, we can redo our prior analysis at the monthly and weekly frequency.

The sample period is from July 1990 to Dec 2016, which is a much shorter sample compared with the US data. As a result, the statistical power may be weaker than our previous analysis. Also, note that all the market return are value-weighted, therefore mainly representing the large companies.

In Section A of Figure 2.14, we report our findings for the monthly frequency using the global market return. There is a similar concentration of predictive power using the intermediate-term moving averages. Our findings at the weekly frequency are reported in Section B and share the same general shape across various lags as the monthly results in Section A. Recall that the information within the horizon of $l < 13\ weeks$ ($\approx$ 3 months) is not covered in the monthly analysis, therefore weekly level graph has an extended curve in the left relative to the monthly level graph. We observe a "dip" in the predictive power using $MA(3)^{\ week}$, $MA(4)^{\ week}$ and $MA(5)^{\ week}$ with a negative t-statistic using $MA(3)^{\ week}$. This appears to be an indication of a short-term reversal.

Excluding the US from the Global market portfolio, our findings are entirely different, as reported in Section C of Figure 2.14. Without the US companies, the predictive power of moving averages does not concentrate on the intermediate-term anymore. Instead, the predictive power is strong at short-term lags using $MA(3)^{\ month}$ and $MA(4)^{\ month}$. This distinct result after excluding US companies indicates that the predictive power of intermediate-term moving averages is solely driven by large-cap US companies[24], while large-cap non-US companies exhibit strong predictive power only in the short-term. Since the intermediate-term predictive power is similar to the "echo" effect, our result also implies the absence of "echo" outside the US. This finding is consistent with the finding in Goyal and Wahal (2015). In Section D we present our results at the weekly frequency. Note that if we exclude the horizon of $l < 13\ weeks$, the weekly graph in Section D will be very similar to the monthly graph in Section C. Section D shows that there is also a "dip" in the weekly level predictive power in the nearest horizons. The predictive power of moving averages is weak when using $MA(3)^{\ week}$ $MA(4)^{\ week}$, and even exhibits a negative t-statistic using $MA(3)^{\ week}$. The predictive power of moving averages peaks around $MA(20)^{\ week}$ and decays at

[24] Note that most of the world's largest companies are in the U.S., therefore the global value-weighted market return should have a large similarity to the U.S. value-weighted return.

longer lags. The low predictive power within horizons with $l < 13\ weeks$ may suggest that short-term reversal is a world-wide phenomenon.

In Section E of Figure 2.14 we report our findings for the predictive power of moving averages using monthly European market excess returns. We find that the predictive power is relatively strong and mostly concentrated on intermediate-term lags. In Section F of Figure 2.14 we report our findings using weekly European excess returns. The plot shows a negative t-statistic when using $MA(3)^{\ week}$ and $MA(4)^{\ week}$ and relatively higher predictive power at intermediate-term lags. In Section G and Section H we present further evidence that the North American market return exhibits a similar pattern of intermedium-term predictive power to the US and global result. This is to be expected since this index is mainly composed of large US companies. It is worthwhile noting that the significance in this case is weaker than the one for the US market only.

In Section I of Figure 2.14 we plot the predictive power at the monthly frequency using the Japanese market. We note the very high predictive power in the short-term which decays at longer lags. In Section J we show that the predictive power using weekly returns is much weaker with insignificant t-statistics and low R^2. The negative *t-statistics* using $MA(3)^{\ week}$ and $MA(4)^{\ week}$ suggest that short-term reversal is also prevalent in Japan.

Finally, we report out findings for the Asia-pacific region (excluding Japan) in Section K and Section L. We note that the predictive power of short-term moving average indicators is very strong. This evidence is present and strong at both monthly and weekly frequencies. The predictive power decays over longer horizons, suggesting a very "sluggish" return for stocks in the Asia-pacific region.

Overall, a comparison between global and global (exclude the US) results reveals that the predictive power of intermediate-term moving averages is due mostly to large-cap US companies. This finding is consistent with the finding in Goyal and Wahal (2015) that the "echo" effect only exists in the U.S. European market returns exhibit a similar intermediate-term predictive power which shifts somewhat towards longer lags. In contrast, Japanese market shows short-term predictive power only using moving average indicators. The absence of the predictive power of intermediate-term moving averages suggests a possible explanation as to why the existing literature fails to find momentum in the Japanese stock market (e.g., Griffin, Ji & Martin 2003) since the price trend is concentrated mostly at the short-term horizons. Most interestingly, in the Asia-pacific (excluding Japan) region we find that the predictive power of short-term moving average indicators is strong both at the monthly as well as the weekly frequency. This finding implies that stocks in developing markets have the most "sluggish" return and the strongest short-term price trend. If the Chinese stock market is taken as an example[25], our finding may explain why Griffin, Ji and Martin (2003) and Wang and Chin (2004) failed to find evidence of momentum using a formation period of 3 to 12 months in the Chinese stock market. Moreover, Pan, Tang and Xu (2013) find that only *weekly level* momentum exists in the Chinese stock market. Furthermore, they also report the existence of significant weekly momentum in multiple countries in the Asia-pacific region.

It is noteworthy that almost all international weekly level results have negative t-statistic using $MA(3)^{week}$, capturing the well-known short-term reversal effect in the weekly level and suggesting it is a world-wide phenomenon. Since we only have the

[25] Note that large Chinese companies have a great impact on the Asia-pacific (exclude Japan) index.

value-weighted market return, our understanding to the predictive power of moving average indictors using international stock returns is still limited to companies with the largest market capitalization since they dominate value-weighted market indices. It would be interesting to explore whether and how this result carries over when using international equal-weighted portfolios.

11. Conclusion

Using US data, we find that the predictive power of the intermediate-term (around 7 to 15 months) moving average indicators is driven by the largest 10% companies. This predictive power is only concentrated on three calendar months and economic recessions. Similar to the idea of Novy-Marx (2012), the concentration of predictive power on the intermediate term contradicts the intuition about price continuation (momentum) which suggests that "rising price keeps rising and falling price keeps falling." Instead, it is more like an "echo" effect as described by Goyal and Wahal (2015). In contrast, the predictive power of the short-term moving averages is stronger for small-to-medium size companies. Also, at the weekly return frequency, short-term moving average indicators have strong predictive power for over 50% of the cross-section. This predictive power of short-term technical indicators does not rely on any particular calendar month. It is strong at short lags and decays with lag length, in line with the intuition about price continuation that "rising price keeps rising and falling price keeps falling." Moreover, in the cross-section, market capitalization is negatively and monotonically related to the predictive power of the short-term momentum indicator. Overall, the predictive power of both short-term and intermediate-term indicators seems to capture two distinct phenomena.

Using international stock returns suggests that the predictive power of *intermediate-term* moving averages appear to be strongest in the U.S., while the stock returns in countries in the Asia-pacific region exhibit greater predictive power using *short-term* moving average indicators.

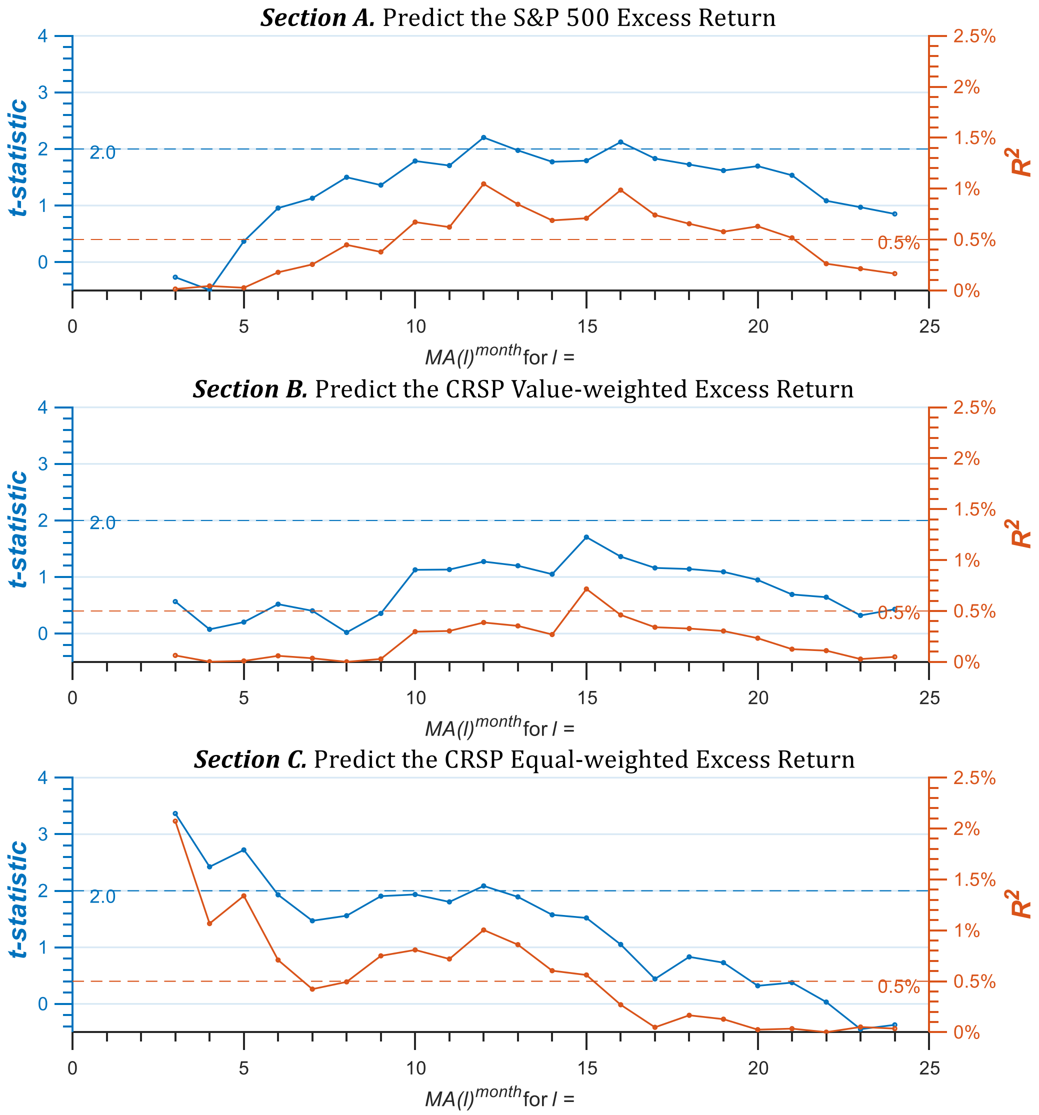
We find that momentum indicators capture slightly different information to that of the moving average indicator. Replicating the result using momentum indicator yields a qualitatively similar result. However, we show that momentum indicators have weaker and shorter-lasting predictive power than that offered by moving average indicators.

Our result has several implications: Firstly, the predictive power of short-term moving averages is very strong for over 50% of the cross-section and gradually decays over time, in line with the intuition regarding price trends. In contrast, the predictive power of intermediate-term moving averages appears to be a distinct phenomenon and applies to only the largest 10% companies, concentrated only on three calendar months. Therefore, the latter effect is more like a calendar/seasonal effect. The only shared characteristic by the two effects is that they are both stronger during economic contractions and weaker during economic expansions.

Secondly, we find that market capitalization is the single factor which well explains the short-term predictive power in the cross-section. If the level of predictive power of trend-following technical indicator can represent the level of price trend, the smaller companies exhibit stronger short-term price continuation while the larger companies exhibit weaker and even “negative price trend” in the short-term. This indicates the price trend favors companies with smaller market capitalization. Any theory purporting to explain this price trend needs to explain why market capitalization is negatively correlated with the magnitude of price continuation. Information frictions and liquidity issues are closely related to the market capitalization of the underlying asset and, thus, could help explain the source of the price trend. We leave these important issues to future research.

12. Figures

Figure 2.1 Predictive regression results on market indices (monthly), 1963:07 to 2016:12

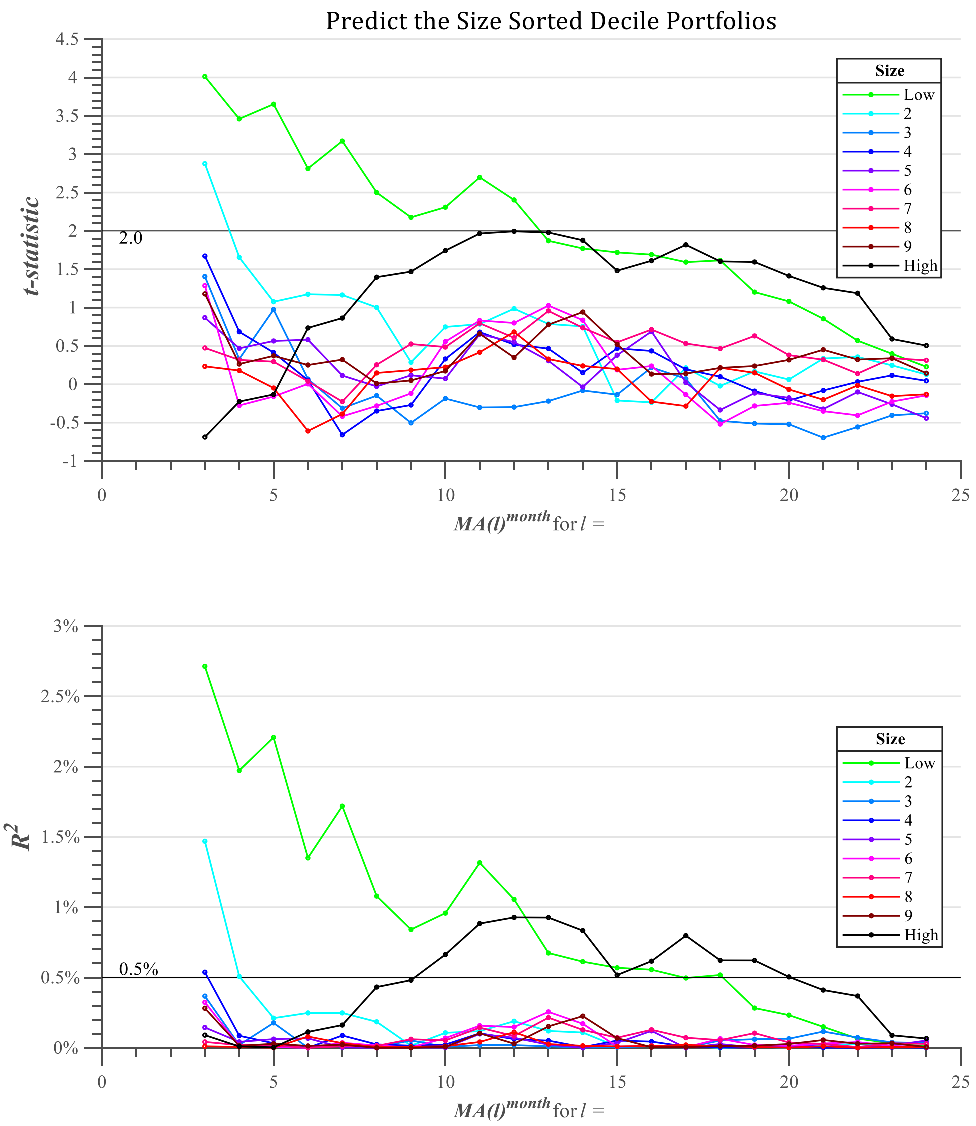


Notes. Section A, B, and C reports estimation results for the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) at time $t + 1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{\ month}$ with $l = 3, 4, 5, \dots, 23, 24\ months$ generated for each market indices. We denoted each $MA(l)^{\ month}$ on the horizontal axis. Section A, B, and C report the estimation results of the 22 predictive regressions on the S&P 500, CRSP value-weighted, and CRSP equal-weighted monthly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{\ month}$.

Figure 2.2 Predictive regression results on size-sorted decile portfolios (monthly), 1963:07 to 2016:12



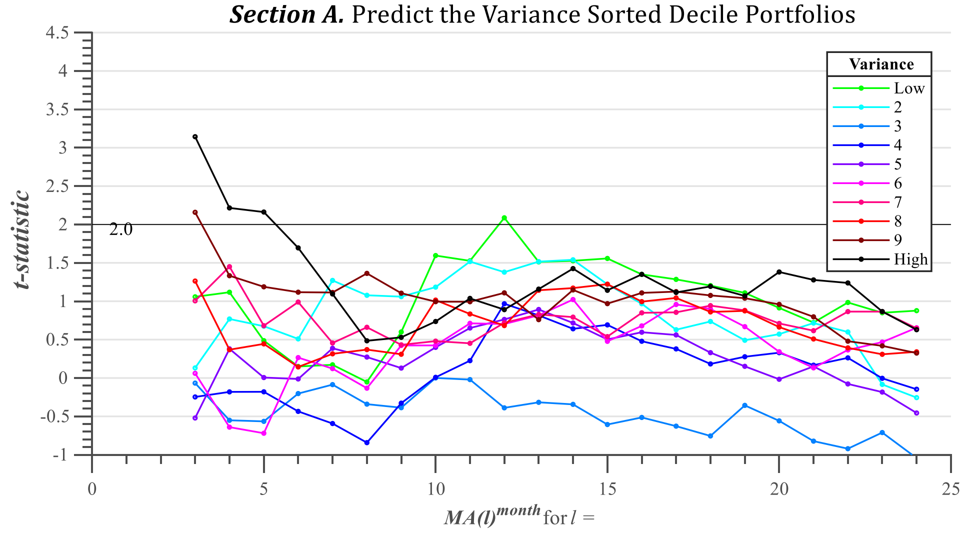
Notes. Figure 2 reports estimation results for the predictive regression model,

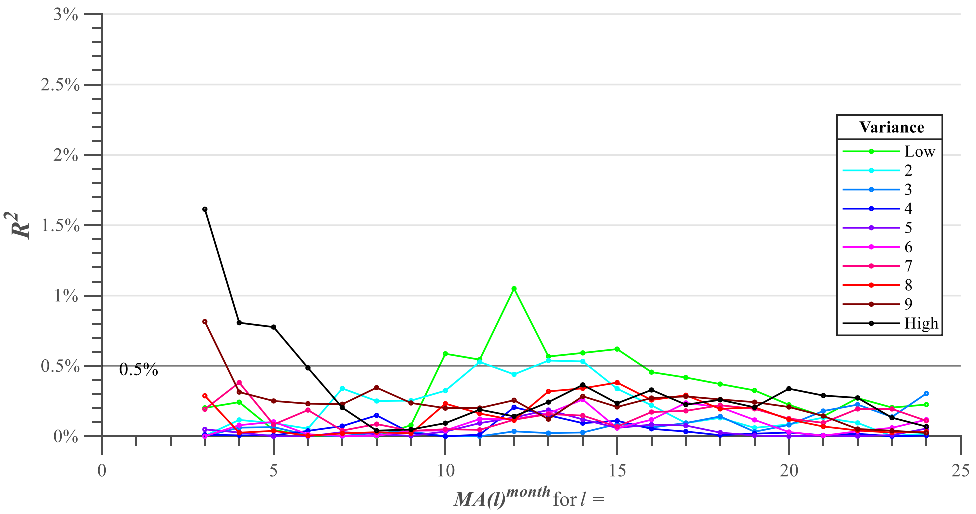
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \dots, 23, 24\ months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

For each of the 10 market capitalization (size) sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{month}$.

Figure 2.3 Predictive regression results on other decile portfolios (monthly), 1963:07 to 2016:12





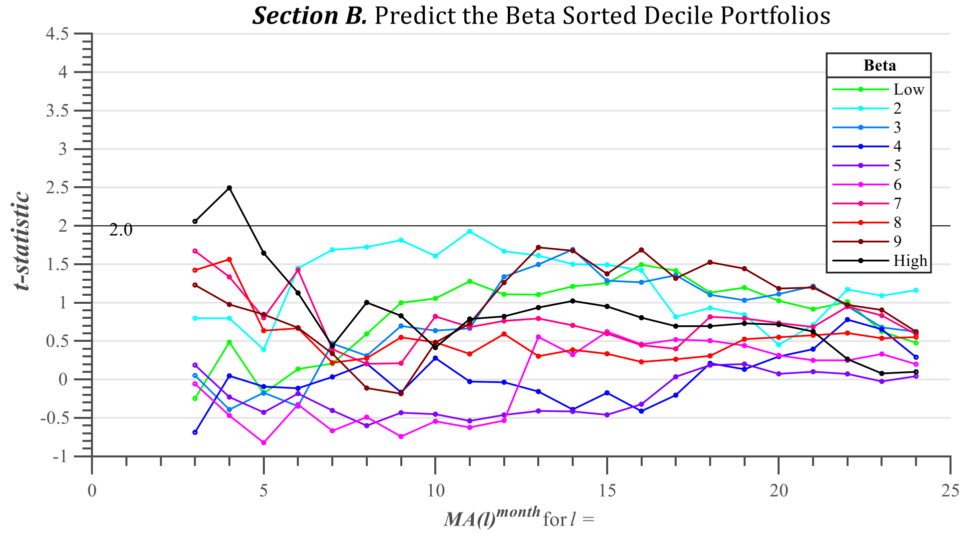
Notes. Section A reports estimation results for the predictive regression model,

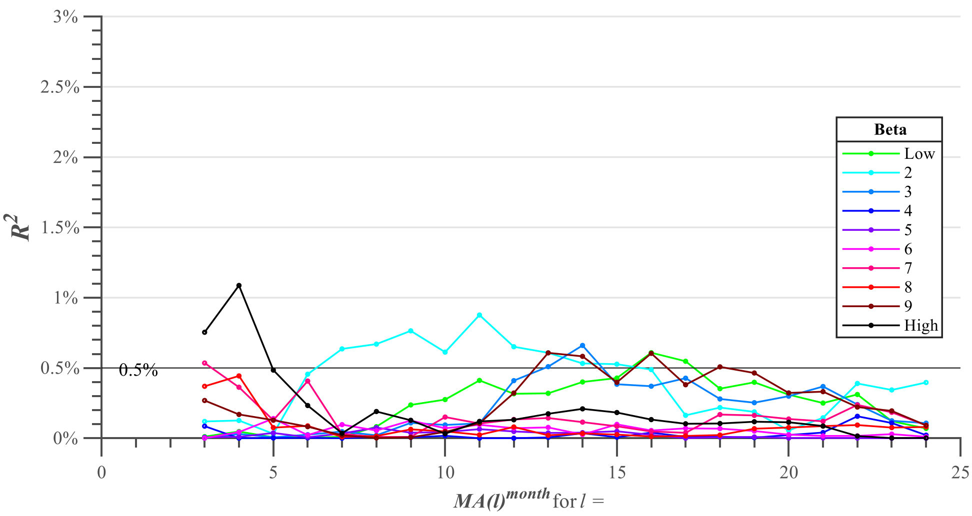
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \dots, 23, 24$ $months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

For each of the 10 variance sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{month}$.

(Figure 2.3 continued)





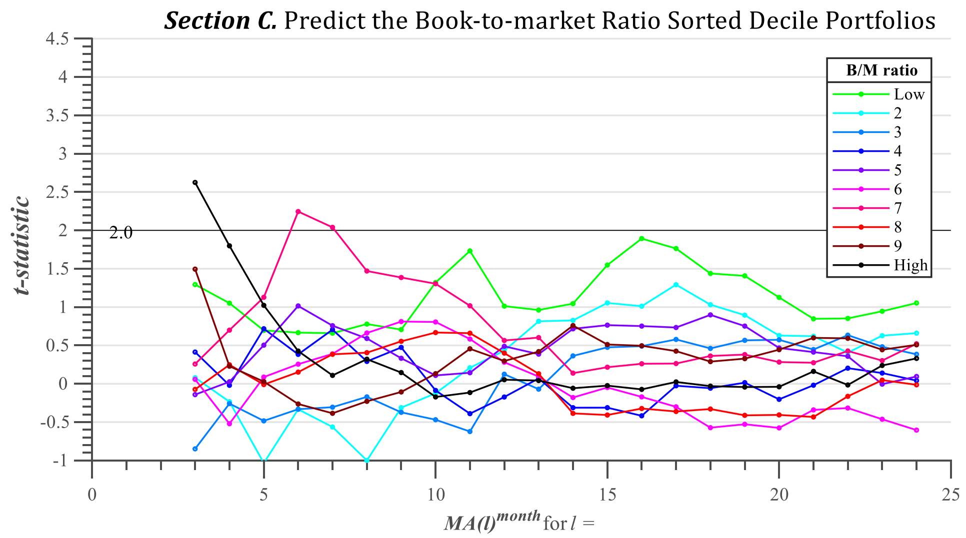
Section B reports estimation results for the predictive regression model,

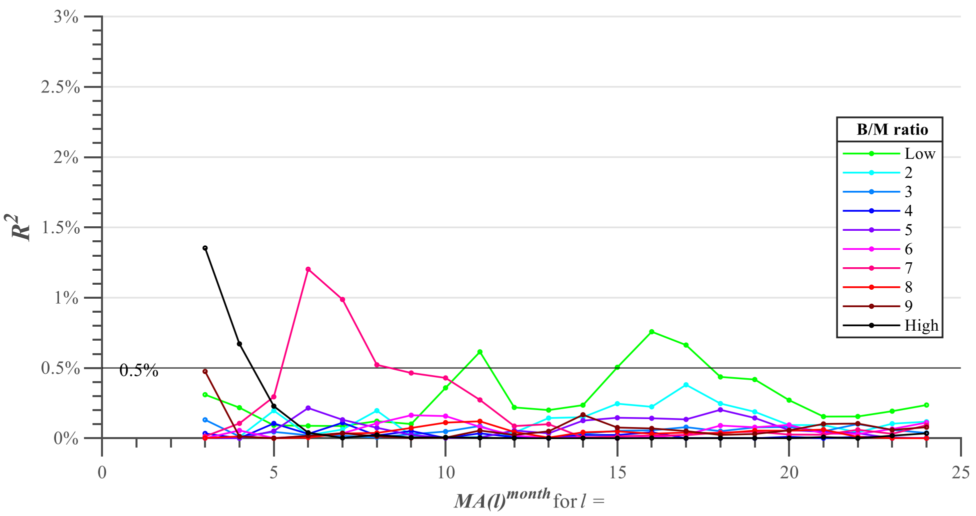
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \ldots, 23, 24$ *months* generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

For each of the 10 beta sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{month}$.

(Figure 2.3 continued)





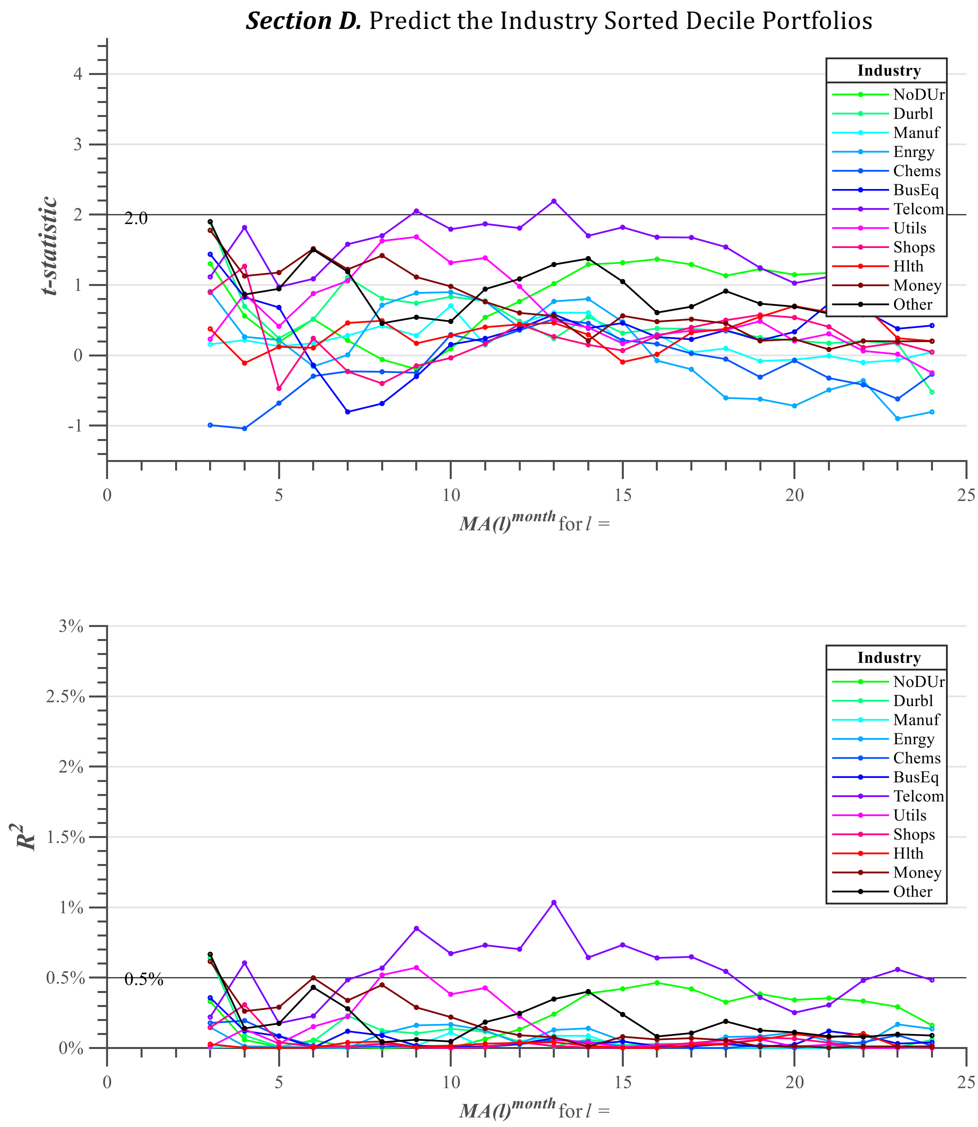
Section C reports estimation results for the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \ldots, 23, 24$ $months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

For each of the 10 book-to-market ratio sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{month}$.

(Figure 2.3 continued)



Section D reports estimation results for the predictive regression model,

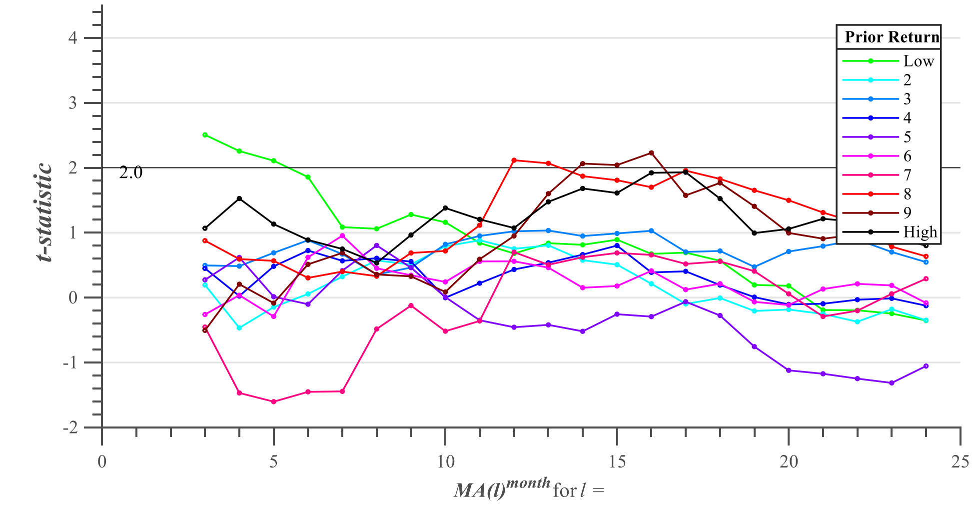
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

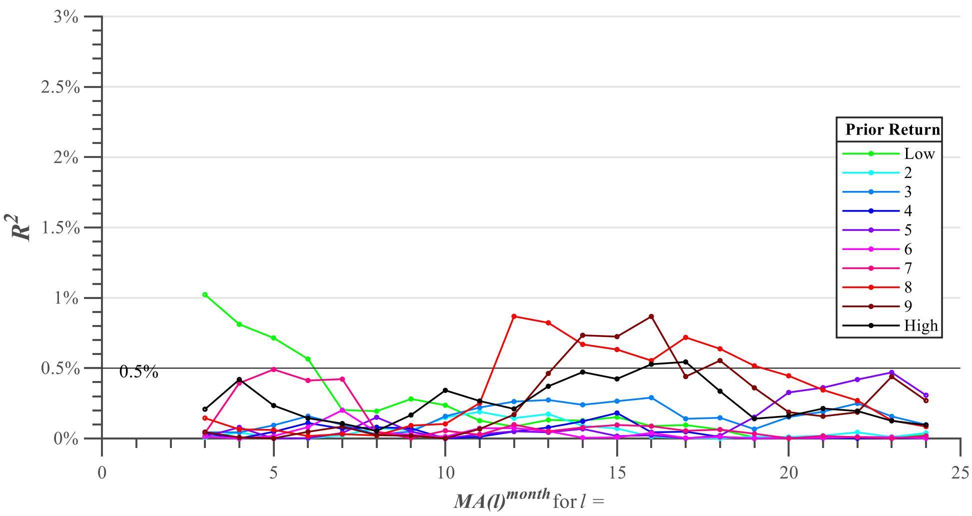
where r_{t+1} is the monthly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \ldots, 23, 24$ $months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

For each of the 13 industry sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics*. Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{month}$.

(Figure 2.3 continued)

Section E. Predict the Momnetum Sorted Decile Portfolios





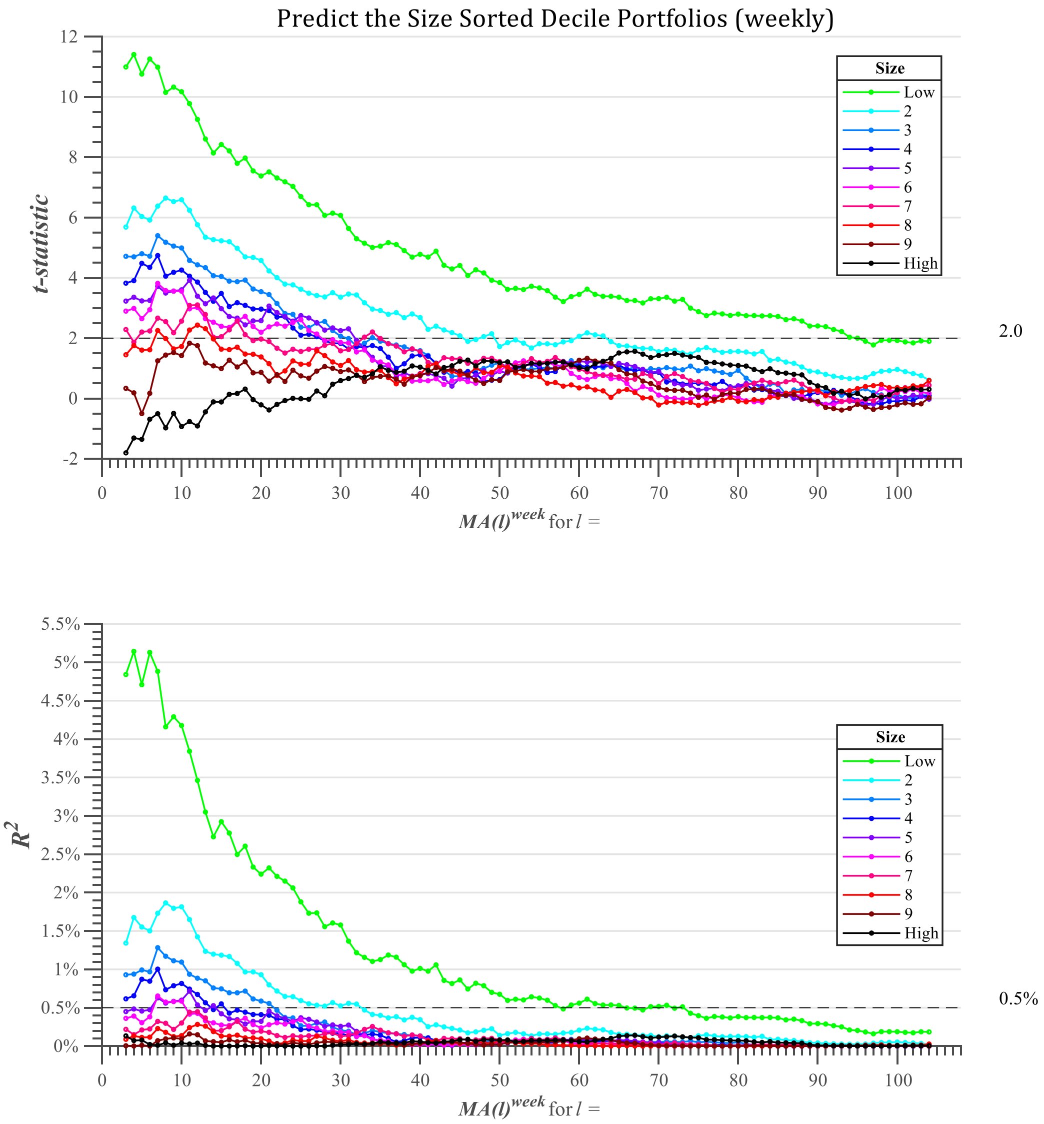
Section E reports estimation results for the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \dots, 23, 24$ $months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

For each of the 10 momentum sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{month}$.

Figure 2.4 Predictive regression results on size-sorted deciles (weekly), 1963:07 to 2016:12



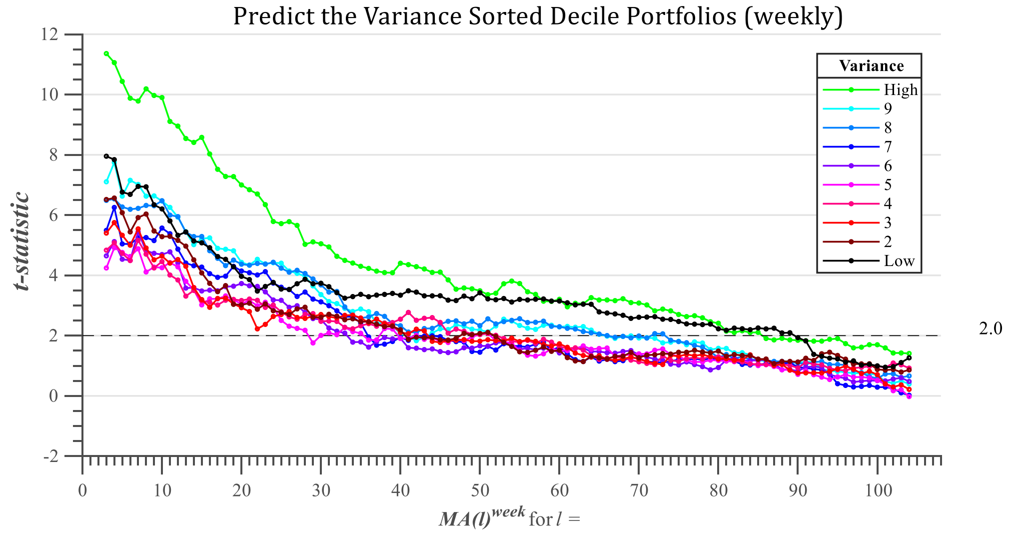
Notes. Figure 5 reports estimation results for the predictive regression model,

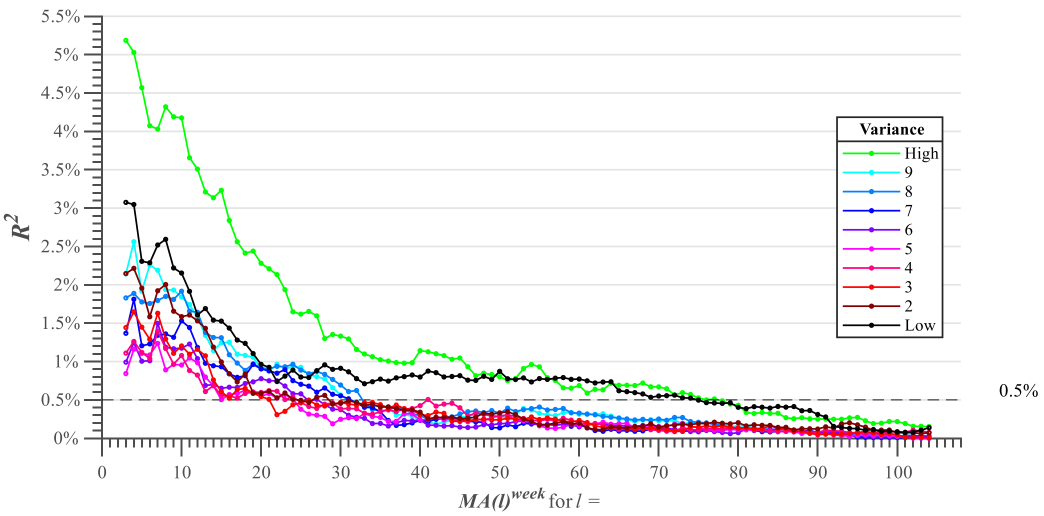
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\ week}$ with $l = 3, 4, 5, \ldots, 103, 104$ $weeks$ generated for each price indices. We denoted each $MA(l)^{\ week}$ on the horizontal axis.

For each of the 10 market capitalization (size) sorted decile portfolios, this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{\ week}$.

Figure 2.5 Predictive regression results on equal-weighted variance sorted deciles (weekly), 1963:07 to 2016:12





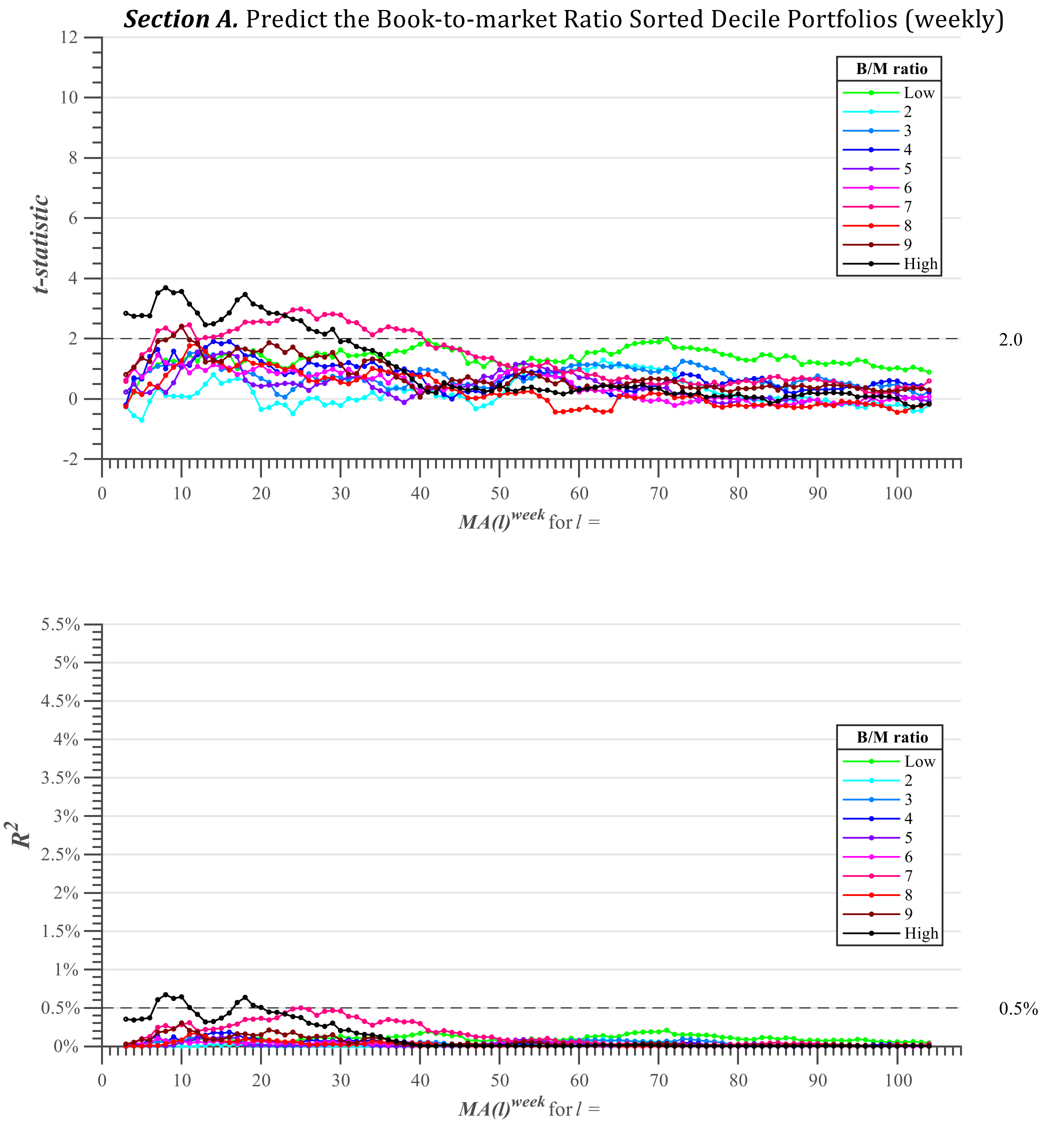
Notes. Figure 6 reports estimation results for the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\,week}$ with $l = 3, 4, 5, \ldots, 103, 104\ weeks$ generated for each price indices. We denoted each $MA(l)^{\,week}$ on the horizontal axis.

For each of the 10 variance sorted decile portfolios (equal-weighted), this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{\,week}$.

Figure 2.6 Predictive regression results on other sorted deciles (weekly), 1963:07 to 2016:12



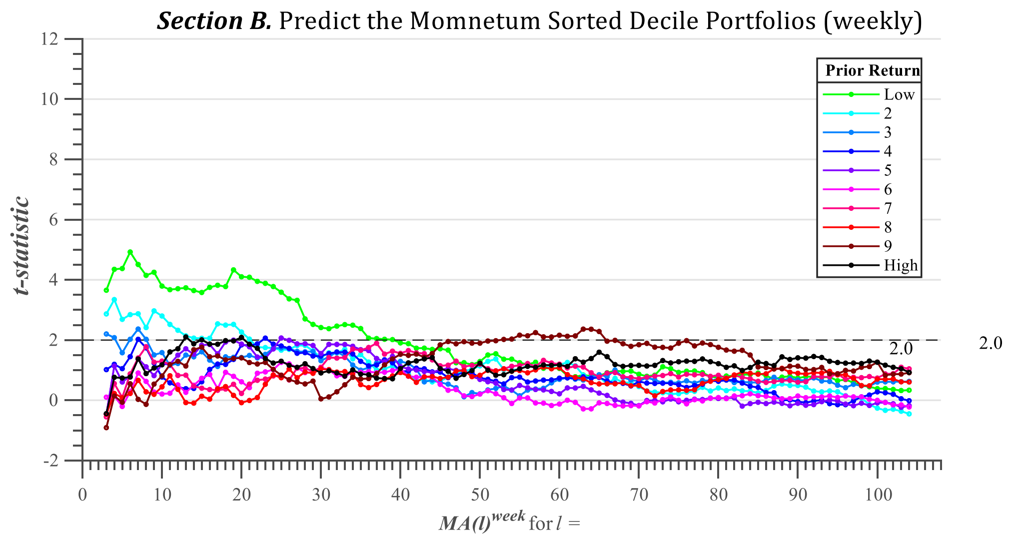
Notes. Section A reports estimation results for the predictive regression model,

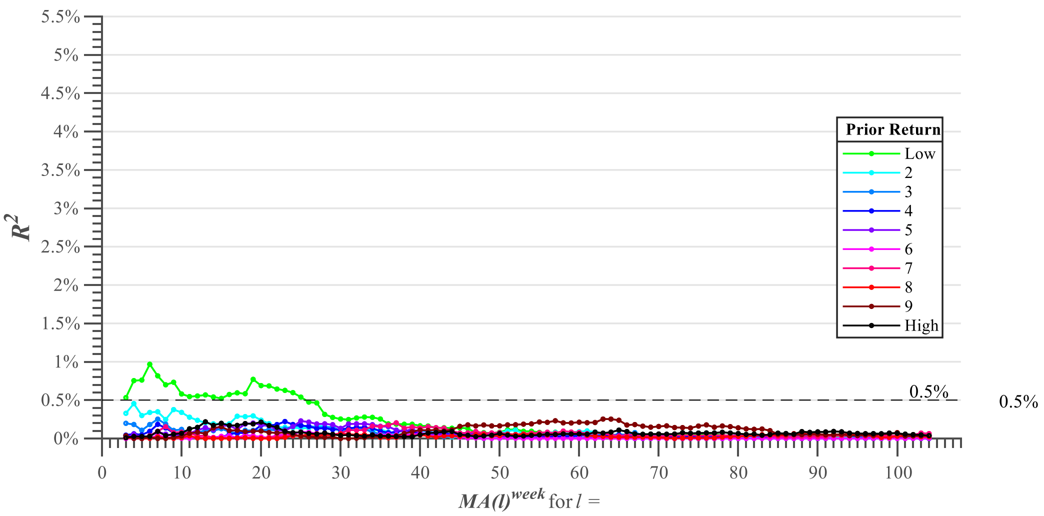
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\,week}$ with $l = 3, 4, 5, \dots, 103, 104\ weeks$ generated for each price indices. We denoted each $MA(l)^{\,week}$ on the horizontal axis.

For each of the 10 book-to-market ratio sorted decile portfolios, this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{\,week}$.

(Figure 2.6 continued)





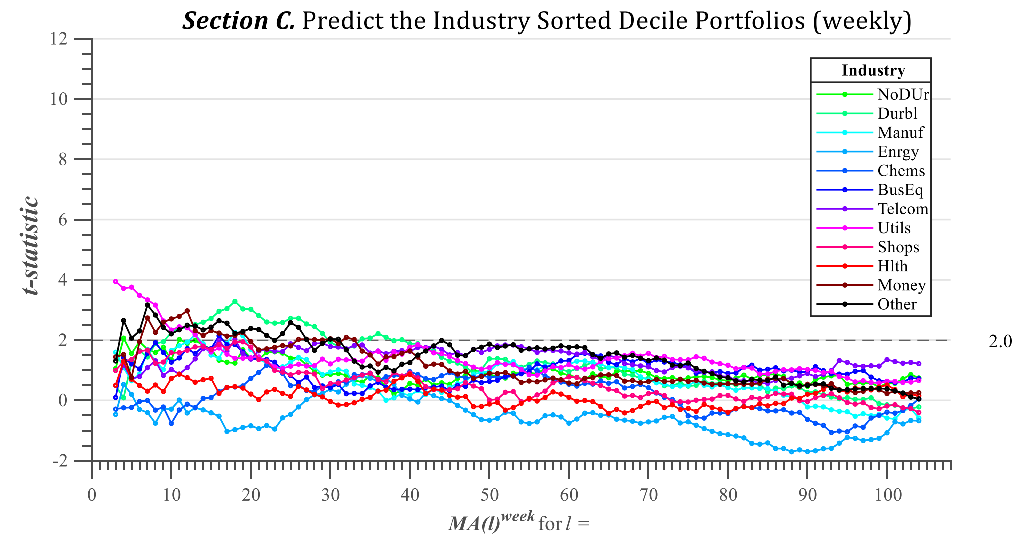
Section B reports estimation results for the predictive regression model,

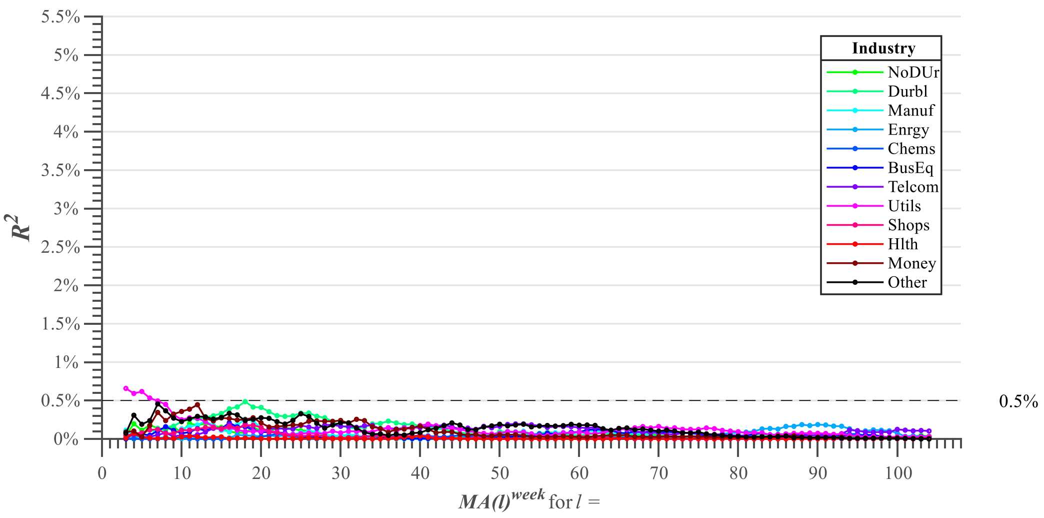
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\,week}$ with $l = 3, 4, 5, \ldots, 103, 104$ *weeks* generated for each price indices. We denoted each $MA(l)^{\,week}$ on the horizontal axis.

For each of the 10 momentum (2-12 prior return) sorted decile portfolios, this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{\,week}$.

(Figure 2.6 continued)





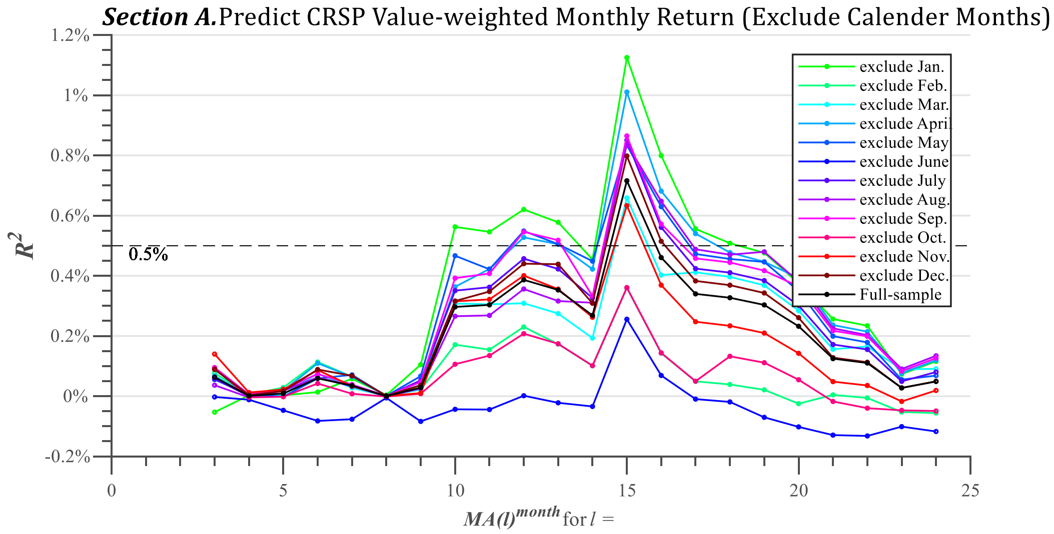
Section C reports estimation results for the predictive regression model,

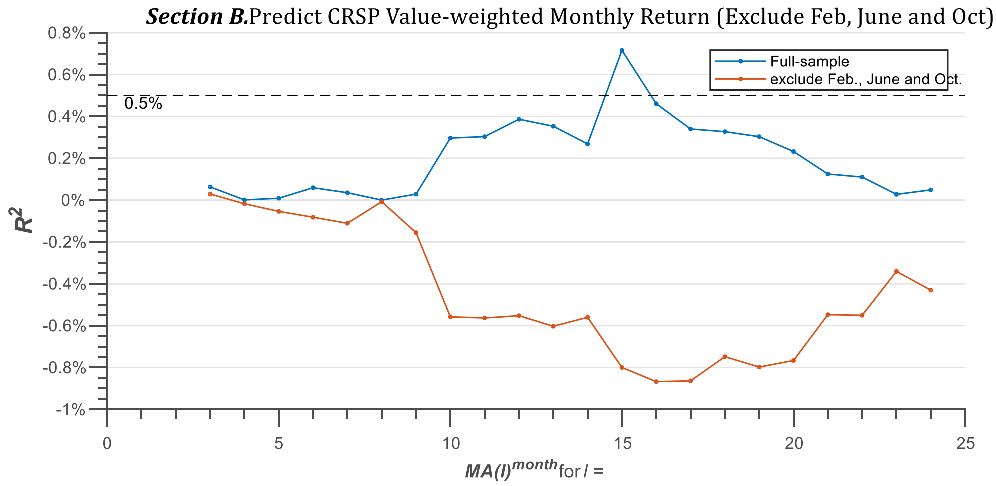
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\ week}$ with $l = 3, 4, 5, \ldots, 103, 104$ *weeks* generated for each price indices. We denoted each $MA(l)^{\ week}$ on the horizontal axis.

For each of the 13 industry sorted decile portfolios, this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MA(l)^{\ week}$

Figure 2.7 Sub-sample results regarding calendar months, 1963:07 to 2016:12





Notes.

Section A reports the full-sample R^2 *statistic* and sub-sample R^2 *statistics* of the 22 predictive regressions by excluding data points in each of the calendar month from the sample, as given by (4) in the text. Section B reports the full-sample R^2 *statistic* and sub-sample R^2 *statistics* by excluding data points in February, June and October from the sample.

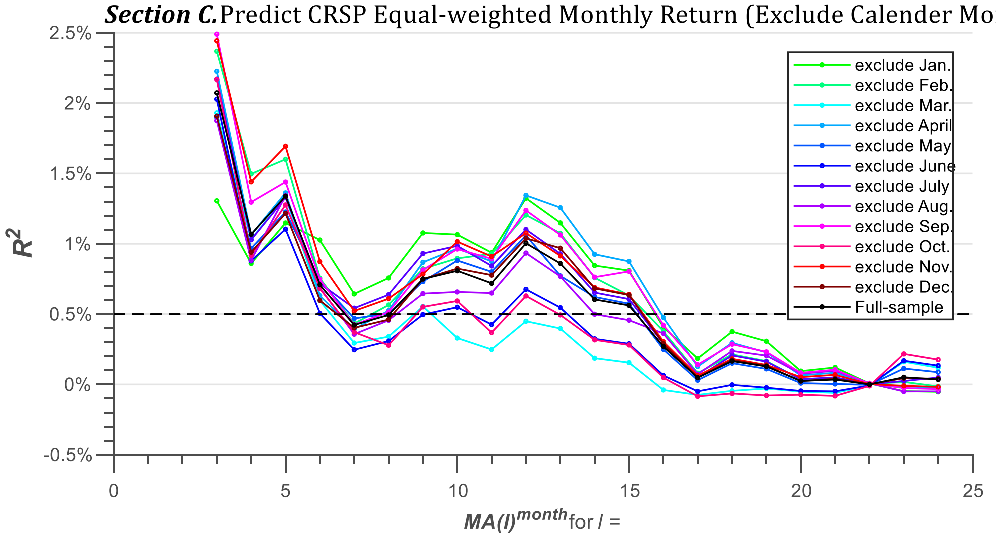
The full-sample and sub-sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

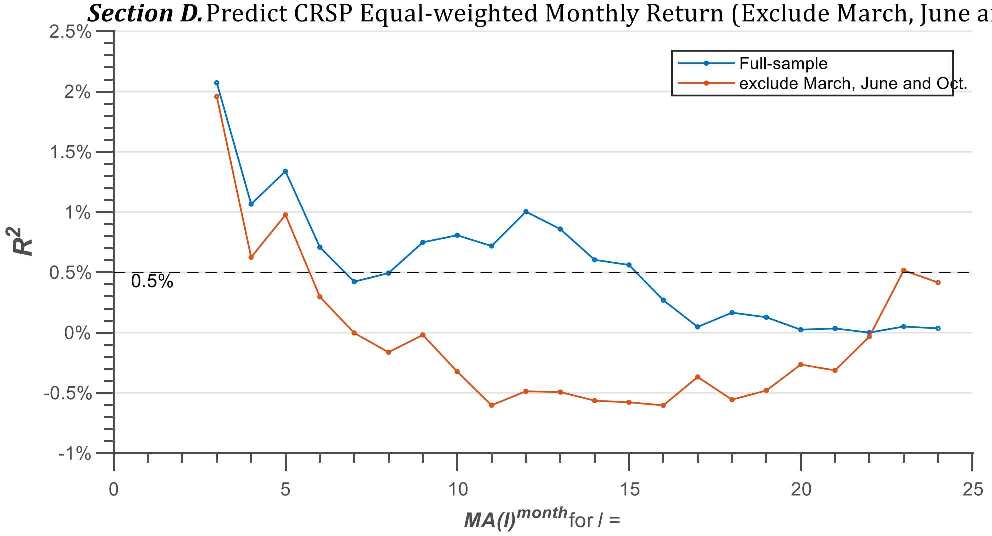
where r_{t+1} is the CRSP value-weighted monthly excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \dots, 23, 24$ $months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

(Figure 2.7 continued)

Section C. Predict CRSP Equal-weighted Monthly Return (Exclude Calender Months)



Section D. Predict CRSP Equal-weighted Monthly Return (Exclude March, June and Oct)



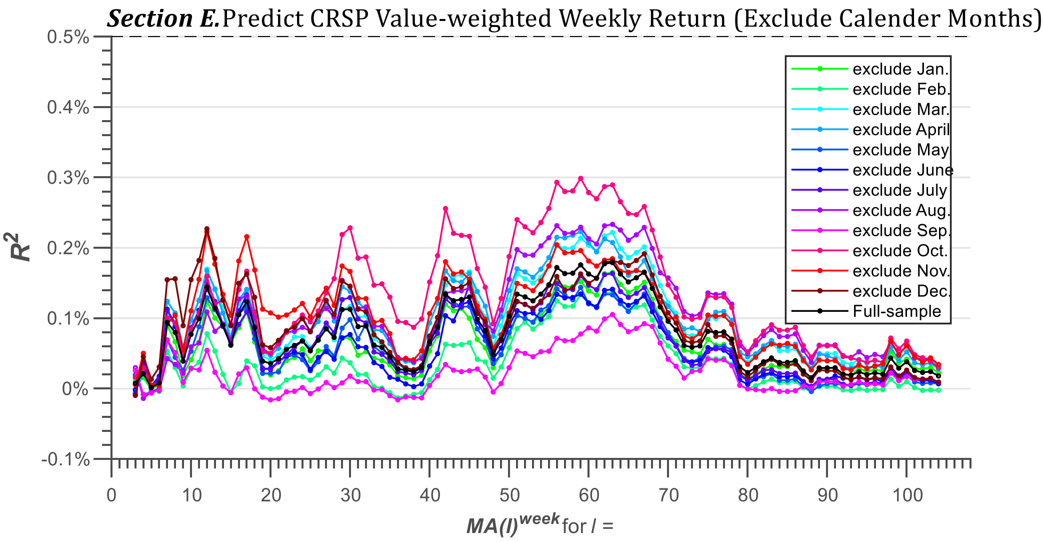
Section C reports the full-sample R^2 *statistic* and sub-sample R^2 *statistics* of the 22 predictive regressions by excluding data points in each of the calendar month from the sample, as given by (4) in the text. Section D reports the full-sample R^2 *statistic* and sub-sample R^2 *statistics* by excluding data points in March, June and October from the sample.

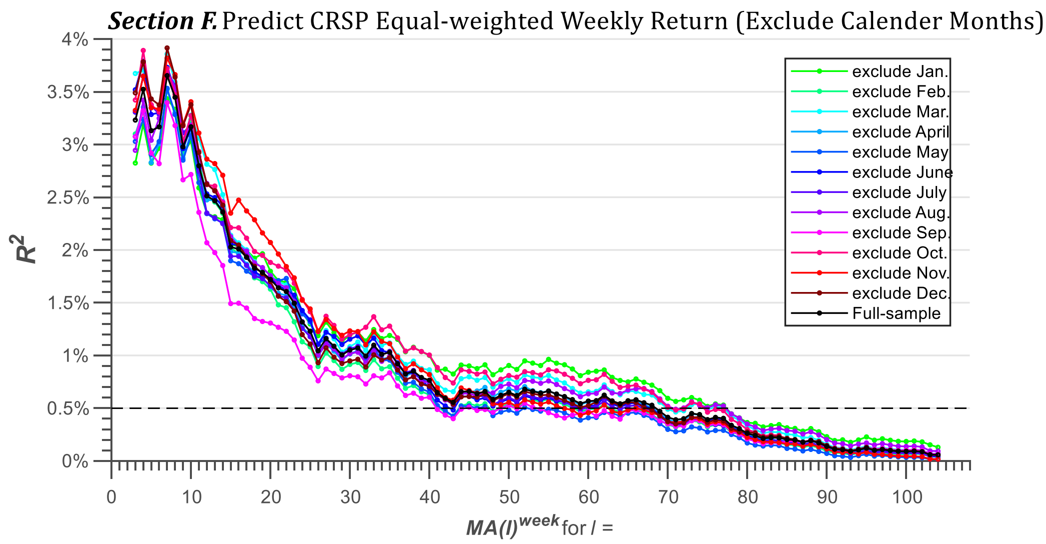
The full-sample and sub-sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the CRSP equal-weighted monthly excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{\ month}$ with $l = 3, 4, 5, \ldots, 23, 24$ *months* generated for each price indices. We denoted each $MA(l)^{\ month}$ on the horizontal axis.

(Figure 2.7 continued)





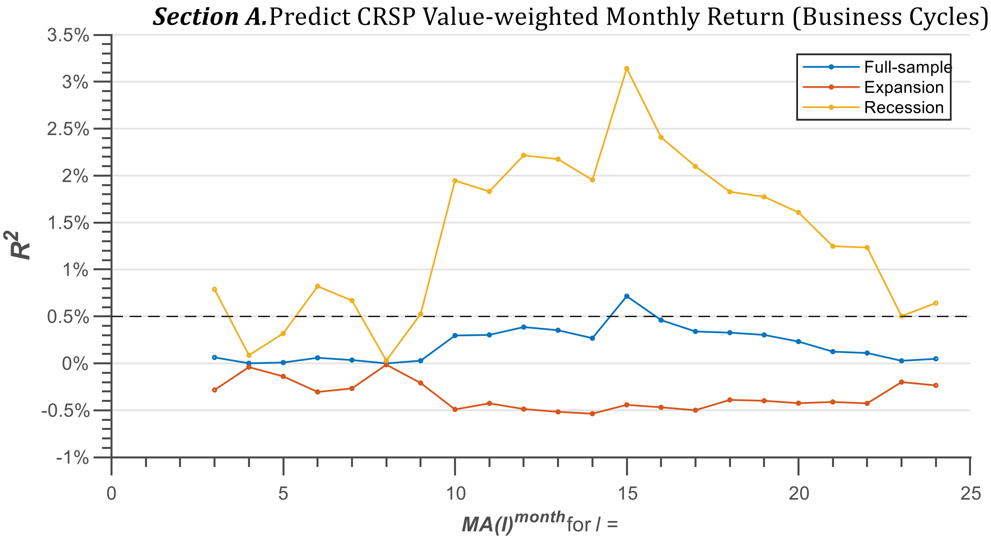
Section E and F report the full-sample R^2 *statistic* and sub-sample R^2 *statistics* of the 22 predictive regressions by excluding data points in each of the calendar month from the sample, as given by (4) in the text. Section E and F report results on CRSP value-weighted and equal-weighted weekly return, respectively.

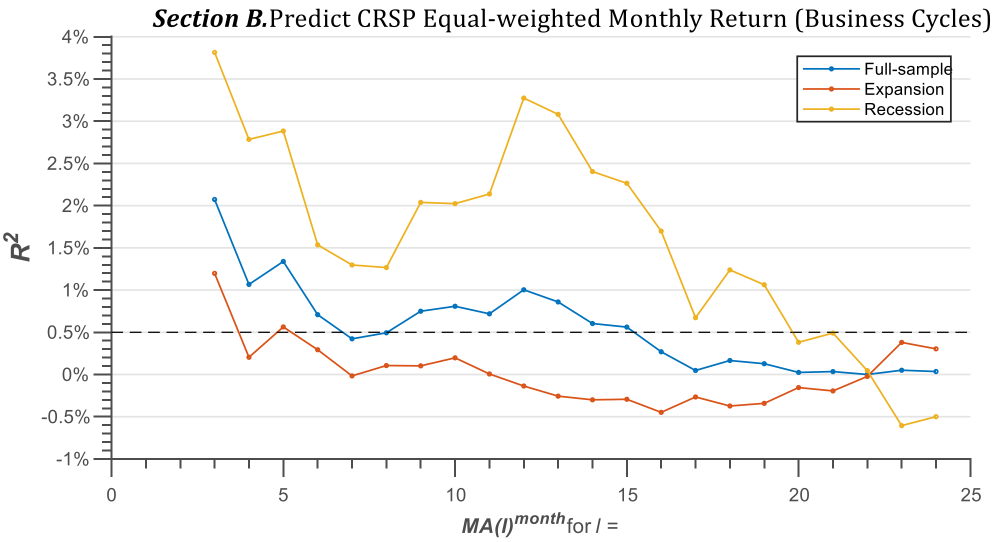
The full-sample and sub-sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\,week}$ with $l = 3, 4, 5, \dots, 103, 104$ $weeks$ generated for each price indices. We denoted each $MA(l)^{\,week}$ on the horizontal axis.

Figure 2.8 Sub-sample results regarding business cycles (monthly), 1963:07 to 2016:12





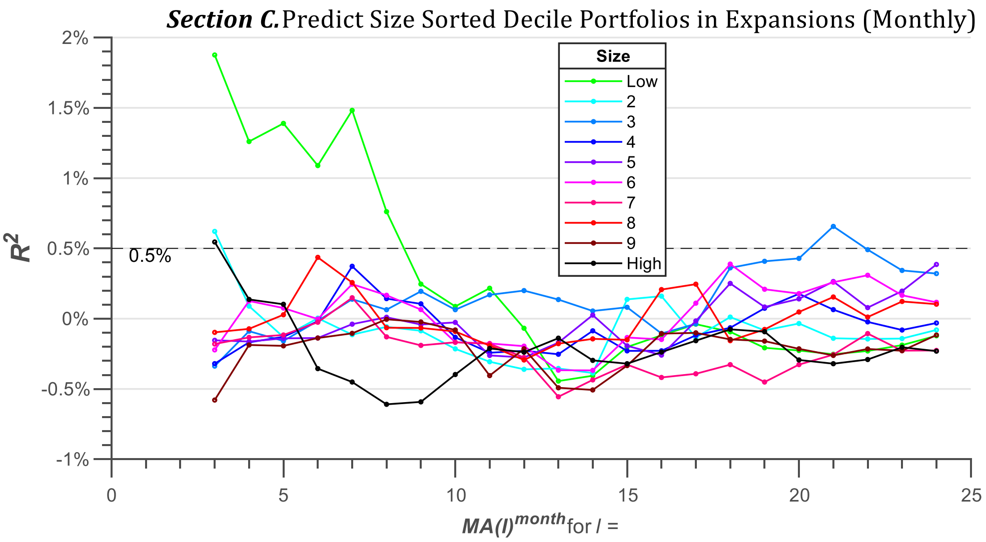
Notes. Section A and B report the full-sample R^2 *statistic* and sub-sample R^2 *statistics* using the NBER-dated business-cycle, as given by (4) in the text. Section A and B report result on CRSP value-weighted and equal-weighted monthly return, respectively.

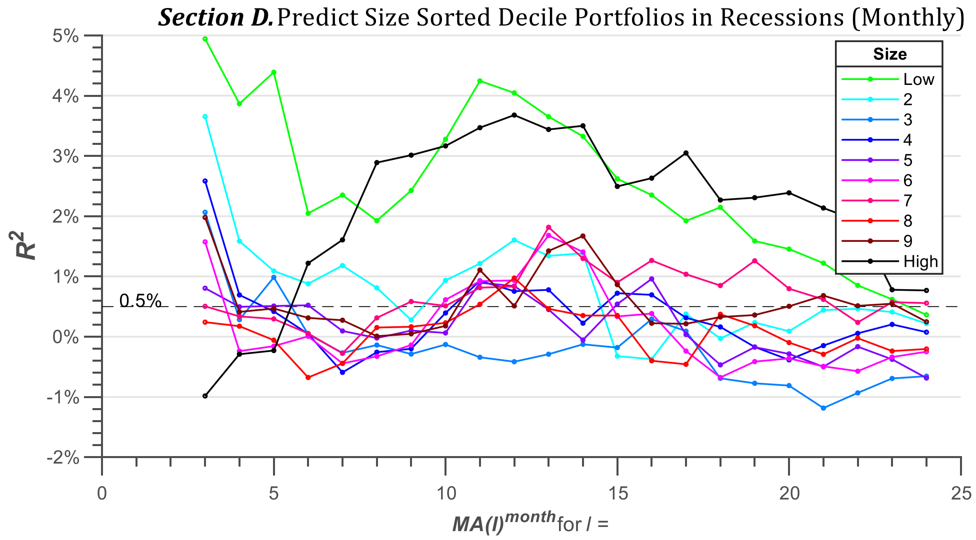
The full-sample and sub-sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the CRSP value-weighted/equal-weighted monthly excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month}$ with $l = 3, 4, 5, \ldots, 23, 24\ months$ generated for each price indices. We denoted each $MA(l)^{month}$ on the horizontal axis.

(Figure 2.8 continued)





Section C and D report the sub-sample R^2 *statistics* on the market capitalization (size) sorted decile portfolios (monthly) using the NBER-dated business-cycle, as given by (4) in the text. Section C and D report result on expansions and recessions, respectively.

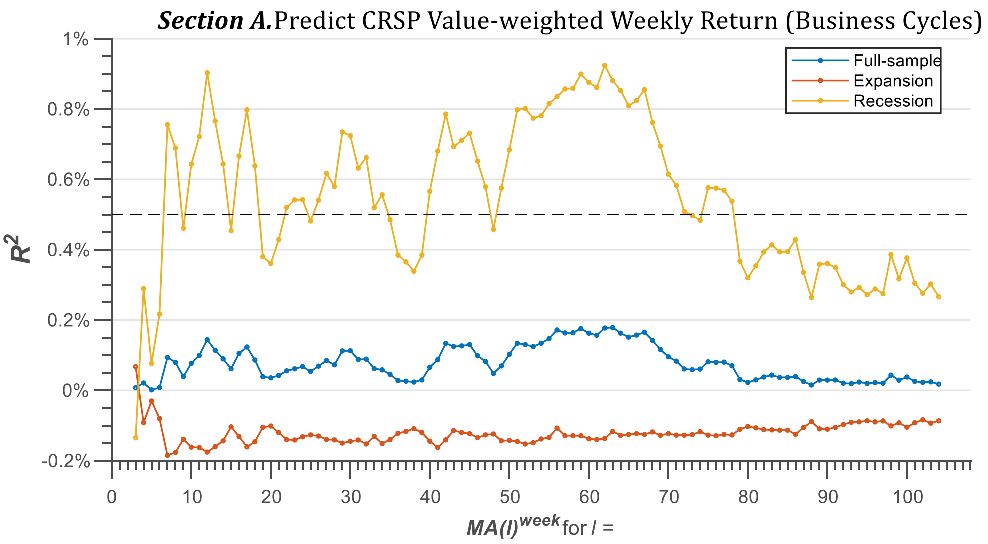
The sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

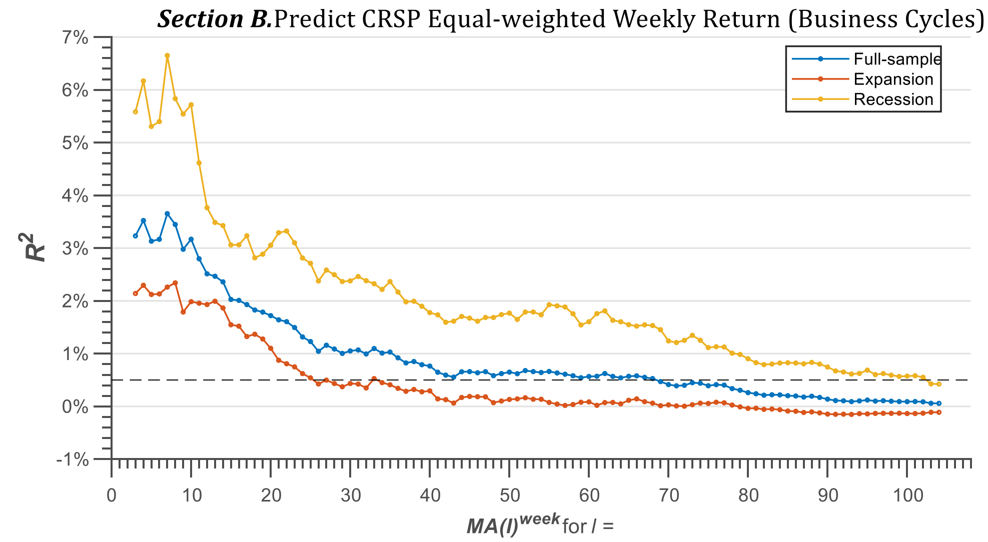
where r_{t+1} is the portfolio monthly excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{\,month}$ with $l = 3, 4, 5, \dots, 23, 24$ *months* generated for each price indices. We denoted each $MA(l)^{\,month}$ on the horizontal axis.

Figure 2.9 Sub-sample results regarding business cycles (weekly), 1963:07 to 2016:12

CRSP VW index(weekly, business cycle)



CRSP EW index(weekly, business cycle)



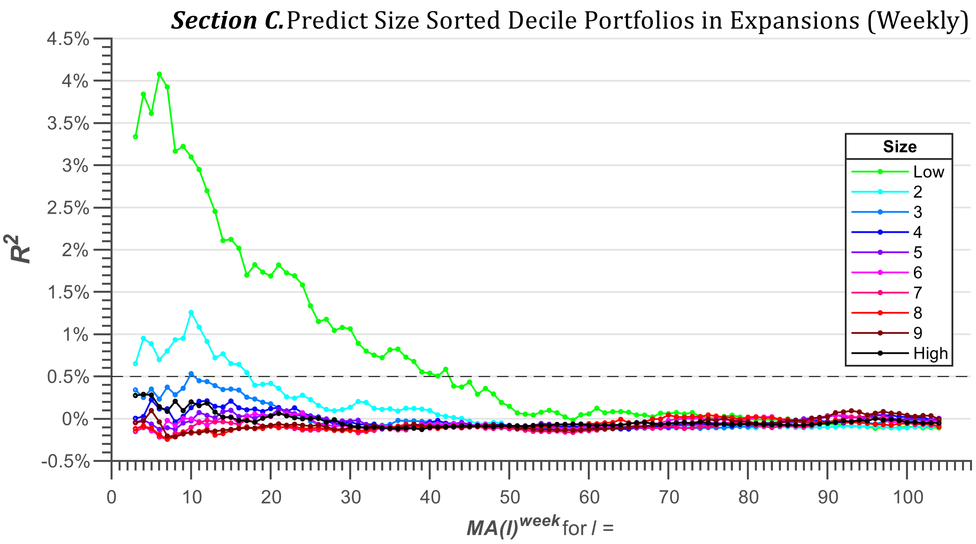
Notes. Section A and B report the full-sample R^2 *statistic* and sub-sample R^2 *statistics* using the NBER-dated business-cycle, as given by (4) in the text. Section A and B report result on CRSP value-weighted and equal-weighted monthly return, respectively.

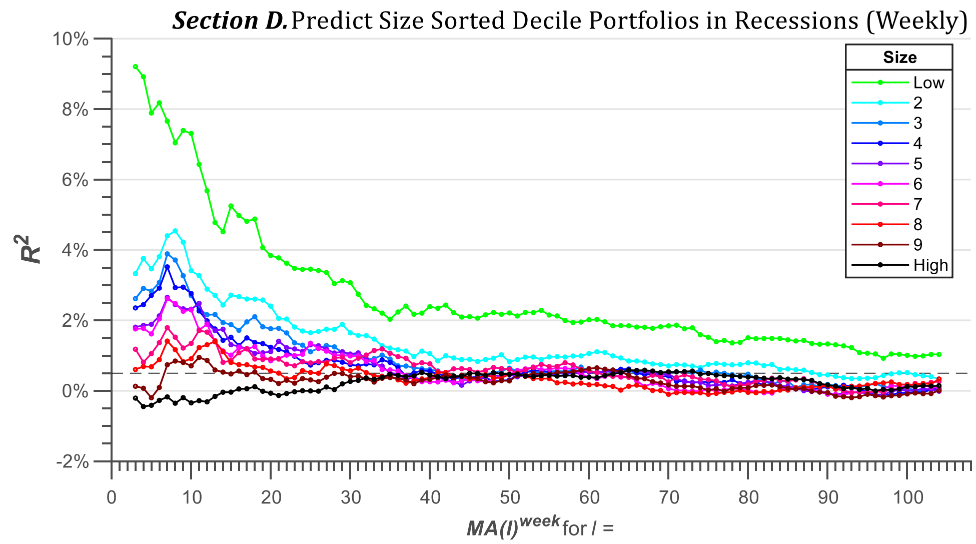
The full-sample and sub-sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the CRSP value-weighted/equal-weighted weekly excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MA(l)^{\,week}$ with $l = 3, 4, 5, \dots, 103, 104$ *weeks* generated for each price indices. We denoted each $MA(l)^{\,week}$ on the horizontal axis.

(Figure 2.9 continued)





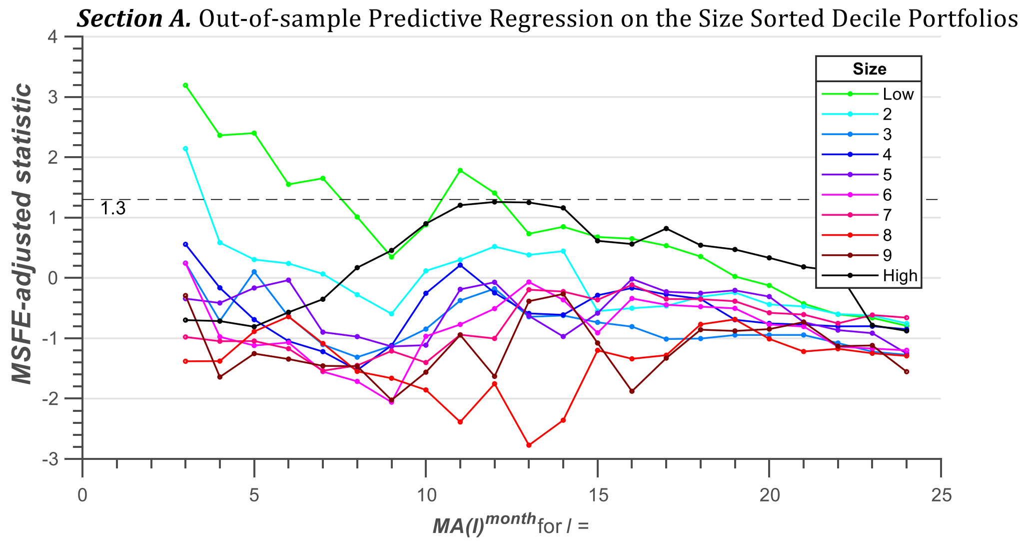
Section C and D report the sub-sample R^2 *statistics* on the market capitalization (size) sorted decile portfolios (weekly) using the NBER-dated business-cycle, as given by (4) in the text. Section C and D report result on expansions and recessions, respectively.

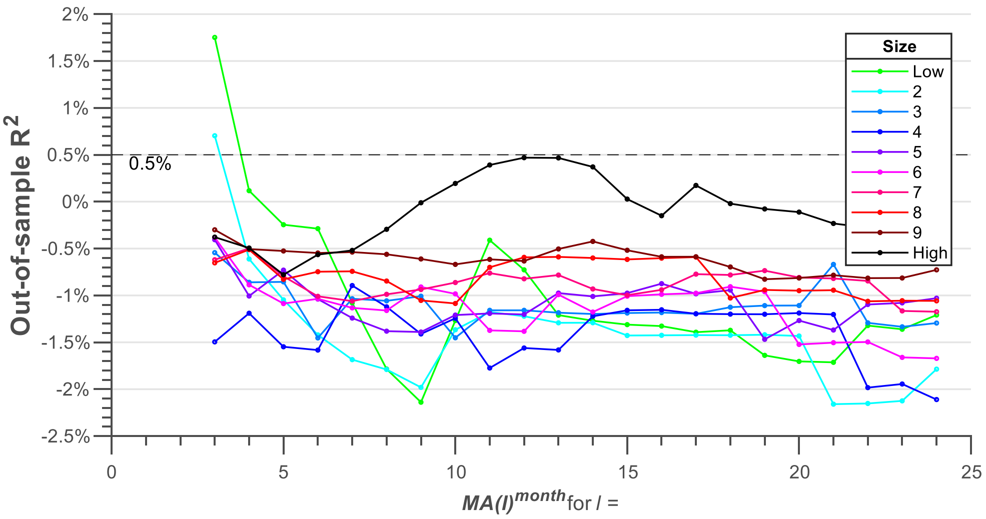
The sub-sample estimation results are based on the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the portfolio weekly excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{\ week}$ with $l = 3, 4, 5, \dots, 103, 104$ *weeks* generated for each price indices. We denoted each $MA(l)^{\ week}$ on the horizontal axis.

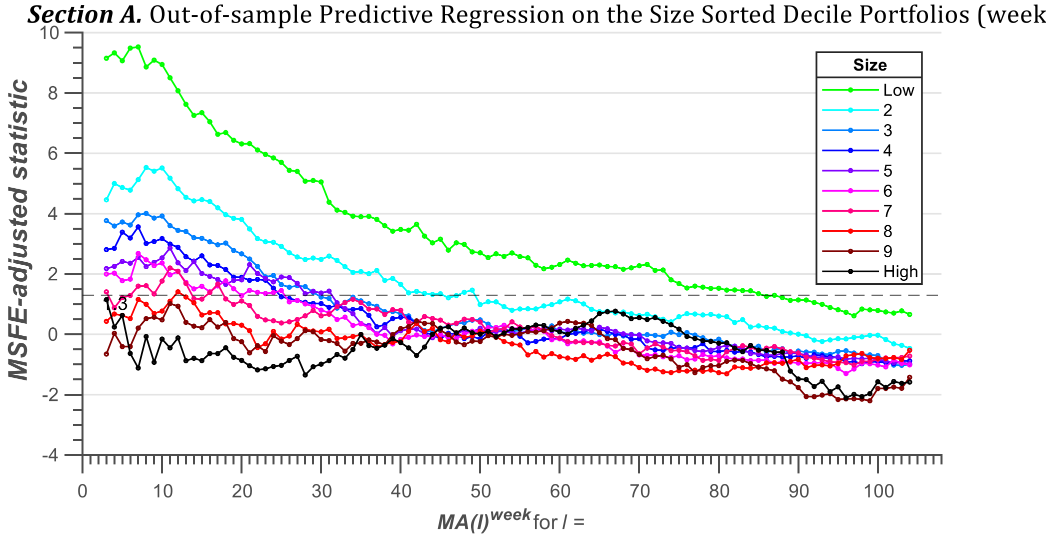
Figure 2.10 Out-of-sample results on the size sorted deciles (monthly), 1968:07 to 2016:12

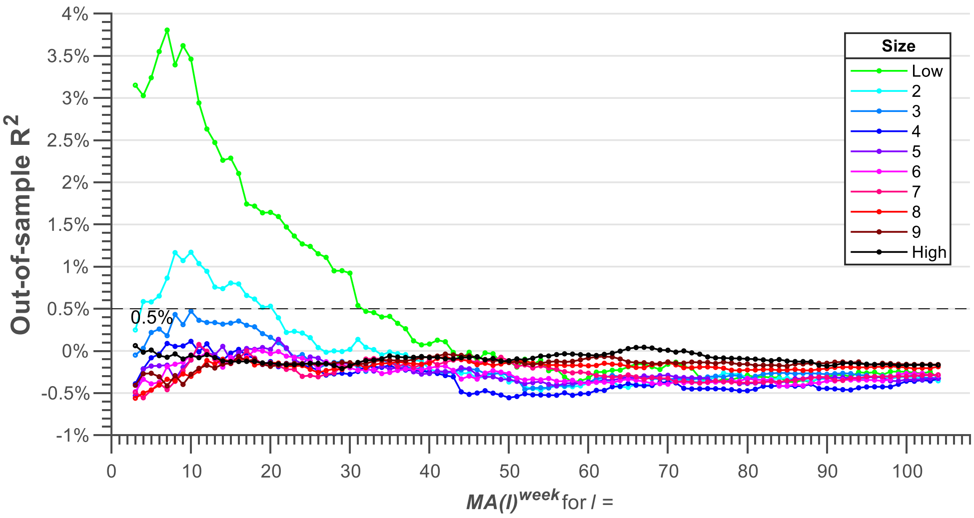




Notes. Section A and B report the out-of-sample estimation result on the market capitalization (size) sorted decile portfolios (monthly). The benchmark, historical average forecast, is given by (5) and (6) in the text. Section A reports the adjusted *MSFE statistic (Clark & West 2007)* for testing the null hypothesis that the historical average MSFE is less or equal to the technical indicator forecast MSFE. Note that the MSFE around 1.3 indicates significant at 10 % signified level.
Section B reports the out-of-sample R^2 which measures the proportional reduction in mean squared forecast error (MSFE) for the technical indicator forecast compared with the historical average forecast.

Figure 2.11 Out-of-sample results on the size sorted deciles (weekly), 1973:01 to 2016:12

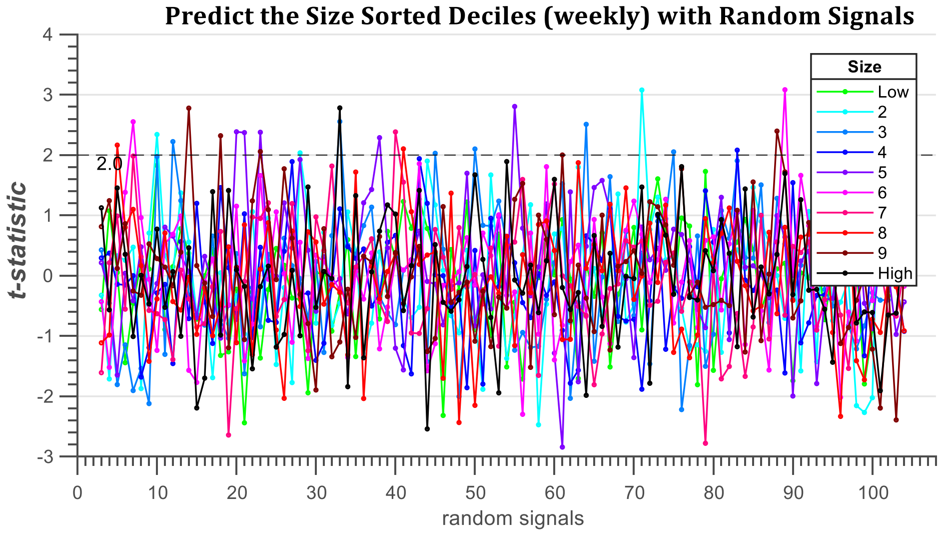


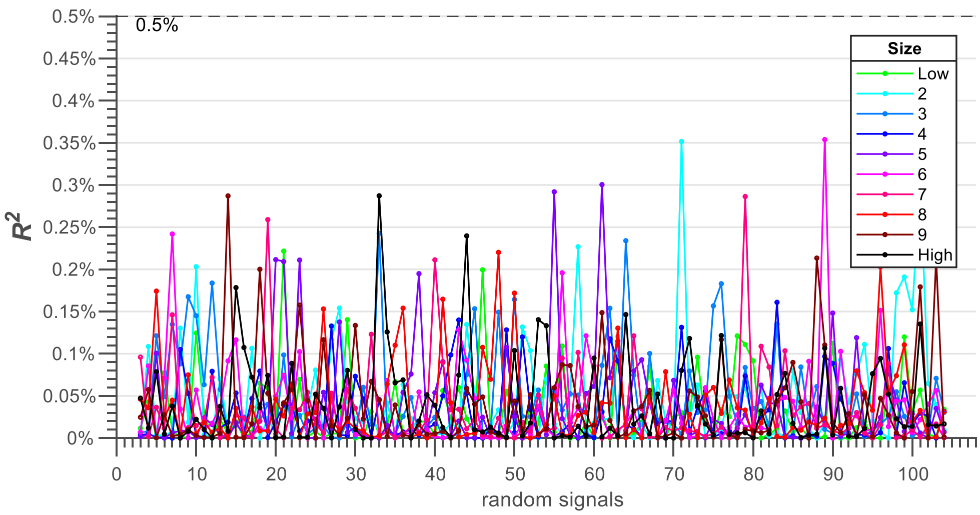


Notes. Section A and B report the out-of-sample estimation result on the market capitalization (size) sorted decile portfolios (weekly). The benchmark, historical average forecast, is given by (5) and (6) in the text. Section A reports the adjusted *MSFE statistic (Clark & West 2007)* for testing the null hypothesis that the historical average MSFE is less or equal to the technical indicator forecast MSFE. Note that the MSFE around 1.3 indicates significant at 10 % signified level.

Section B reports the out-of-sample R^2 which measures the proportional reduction in mean squared forecast error (MSFE) for the technical indicator forecast compared with the historical average forecast.

Figure 2.12 Predictive regression results using random signals (weekly), 1963:07 to 2016:12





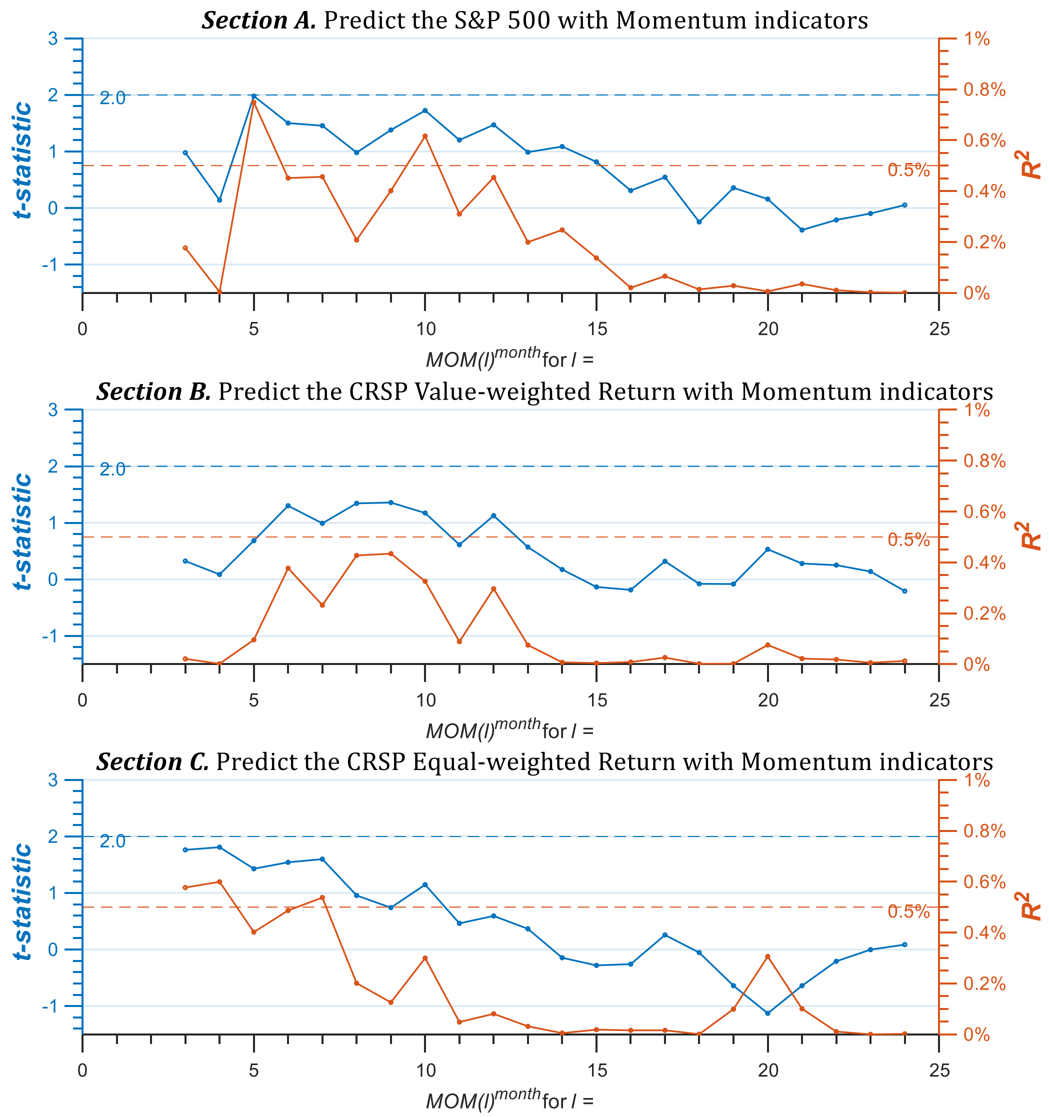
Notes. Figure 13 reports estimation results for the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a portfolio at time $t+1$; $S_{i,t}$ is the random signal which generates a 1 or 0 signal randomly with 50%/50% probability at each time t. We use 102 sets of random signals.

For each of the 10 market capitalization (size) sorted decile portfolios, this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given set of random signal.

Figure 2.13 Predictive regression results using the momentum indicators, 1963:07 to 2016:12

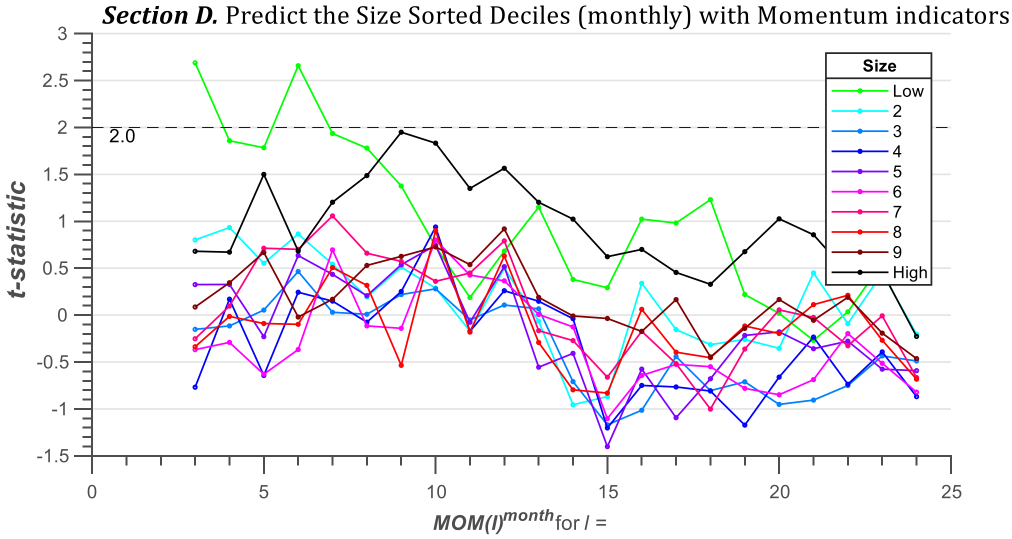


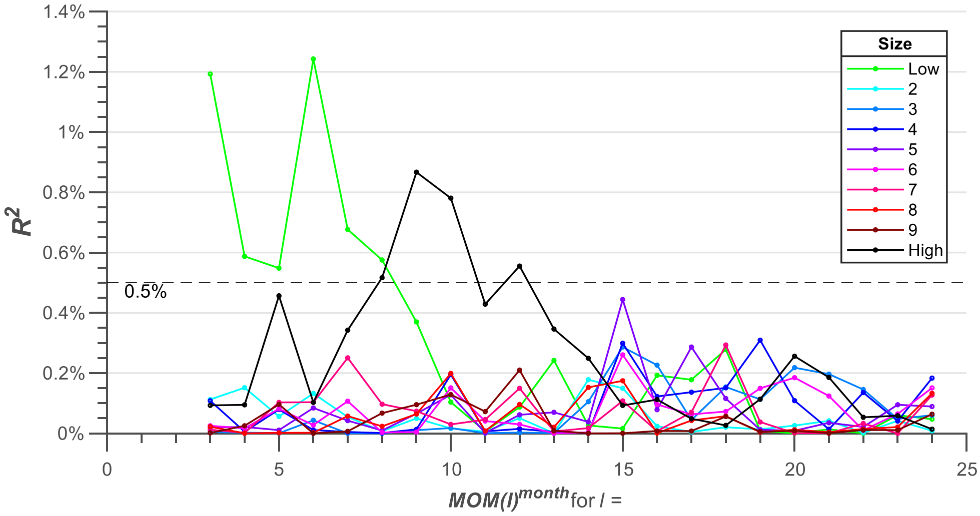
Notes. Section A, B, and C report estimation results for the predictive regression model,

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly market excess return (in percent) at time $t + 1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MOM(l)^{month}$ with $l = 3, 4, 5, \dots, 23, 24$ *months* generated for each price indices. We denoted each $MOM(l)^{month}$ on the horizontal axis. Section A, B, and C report the estimation results of the 22 predictive regressions on the S&P 500, CRSP value-weighted, and CRSP equal-weighted monthly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MOM(l)^{month}$.

(Figure 2.13 continued)





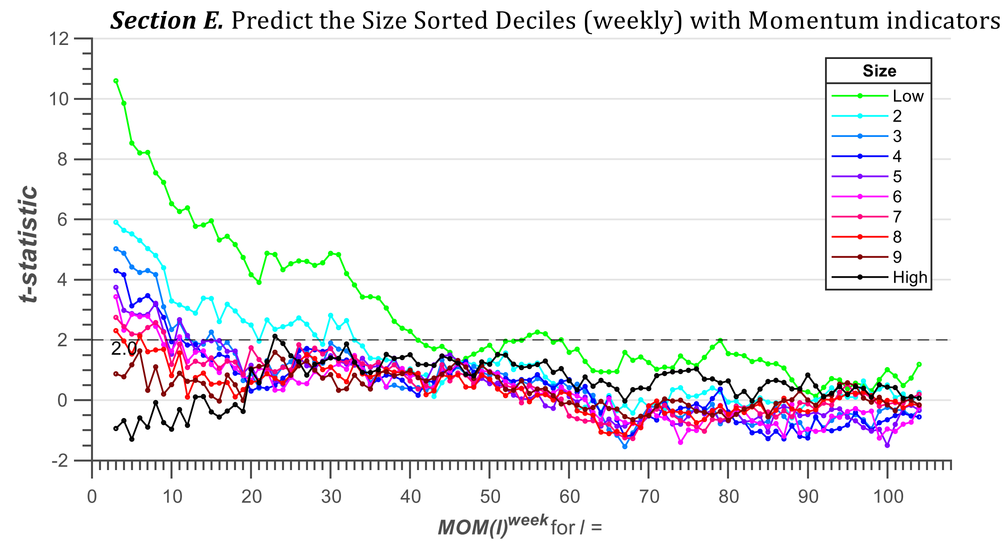
Section F reports estimation results for the predictive regression model,

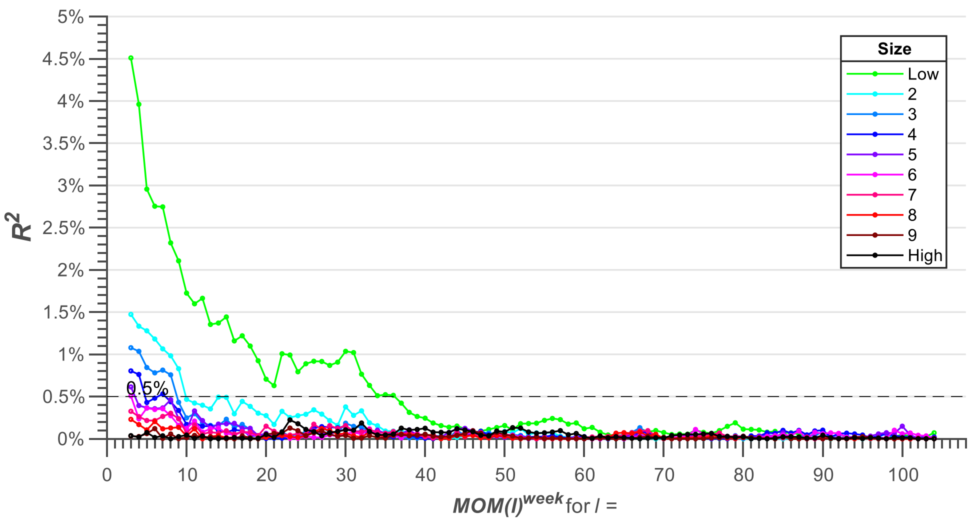
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the monthly equity risk premium (in percent) of a decile portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MOM(l)^{\,month}$ with $l = 3, 4, 5, \ldots, 23, 24\ months$ generated for each price indices. We denoted each $MOM(l)^{\,month}$ on the horizontal axis.

For each of the 10 market capitalization (size) sorted decile portfolios, this figure reports the estimation results of the 22 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MOM(l)^{\,month}$.

(Figure 2.13 continued)





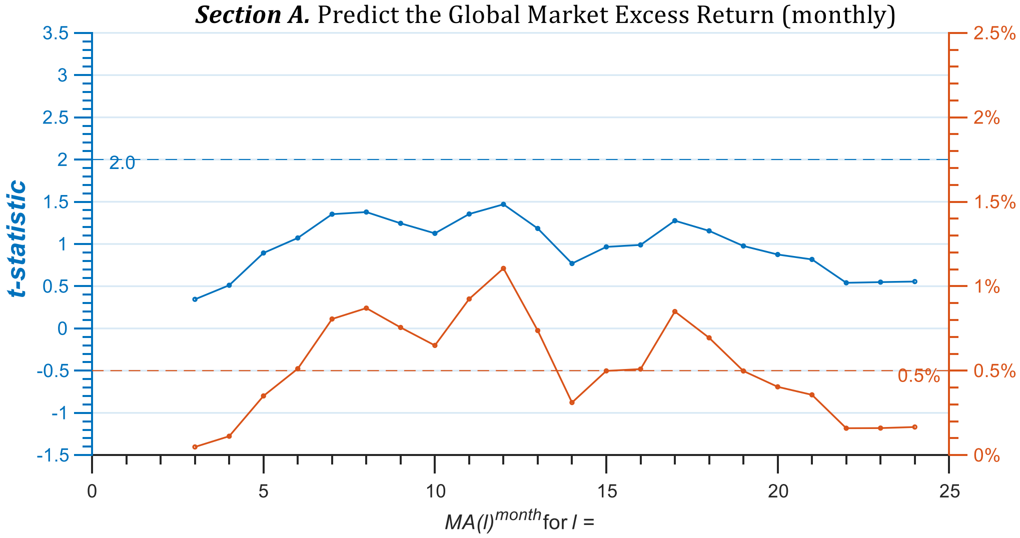
Section G reports estimation results for the predictive regression model,

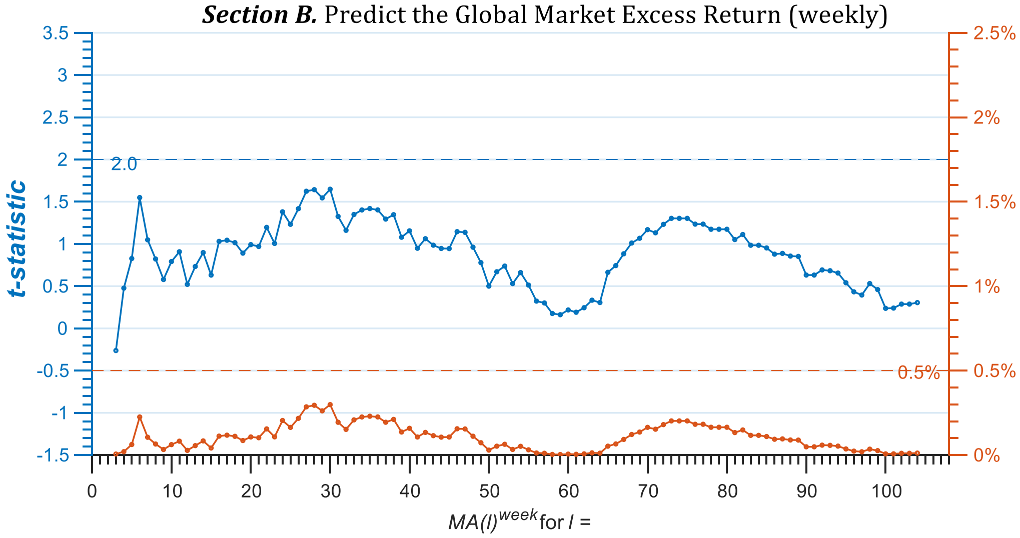
$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$$

where r_{t+1} is the weekly equity risk premium (in percent) of a decile portfolio at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 102 technical indicators $MOM(l)^{week}$ with $l = 3, 4, 5, \ldots, 103, 104$ $weeks$ generated for each price indices. We denoted each $MOM(l)^{week}$ on the horizontal axis.

For each of the 10 market capitalization (size) sorted decile portfolios, this figure reports the estimation results of the 102 predictive regressions. Top panel reports the heteroskedasticity-consistent *t-statistics* and bottom panel reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting the risk premium of a given portfolio using a given technical indicator $MOM(l)^{week}$

Figure 2.14 International predictive regression results, 1990:07 to 2016:12



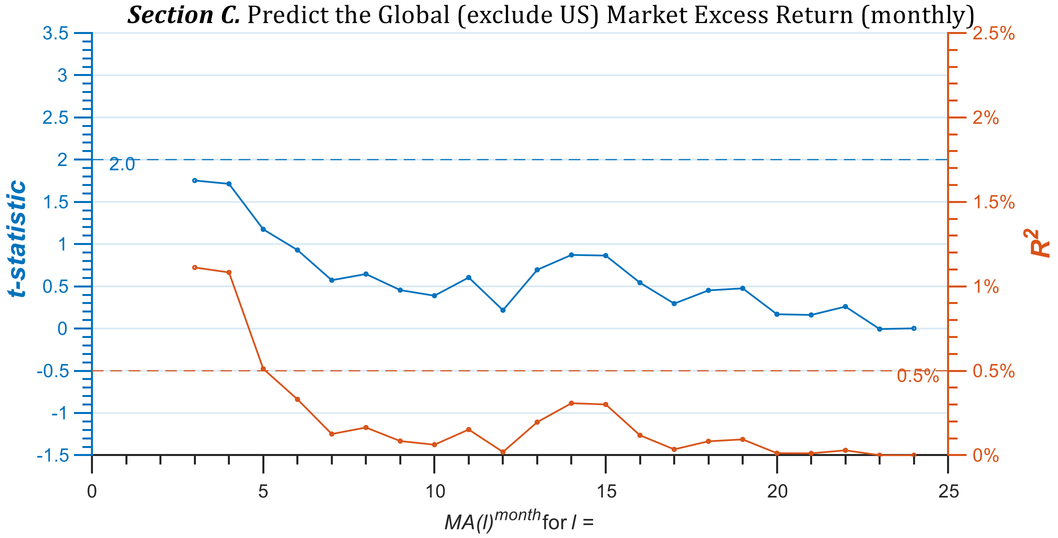


Notes. Section A and B report estimation results for the predictive regression model,
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

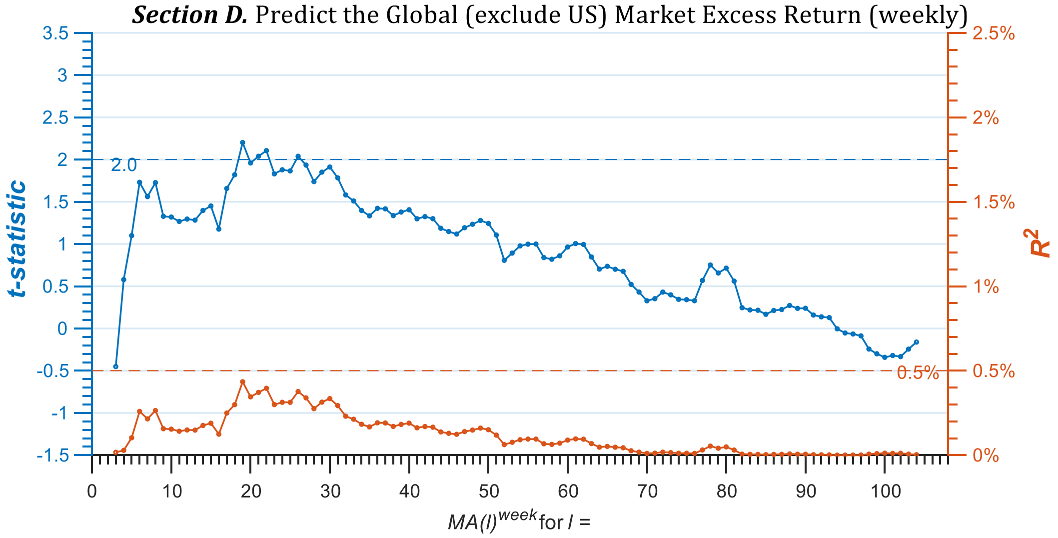
where r_{t+1} is the monthly/weekly Global market excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month/week}$ with $l = 3, 4, 5, \dots, 23, 24\ months$ or $l = 3, 4, 5, \dots, 103, 104\ weeks$ and generated for each price indices. We denoted each $MA(l)^{month/week}$ on the horizontal axis. Section A and B report the estimation results on the global market monthly and weekly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics*. Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{month}$.

(Figure 2.14 continued)

Section C. Predict the Global (exclude US) Market Excess Return (monthly)



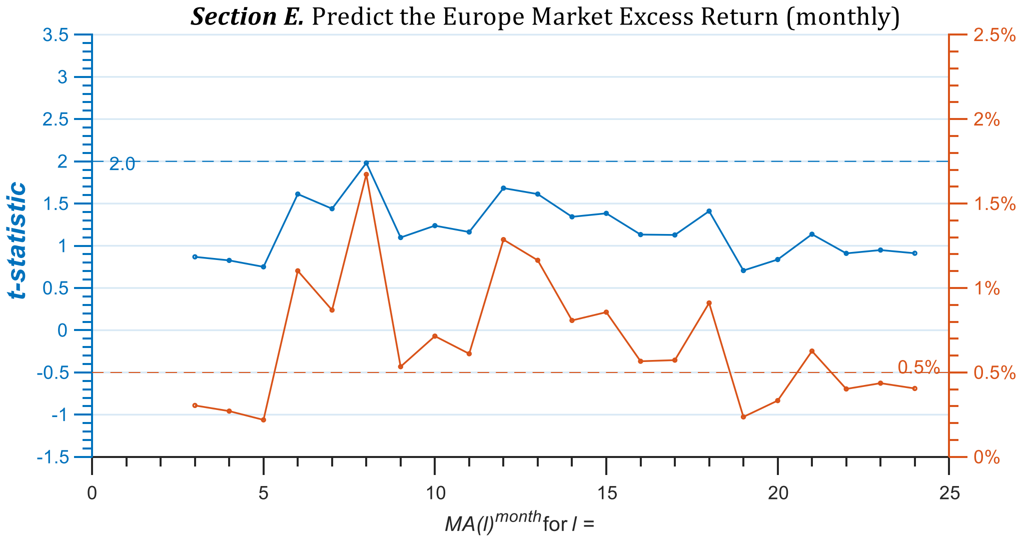
Section D. Predict the Global (exclude US) Market Excess Return (weekly)

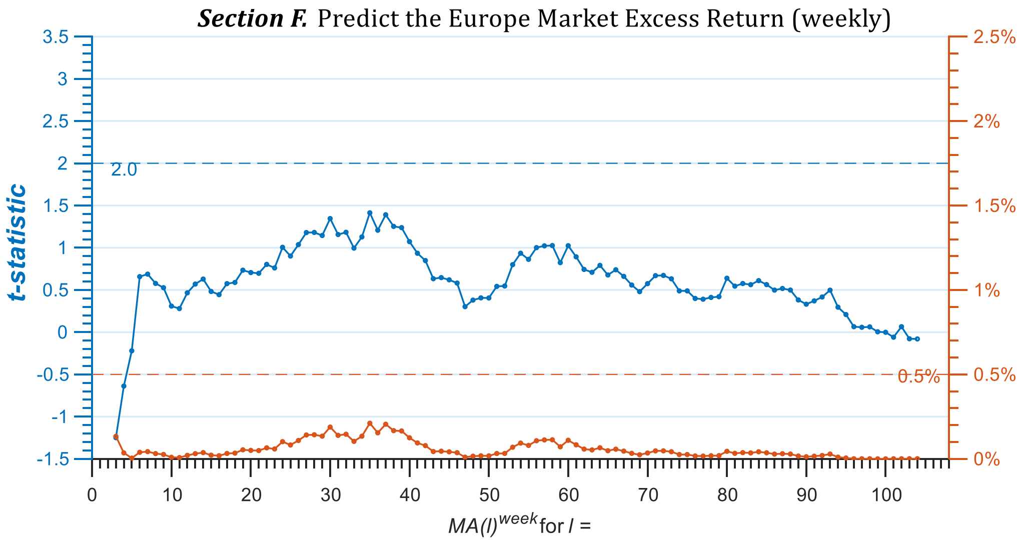


Section C and D report estimation results for the predictive regression model,
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

where r_{t+1} is the monthly/weekly Global (exclude US) market excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{\ month/week}$ with $l = 3, 4, 5, \dots, 23, 24$ $months$ or $l = 3, 4, 5, \dots, 103, 104$ $weeks$ and generated for each price indices. We denoted each $MA(l)^{\ month/week}$ on the horizontal axis. Section A and B report the estimation results on the global market (exclude US) monthly and weekly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics*. Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{\ month}$.

(Figure 2.14 continued)

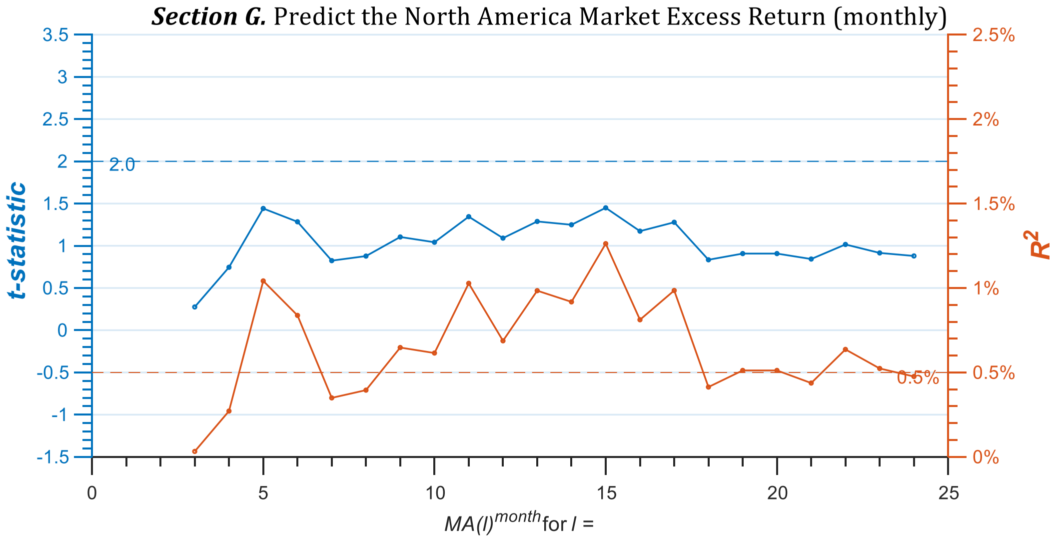


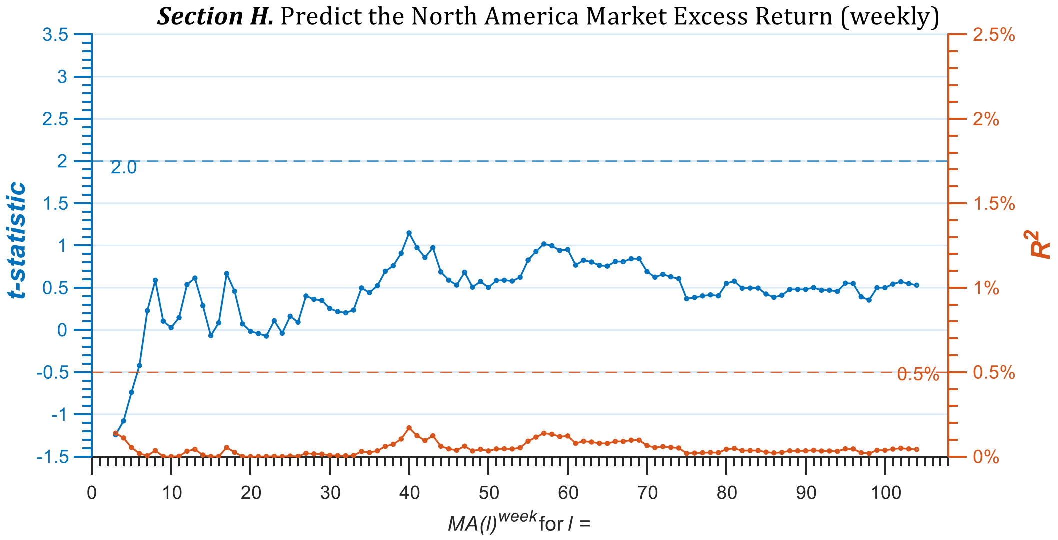


Section E and F report estimation results for the predictive regression model,
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

where r_{t+1} is the monthly/weekly Europe Market excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month/week}$ with $l = 3, 4, 5, \dots, 23, 24\ months$ or $l = 3, 4, 5, \dots, 103, 104\ weeks$ and generated for each price indices. We denoted each $MA(l)^{month/week}$ on the horizontal axis. Section A and B report the estimation results on the Europe market monthly and weekly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{month}$.

(Figure 2.14 continued)



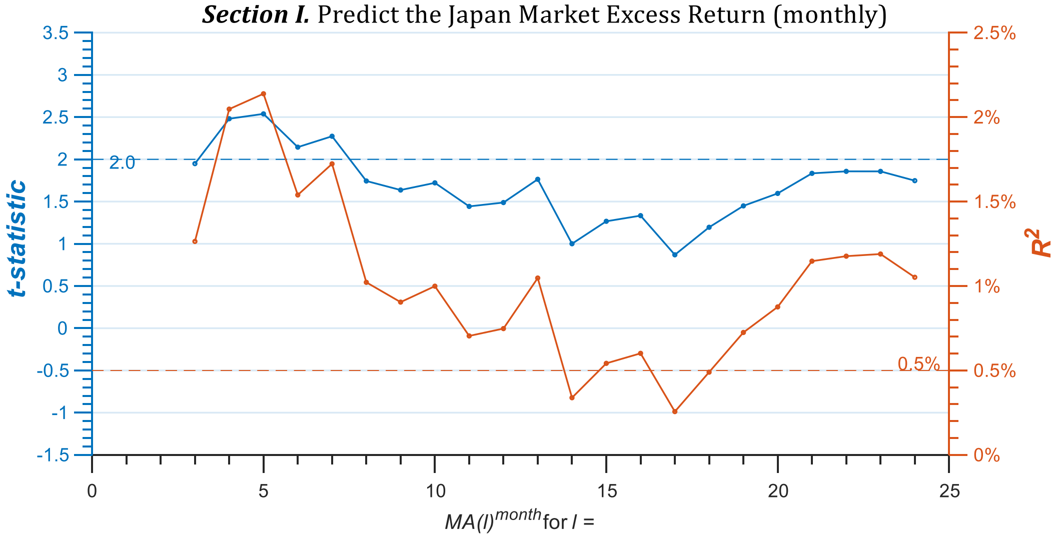


Section G and H report estimation results for the predictive regression model,
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

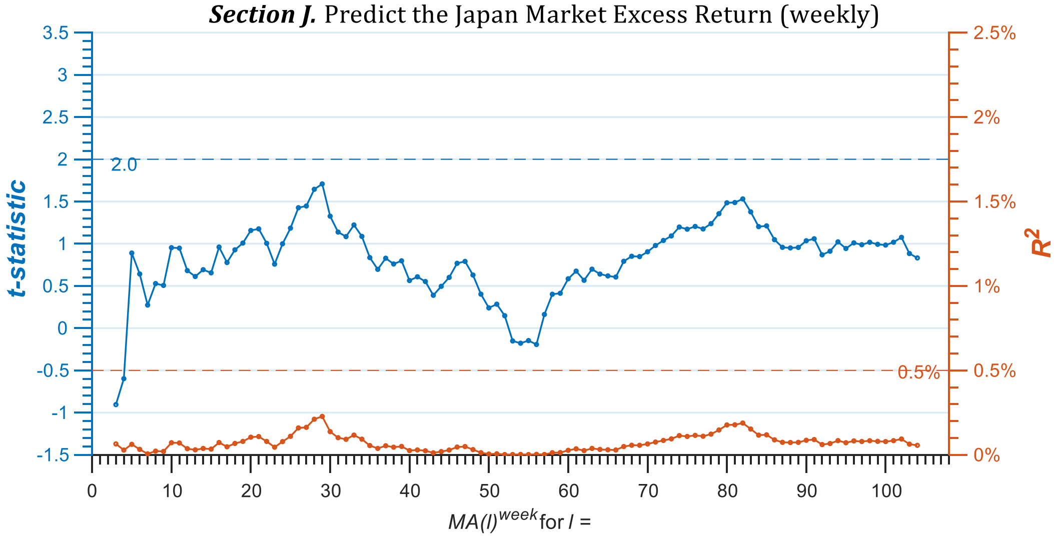
where r_{t+1} is the monthly/weekly North America market excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month/week}$ with $l = 3, 4, 5, \ldots, 23, 24$ *months* or $l = 3, 4, 5, \ldots, 103, 104$ *weeks* and generated for each price indices. We denoted each $MA(l)^{month/week}$ on the horizontal axis. Section A and B report the estimation results on the North America market monthly and weekly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{month}$.

(Figure 2.14 continued)

Section I. Predict the Japan Market Excess Return (monthly)



Section J. Predict the Japan Market Excess Return (weekly)

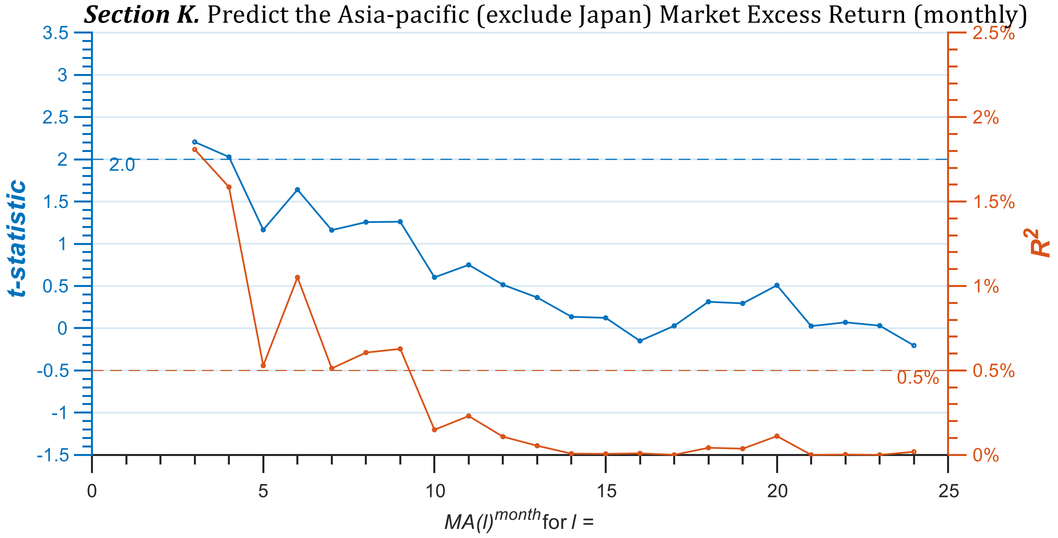


Section I and J report estimation results for the predictive regression model,
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

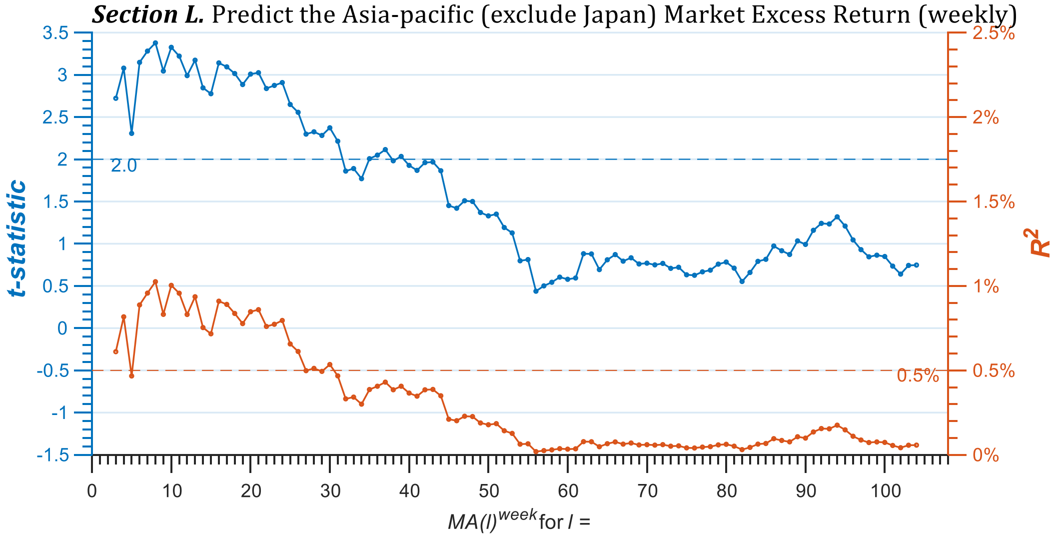
where r_{t+1} is the monthly/weekly Japan market excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MA(l)^{month/week}$ with $l = 3, 4, 5, \ldots, 23, 24\ months$ or $l = 3, 4, 5, \ldots, 103, 104\ weeks$ and generated for each price indices. We denoted each $MA(l)^{month/week}$ on the horizontal axis. Section A and B report the estimation results on the Japan market monthly and weekly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics.* Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{month}$.

(Figure 2.14 continued)

Section K. Predict the Asia-pacific (exclude Japan) Market Excess Return (monthly)



Section L. Predict the Asia-pacific (exclude Japan) Market Excess Return (weekly)



Section I and J report estimation results for the predictive regression model,
$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}$

where r_{t+1} is the monthly/weekly Asia-pacific (exclude Japan) market excess return (in percent) at time $t+1$; $S_{i,t}$ is the trading signal generated by a technical indicator at time t. We use 22 technical indicators $MOM(l)^{month/week}$ with $l = 3, 4, 5, \dots, 23, 24\ months$ or $l = 3, 4, 5, \dots, 103, 104\ weeks$ and generated for each price indices. We denoted each $MA(l)^{month/week}$ on the horizontal axis. Section A and B report the estimation results on the Asia-pacific (exclude Japan) market monthly and weekly excess return, respectively. The left vertical axis (blue) reports the heteroskedasticity-consistent *t-statistics* and right vertical axis (orange) reports the R^2 *statistics*. Each point in the figure reports the *t-statistic* and R^2 *statistic* of predicting a given market risk premium using a given technical indicator $MA(l)^{month}$.

Statement of Authorship

Title of Paper	**SHORT-TERM REVERSAL, STATE OWNERSHIP, INSTITUTIONAL OWNERSHIP, AND THE FAMA-FRENCH FIVE-FACTOR MODEL IN THE CHINESE STOCK MARKET**
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	

Principal Author

Name of Principal Author (Candidate)	Mingwei Sun		
Contribution to the Paper	Conducted the data collection and empirical data analysis, wrote manuscript.		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	28/6/2018

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Supervised development of work, helped in data interpretation, evaluated the manuscript.		
Signature		Date	28/6/2018

Name of Co-Author	Jiun-Lin Chen		
Contribution to the Paper	Supervised development of work, helped in data interpretation.		
Signature		Date	29/6/2018

Please cut and paste additional co-author panels here as required.

CHAPTER 3: SHORT-TERM REVERSAL, STATE OWNERSHIP, INSTITUTIONAL OWNERSHIP, AND THE FAMA-FRENCH FIVE-FACTOR MODEL IN THE CHINESE STOCK MARKET

Abstract

We find that the five-factor asset pricing model proposed by Fama and French (2015) is a better description of Chinese stock market return than the three-factor model. However, a substantial return spread generated by shorting past winners and buying past losers, i.e., the short-term reversal (STR), is poorly explained by the five-factor asset pricing model. We propose an STR factor, which delivers substantial improvement to the conventional three-factor/five-factor asset pricing model in explaining not only the STR spread but also all the other left-hand-side portfolios we examined. Moreover, we find two factors based on state ownership and institutional ownership also provides additional and useful information to the three-factor/five-factor model. Overall, our result suggests that the five-factor asset pricing model is not a complete description of the Chinese stock market return.

1. Introduction

Fama and French (2015) proposed a five-factor asset pricing model which helps better explain U.S. stock return than the original three-factor model (Fama & French 1993). Fama and French (2016) further suggest that the five-factor model can better explain many pricing anomalies. In other markets besides the U.S, for example, Fama and French (2017) examine the explanatory power of the five-factor model in North America, Europe, Japan, and Asia Pacific. As an out-of-sample test, the current study examines the five-factor asset pricing model in the Chinese stock market.

The Chinese stock market has become increasingly relevant to both the academics and practitioners of finance. As per data from China Securities Regulatory Commission, by market capitalization, the Chinese stock market has become the second largest stock market worldwide since 2015. In this paper, we constructed the five-factors using Chinese firm data following Fama and French (2015). We find that the five-factor model provides superior explanatory power compared to the three-factor model in explaining the daily return of the Chinese stock market. We contribute to the literature which has examined only the monthly-level performance of the five-factor model in China (see Guo et al. 2017; Li et al. 2017). Next, we took the five-factor model as the baseline model and proposed three factors that capture additional information in explaining the average returns of the Chinese stock market.

Based on the three-factor model of Fama and French (1993), Carhart (1997) proposed a momentum factor which helps better explain the expected return of the U.S., and the vast literature has examined the momentum factor extensively. However, although momentum seems to be everywhere (e.g. Asness, Moskowitz & Pedersen 2013; Fama & French 2012), it is absent in China (e.g. Cakici, Chatterjee & Topyan 2015; Chui, Titman & Wei 2010; Griffin, Ji & Martin 2003; Li et al. 2017; Wang & Chin 2004). Like others, we observe no momentum effect in daily/monthly return of the Chinese stock market but identify substantial short-term reversal in our double-sorted portfolios formed on market cap and past cumulative return. The short-term reversal returns are poorly explained by the three-factor/five-factor model. More intersetingly, we propose an short-term reversal factor (STR) that boosts the explanatory power of the three-factor/five-factor model not only on the double-sorted portfolios formed on market cap and past cumulative return but also on all the other left-hand-side portfolios we examined, including the Chinese mutual funds' return. Therefore, rather than a momentum factor widely examined in the literature, we stress the importance of adding an STR factor in better describing the Chinese stock market return.

In addition to the STR factor, we constructed two additional factors based on the ownership structure (state ownership and institutional ownership) of the listed firms, and find they can enhance the explanatory power of the three-factor/five-factor model. The first factor is based on the state (government) ownership of the listed companies, which is a unique feature of the Chinese stock market. Existing literature suggests that state ownership has a negative impact on firm value and performance. Sun and Tong (2003) find that state ownership has a negative impact on a firm's performance. Similarly, Wei, Xie and Zhang (2005) find that firm value is negatively related to state ownership, and they argue a lower firm value is due to the agency problem arises from the appointment of top managers by the government without meaningful personal ownership in the firm. Furthermore, Fan, Wong and Zhang (2007) find that the companies with politically connected CEOs underperform those without political connected CEOs in China. Although the non-tradable share reform[26] completed at the end of 2006 has considerably reduced the number of companies with state-own equity, our sample suggests 635 of the 3116 companies still have non-zero state ownership by the end of 2006. We thus construct a state ownership factor (SO) by longing the companies with zero state ownership and shorting companies with high state ownership, yielding a positive spread[27] and suggesting that the return of companies without state ownership outperform the counterparts with state ownership. More interestingly, compared with the conventional three-factor/five-factor model, adding this factor boosts the explanatory power on most left-hand-side portfolios we examined. Our last factor is based on institutional ownership. The equity ownership by an institutional investor may help deliver a better corporate governance mechanism, better management monitoring, and better shareholder protection, suggesting a robust long-

[26] During 2005 to 2006, the Chinese government launched a reform to convert non-tradable shares to tradable shares after provides a compensation plan to the tradable shareholders. State-own equity accounts for most of the non-tradable shares.

[27] We also obtain a positive spread on the other type of state ownership factor using "Low-minus-None" and "High-minus-Low".

term firm performance. Moreover, we argue institutional ownership is highly relevant to the Chinese firms since the listed companies have relatively weaker corporate governance and shareholder protection compared with the developed markets (Bai, C-E et al. 2004; Sun & Tong 2003; Wei, Xie & Zhang 2005). Cornett et al. (2007) find that the institutional investors which less likely to have a business relationship with a firm have a positive impact on the performance of the firm. Yuan, Xiao and Zou (2008) find equity ownership by mutual funds has a positive effect on the performance of Chinese companies. Elyasiani and Jia (2010) find a positive relationship between firm performance and institutional ownership stability. Along this line, we proposed am institutional ownership factor (IO) buying companies with high institutional ownership and shorting companies with low institutional ownership. We find that adding this factor help improve the explanatory power of the three-factor model.

2. Data

Our sample includes all A-shares, which are all companies traded in Chinese RMB in Shanghai and Shenzhen Stock exchange. The A-shares include all stocks traded in Shanghai and Shenzhen Main Board, Shenzhen Small and Medium-sized Enterprise Board (SMEB) and Growth Enterprise Market (GEM). The accounting data, daily and monthly return data (consider dividend reinvestment), and risk-free rate are retrieved from the China Stock Market & Accounting Research database (CSMAR). The sample period is from Jan 2004 to Dec 2017. The reason for the sample to start from 2004 is that the institutional ownership and state ownership data are available only since 2003, which are used to construct the factors starting from 2004. To our knowledge, we are the first to conduct empirical asset-pricing exercise using these data. We have a sufficient number of observations given that we focus on daily return. Moreover, we argue that the Chinese stock market before 2004 is of little interest today since it has vastly changed.

Table 3.1 presents an overview of our sample. There were around 1350 listed firms from 2004 to 2006. The number of the listed firms enlarged greatly between 2009 and 2011 and between 2014 and 2017. There are 3346 firms in the sample by the end of 2017. The three columns to the right show the summary statistics of the market capitalization, from which we can witness the market's "price roller coaster." The average firm market capitalization tripled from 1.68 billion RMB to 5.94 billion RMB between 2006 and 2007, suggesting the dramatic market bubble before the global financial crisis (GFC). In the following year, more than 50% of the total market value vaporized with the outburst of GFC. In 2009, the average market cap re-bounces substantially to a new high of 8.83 billion RMB, and stay until 2013. In 2004-2015, the market experienced a short-lasting bull market, pushing average market cap to 14.77 billion RMB and reaching a total market capitalization of 41471 billion RMB [28] by the end of 2015. Finally, the difference between the average and the median market cap reveals the presence of giant companies which pump up the mean.

[28] Alternatively, this is 41.5 trillion RMB, or around 6.5 trillion US dollar. Since 2015, the Chinese stock market has become the second largest stock market by total market cap.

3. The playing fields

3.1 Book-to-market, operating profitability and investment style

Although the focus of the current paper is not the five-factor model, for performance measurement and comparison, we still construct double-sorted five by five portfolios on *Size* (market cap) and *B/M* (Book-to-market equity ratio), *Size* and *OP* (operating profitability), and *Size* and *Inv* (investment style). *Size* is the floating market capitalization [29]. *B/M* is $\text{book equity (BE)}/\text{market equity (ME)}$, where $\text{BE} = \text{stockholder' equity} + \text{deferred income tax liability} - \text{deferred income tax assets} - \text{book value of preferred stock}$. *OP* is defined as $\text{operating profit}/\text{BE}$. *Inv* is the difference between the total asset this year and that of last year, divided by the total asset last year. The accounting data is from the annual financial report. At the end of June at year t, we use 20th, 40th, 60th and 80th *Size* percentile (end of June of year t data) of the all A-shares excluding GEM stocks[30] as the breakpoints to sort all A-shares into five quintiles. At the same time, we use the 20th, 40th, 60th and 80th percentile of *B/M*, *OP* and *Inv* (end of fiscal year t-1 data) to sort all A-shares into quintiles. Taking the intersections of *Size* quintiles and *B/M* quintiles, *Size* quintiles and *OP* quintiles, and *Size* quintiles and *Inv* quintiles, we obtain three sets

[29] Floating market capitalization is the market value of tradable shares in the market. Guo et al. (2017) use total market capitalization for their portfolio construction and thus may have overweighed old state-own companies which have lots of non-tradable shares.

[30] This choice of breakpoints is similar to Fama and French (2015) and Guo et al. (2017), because using the breakpoints while excluding GEM stocks help mitigate the impact of small stocks.

of 25 value-weighted (VW) double-sorted portfolios. They are value-weighted based on floating market capitalization at the end of June at year t.

3.2 Momentum and short-term reversal

Existing literature fail to find significant momentum (factor) in China (Cakici, Chatterjee & Topyan 2015; Chui, Titman & Wei 2010; Griffin, Ji & Martin 2003; Li et al. 2017; Wang & Chin 2004). Chan, Jegadeesh and Lakonishok (1996) suggest price continuation is due to the gradual market response to the information. Hirshleifer (2001) and Daniel, KD, Hirshleifer and Subrahmanyam (2001) argue that the psychological biases will increase under more uncertainty. Zhang (2006) provide further supporting evidence that momentum is stronger for stocks with higher information uncertainty. In the case of China, it is surprising that there is no momentum in this relatively less transparent market suffering from macroeconomic uncertainty and policy uncertainty, and full of individual investors. However, it is possible that momentum/reversal exist in a different format. We briefly explore the past cumulative return sorted portfolios using our updated data. We sort stocks into VW 25 double-sorted portfolios formed on past cumulative return and *Size*. The portfolios are constructed daily by sorting all A-shares into quintiles by past cumulative return and *Size*, respectively. The breakpoints are the 20th, 40th, 60th and 80th percentile of the all A-shares excluding GEM stocks based on the past cumulative return, which is calculated using the rolling windows between (trading) day t-251 and day t-21, day t-251 and day t-63, day t-251 and day t-2, and so on. As shown in Table 3.2, we use the windows to denote the double-sorted portfolios as (251,21), (251,63), (251,2), … To be included in the portfolio, the company must exist in the market at the start of the window and has a good return at the end of the window. Also, all stocks must have a good return at t-1 since the portfolios are rebalancing at the end of day t-1. At the end of day t-1, we take the intersections of past cumulative return quintiles and *Size* quintiles to form 25 VW portfolios for thirteen types of window. Again, these portfolios are value-weighted based on floating market capitalization.

Table 3.2 shows the average return of high past cumulative return portfolio minus that of low past cumulative return portfolio for each set of portfolios, which are sorted by a decreasing length of past cumulative return window. The portfolios based on a one-year window (251,21) suggest that there is no significant momentum effect in the Chinese stock market. In contrast, portfolio based on (251,2) window exhibits a strong reversal effect. This difference implies that, when we include the nearest 21 trading days in the window, the reversal appears. In other words, the reversal effect captured in (251,2) window is entirely driven by a reversal effect within the latest 21 trading days.

To obtain a detailed range of the reversal effect in China, we examine other past cumulative return windows[31]. Table 3.2 shows that the portfolios based on a (125,2) window show powerful reversal effect. In contrast, there is no momentum/reversal on the (125,63) window. The difference between (125,2) and (125,64) suggests the reversal only exist within the past 64 trading days. A comparison between the portfolios

[31] 251 days and 125 days window approximately cover one-year, half-year of past return data, respectively. 63 days, 43ays and 21 days cover 3-month, 2-month and 1-month of past return, respectively. 10 days and 5 days cover half-a-month and one-week of past return, respectively. Although the windows are chosen arbitrarily, we believe they describe a comprehensive picture of momentum/reversal effect in China.

based on (64,2) and (64,43) window suggests strong reversal within 43 trading days but no significant momentum/reversal between the interval t-64 to t-43. The portfolios based on (43,2) window result show stronger reversal than before. Interestingly, we start to observe some reversal effect for portfolios based on (43, 22) windows, indicating the reversal effect starts to appear when we enter the past 43 days window. However, moving from (43,2) to (43,21), we can observe a substantial reduction in the absolute values of the returns, indicating that the reversal effect is stronger within the 21 trading days. A comparison between (21,2) and (21,10) window suggests there the past ten trading days have a stronger reversal effect. Finally, we can compare (10,2) with (10,5) and finally locate the most powerful reversal within the past five trading days. This short-term reversal is captured in the last window (5,2), showing the most substantial negative return of -0.13% to -0.28% per day.

Overall, we observe no momentum effect in the Chinese stock market using various windows within one year, while we find substantial short-term reversal effect within a window of 43 past trading days. The short-term reversal effect gets stronger as we shrink the window of cumulative return and is most potent when we use a window of past five days. Also, note that large companies tend to have a lower bug still significant short-term reversal.

We call this a short-term reversal effect and consider it as an anomaly in the Chinse stock market. We use the 25 VW double-sorted portfolios formed on *Size* and the past cumulative return based on the window (5,2) as one of the playing fields because these portfolios generate the highest spreads and may pose a challenge to the asset pricing model. Hereafter, we call it 25 VW *Size-STR* portfolios.

3.3 Institutional ownership

Institutional ownership may be related to stock return through two channels. Firstly, retail investors have played a vital role in the Chinese stock market. By March 2018, 99.73% of the total security accounts belong to individual investors (China Securities Depository and Clearing Co. Ltd, http://www.chinaclear.cn). In this environment, institutional investors might be able to obtain abnormal return consistently because they have a significant advantage over the retail investors. Secondly, institutional ownership may be beneficial to company performance by providing better corporate governance and monitoring mechanism, therefore boosting long-term firm performance. We argue that institutional ownership is especially relevant to the Chinese firms since those companies have relatively weaker corporate governance and shareholder protection compared with the developed markets (Bai, C-E et al. 2004; Sun & Tong 2003; Wei, Xie & Zhang 2005). Therefore, to extrapolate the effect of institutional ownership on firm return, we examine portfolios formed on the amount of institutional ownership.

We use the institutional ownership data from CSMAR. This data includes the percent institutional ownership for most A-shares in the market. It is constructed by identifying the institutional investors from the shareholder file of the interim and annual reports. The category of institutional investors includes fund management company, foreign institutions (QF II), securities brokerage, insurance, social security fund, trust, finance company (exclude banks), and bank. We aggregate the percent holding of all institutional investors and obtain the total percent institutional ownership data for each company.

The summary statistics for the percent institutional ownership data is presented in Appendix 1. Note that not all A-shares have institutional ownership, but most of the companies do. For example, our sample has 3028 firms in 2016, while Appendix 1 suggests that 2765 of them have non-zero institutional ownership.

Following a similar construction process to the other portfolios described above, we construct 25 VW portfolios formed on percent institutional ownership (*IO*) and *Size*. The only difference is that the 25 VW *Size-IO* portfolios rebalance twice every year to utilize as much ownership information as possible. It rebalances at the end of June at year t using percent institutional ownership data at the end of December at year t-1. It also rebalances at the end of December at year t using percent institutional ownership data at the end of June at year t. Since all companies will have published their interim report by the end of December and their annual report by the end of June next year, our construction methodology avoids look-forward bias. To be included in the portfolios, a company must have non-zero institutional ownership data corresponding to the rebalancing date.

3.4 Summary of the playing fields

Table 3.3 presents the summary statistics of all the double-sorted VW portfolios. Overall, we can observe a powerful "size effect," since smaller companies, controlling for the other sorting variables, have monotonically higher return than the larger companies for all 25 VW portfolios. This substantial size effect in China is widely documented in the existing literature (Cakici, Chatterjee & Topyan 2015; Carpenter, Lu & Whitelaw 2015; Guo et al. 2017; Hilliard & Zhang 2015; Hu et al. 2018). Note the small minus big (S-B) returns are significant in most sorts, producing a return spread ranging from 0.03% to 0.11% per day. The only exception are the lowest past cumulative return quintiles.

Regarding the *Size-B/M* portfolios in Panel A, we do not observe a "value effect." For small companies, we even observe negative "value effect," where the high minus low (H-L) spread is negative and significant ($t - statsitic = -1.8$). Whether value effect exist in China is controversial in the literature. The absence of value effect in our result is consistent with the finding of Hilliard and Zhang (2015) and Hu et al. (2018), while there is also literature argue the presence of value effect (Cakici, Chatterjee & Topyan 2015; Carpenter, Lu & Whitelaw 2015; Guo et al. 2017). There is the difference in the weighting method (floating market cap versus total market cap), sample stocks, breakpoints, time interval and database that may affect the outcome. Moreover, we examine daily return instead of monthly return widely used by others.

Panel B and Panel C show some mixed results regarding operating profitability and investment style. The cross-sectional patterns are similar for portfolios formed on both *OP* and *Inv*. Both 25 VW *Size-OP* portfolios and 25 VW *Size-Inv* portfolios have a positive H-L spread for the medium-to-large *Size* quintiles, and a negative H-L spread for the smallest two *Size* quintiles. Nevertheless, two rows of the five *Inv* quintiles have H-L spread that barely significant, while none of the H-L spread for *OP* sorts is significant.

Turn to our "new" playing fields presented in Panel D and Panel E of Table 3.3. The 25 *Size-IO* VW portfolios show positive H-L spread except for one row of *Size* quintiles. The biggest *Size* quintiles show significant H-L spread with 0.03% of daily excess return (7.5% annually). The 25 *Size-STR* VW portfolios in Panel E suggest a substantial short-term reversal effect. H-L spread for all *Size* quintiles are tremendous and negatively significant, generating a daily excess return ranging from -0.13% to -0.28% (that is -32% to -70% annually). Note that the largest *Size* quintiles have the lowest reversal H-L spread.

4. Factor construction

Following the approach of Fama and French (1993), we construct our factors by sorting all A-shares in our sample into 2 × 3 portfolios. The breakpoint for the *Size* groups is the medium floating market capitalization of all the all A-shares excluding GEM stocks at the end of June of year t. The breakpoints for the characteristic groups (*B/M*, *OP*, *Inv*, and *IO*) are the 30th and 70th percentile of the corresponding variable of all the A-shares excluding GEM stocks at the end of December of year t-1. At the end of June of year t, we sort all A-shares independently into two *Size* groups (Small and Big) and three characteristic groups (Low, Neutral and High) using the breakpoints. Then we take the intersection of *Size* group with the characteristic groups, yielding the 2 × 3 value-weighted portfolios denoting as SL, SN, SH, BL, BN, and BH, where S and B indicate small and big portfolio, and L, N, and H denote for low, neutral and high characteristic portfolios. The only exception is that portfolios formed institutional ownership and *Size* are constructed *twice a year* at the end of June (and the end of

December) of year t using *IO* breakpoints at the end of December of year t-1 (and the end of June of year t). Floating market capitalization is the metric for value-weighting.

We use *Size* - *B/M* 2 × 3 portfolios to construct the value factor (HML, High minus Low), which is computed as $\mathrm{HML} = (\mathrm{SH} + \mathrm{BH})/2 - (\mathrm{SL} + \mathrm{BL})/2$. The corresponding $\mathrm{SMB}_{B/M}$(Small minus Big) factor is the average return of three small stock portfolios minus the average return of three big stock portfolios, where $\mathrm{SMB}_{B/M} = (\mathrm{SL} + \mathrm{SN} + \mathrm{SH})/3 - (\mathrm{BL} + \mathrm{BN} + \mathrm{BH})/3$. The RMW (Robust minus Weak) factor is computed using 2 × 3 portfolios formed on *Size* and *OP*, where $\mathrm{RMW} = (\mathrm{SH} + \mathrm{BH})/2 - (\mathrm{SL} + \mathrm{BL})/2$. The corresponding $\mathrm{SMB}_{OP} = (\mathrm{SL} + \mathrm{SN} + \mathrm{SH})/3 - (\mathrm{BL} + \mathrm{BN} + \mathrm{BH})/3$, as well. In contrast, the CMA (conservative minus aggressive) factor is defined as $\mathrm{CMA} = (\mathrm{SL} + \mathrm{BL})/2 - (\mathrm{SH} + \mathrm{BH})/2$. We also construct an IO (institutional ownership) factor, which is defined High percent institutional ownership stock return minus Low percent institutional ownership stock return, $\mathrm{IO} = (\mathrm{SH} + \mathrm{BH})/2 - (\mathrm{SL} + \mathrm{BL})/2$. Similarly, SMB_{OP} and $\mathrm{SMB}_{\mathrm{IO}}$ are constructed in the same way. Using all the 2 × 3 portfolios, we can finally construct the SMB factor, where $\mathrm{SMB} = (\mathrm{SMB}_{B/M} + \mathrm{SMB}_{OP} + \mathrm{SMB}_{\mathrm{INV}} + \mathrm{SMB}_{\mathrm{IO}})/4$.

A similar calculation applies to STR (short-term reversal) factor, where $\mathrm{STR} = (\mathrm{SL} + \mathrm{BL})/2 - (\mathrm{SH} + \mathrm{BH})/2$, which is formed on *Size* and past cumulative return (from day t-5 to day t-2). For comparison purposes, we also construct a conventional momentum (MOM) factor based on 2 × 3 portfolios formed on *Size* and past cumulative return from day t-251 to t-21, where $\mathrm{MOM} = (\mathrm{SH} + \mathrm{BH})/2 - (\mathrm{SL} + \mathrm{BL})/2$. Note that STR and MOM factors are based on the daily-rebalancing portfolios.

Existing literature suggests state (government) ownership has a negative impact on firm value and performance in China (e.g., Fan, Wong & Zhang 2007; Sun & Tong 2003; Wei & Varela 2003; Wei, Xie & Zhang 2005). To examine the effect of state ownership on the expected return of the Chinese stock market, we also construct an additional factor, state ownership (SO) factor. The percent state ownership data is calculated using the "capital structure" data in CSMAR. This dataset classifies the total equity to floating shares and non-tradable shares. We are interested in the proportion of state-own shares which falls into the category of non-floating shares. We then calculate the proportion of state-own shares in the total equity value for each company. The summary of the state-own share data is in Appendix 2. The proportion of state-own equity decreases over time, especially after the non-tradable share reform mostly completed by the end of 2006. Also, the proportion of companies with positive state ownership is decreasing over time. 1005 out of 1263 companies have non-zero state ownership at the end of 2003. By the end of 2016, only 635 out of the 3116 companies have non-zero state ownership.

The number of companies with state-own shares gradually reduces over time and accounts for only a small part of the sample (635 out of the 3116 companies) by the end of 2016. It is thus impractical to construct only high-minus-low SO factor which will only use a small proportion of the total sample. To comprehensively examine the impact of state-own shares, we also include companies with zero (none) state ownership and construct three varieties of SO factors. They are $\mathrm{SO}_{\mathrm{LMH}}$(Low minus High), SO_{NMH} (None minus High), and $\mathrm{SO}_{\mathrm{NML}}$(None minus Low). Using the end of financial year state ownership data, we sort all A-shares into three portfolios: zero (Z), low (L) and high (H) portfolios. The breakpoint for L and H portfolios is the median percent government holding of all A-shares excluding GEM stocks. We then take the intersection of the corresponding small (S) and big (B) portfolios with the Z, L, and H SO portfolios, thereby getting six portfolios: SZ, SL, SH, BZ, BL, and BH. Then $\mathrm{SO_{LMH}} = (\mathrm{SL} + \mathrm{BL})/2 - (\mathrm{SH} + \mathrm{BH})/2$; $\mathrm{SO_{NMH}} = (\mathrm{SZ} + \mathrm{BZ})/2 - (\mathrm{SH} + \mathrm{BH})/2$; $\mathrm{SO_{NML}} = (\mathrm{SZ} + \mathrm{BZ})/2 - (\mathrm{SL} + \mathrm{BL})/2$. These portfolios rebalance at the end of June at year t using the state-own shares data at the end of year t-1.

Table 3.4 presents the summary statistics of all the factors. First of all, Panel A suggests that STR, $\mathrm{SO_{NMH}}$, $\mathrm{SO_{NML}}$, $\mathrm{SO_{LMH}}$ and IO all have a positive average return. We can also observe that market excess return, SMB, STR, $\mathrm{SO_{NMH}}$, and $\mathrm{SO_{NML}}$ are significantly different from zero, however HML, RMW, CMA, MOM, $\mathrm{SO_{LMH}}$, and IO are not. Market premium and SMB have a Sharpe ratio of 0.03 and 0.04, respectively. STR has a Sharpe ratio of 0.20. The conventional MOM factor is insignificant with negative Sharpe ratio, verifying our findings of the absence of momentum in the previous section. Also, note that the mean returns of RMW and CMA are indistinguishable from zero.

Panel B of Table 3.4 presents the correlation matrix of the factors. RMW and HML are negatively correlated with SMB, verifying that small companies tend to have weaker profitability and lower book-to-market equity ratio. The positive correlation between STR and SMB suggest that small (large) companies have stronger(weaker) short-term reversal. Very interestingly, the institutional investors seem to be strong momentum-follower because of the 0.36 correlation coefficient between IO factor and MOM factor, even though there is no momentum return in China. Appendix 3 presents the comparison of our five factors with those available in CSMAR for a cross-validation purpose.

5. Redundancy tests

Among all the factor we proposed, we are interested in whether they capture useful information in explaining the average return in the Chinese stock market. Firstly, we regress each of the factors on market premium, SMB, and HML, to examine whether they are fully explained by the conventional three-factor model.

Table 3.5 presents the result. The three-factor model can adequately explain CMA, MOM, SO_{LMH}, SO_{NML}, SO_{NMH}. CMA factor is redundant in China to the three-factor model as per the insignificant regression intercept, consistent with the finding in Li et al. (2017) and Guo et al. (2017). The insignificant MOM verifies the finding in the existing literature regarding China. It is worthwhile noting that the average return of RMW and IO are insignificant in Table 3.4, but they become significant with an intercept of 0.02 and 0.03 after regressing on the three-factor model, indicating that they may embed additional and useful information to the three-factor model. We now exclude SO_{LMH} and SO_{NML}, while keeping SO_{NMH} which is the most significant SO factor. We also exclude the redundant MOM[32] factor.

After reducing the number of the factors using the three-factor model, we consider the factor spanning test following Fama and French (2015): if the regression intercept of one factor on all the other factors is zero, then the LHS factor is redundant. Table 3.6.1 presents the result of the first factor spanning test where we exclude CMA and RMW from the model. The first column indicates that none of the factors has zero regression intercept when regressing on the other factors. SMB, HML, STR, SO_{NMH}, and IO are not redundant as per the first factor spanning test.

Our second factor spanning test now includes RMW and CMA, as shown in Table 3.6.2. RMW and CMA are not redundant with intercept of 0.02 and 0.01 (t-statistics = 4.19, 2.25), respectively. Interestingly, CMA is not redundant in the factor spanning test while it can be fully explained by the three-factor model. HML is not redundant to the other factors (intercept = 0.02, t-statistic = 3.06). On the daily-level, we confirmed that HML is not redundant, consistent with the monthly analysis result of Guo et al. (2017), even though the value effect is not significant as reported in Table 3.4. STR has a highly significant intercept of 0.18 (t-statistic =11.93) after controlling for other factors. Note that the R^2 statistic for STR is only 4%, a low level partially due to its

[32] We keep CMA in the following section due to its importance in the literature. The focus of the current study is not the five-factor model, so we do not discuss the necessity of CMA in the model.

daily-rebalancing nature. However, $\mathrm{SO_{NMH}}$ and IO seem to be redundant when adding RMW and CMA to the model. We still include $\mathrm{SO_{NMH}}$ and IO in the following analysis to further examine their explanatory power since they are non-redundant in the first factor spanning test. Hereafter, we use SO to denote $\mathrm{SO_{NMH}}$ for ease of presentation.

6. Model performance

Fama and French (2015) proposed the five-factor asset pricing model:

$$R_{it} - R_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it},$$

where $R_{it} - R_{Ft}$ is the portfolio i's return minus the risk-free rate R_{Ft} for day t; Mkt_t is the value-weighted market excess return constructed using all A-shares in our sample; SMB_t, HML_t, RMW_t and CMA_t are size, value, profitability and investment factor.

Adding STR, SO and IO to the five-factor model, we examine the following eight-factor model:

$$R_{it} - R_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + r_i STR_t + g_i SO_t + I_i IO_t + e_{it},$$

where STR_t, SO_t and IO_t are the short-term reversal, the state ownership and the institutional ownership factor, respectively. Note that SO indicates $\mathrm{SO_{NMH}}$ (none state ownership portfolio returns minus high state ownership portfolio returns).

The GRS statistic of Gibbons, Ross and Shanken (1989) tests whether the intercepts in time-series regressions of excess return are jointly indistinguishable from zero. Following Fama and French (2015), we use GRS statistic and the other three metrics ($A|a_i|$, $\frac{A|a_i|}{A|\bar{r}_i|}$ and $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$) to measure the model performance of the additional factors, STR_t, SO_t and IO_t, comparing to the three-factor/five-factor model. GRS statistic test the hypothesis that all regression intercepts are jointly indistinguishable from zero, i.e. the asset pricing model fully expla,in expected returns. $A|a_i|$ is the average absolute value of the regression intercepts. $\frac{A|a_i|}{A|\bar{r}_i|}$ is the average absolute value of the regression intercepts scaled by the average absolute value of the deviation of each portfolio's excess return from the cross-section average. Following Fama and French (2015), we also estimate $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ which measures the proportion of the variance of LHS expected return left unexplained, where $\hat{a}_i^2$ is the difference between the squared estimate of the regression intercept and its standard error for portfolio i; $\hat{u}_i^2$ is the difference between the square of the realized deviation, $\bar{r}_i^2$, of portfolio i and the square of its standard error; $A(\hat{a}_i^2)$ and $A(\hat{u}_i^2)$ are the average value of $\hat{a}_i^2$ and $\hat{u}_i^2$, respectively. For all the model performance metrics, a lower level indicates better model explanatory power.

Table 3.7 presents the model performance measures for each set of the 25 VW portfolios. Panel A (Panel B) report model performance results when the three-factor (the five-factor model) is the baseline model. Overall, the GRS statistics are significant for all portfolios, indicating that none of the models is a complete description of the daily expected return in the Chinese stock market. We can observe Panel B have lower performance measures than Panel A, suggesting the five-factor model is a better description of the daily expected return than the three-factor model, confirming the finding in the monthly-level analysis of Guo et al. (2017) and Li et al. (2017). The five-factor model made decent improvements in GRS, $|a_i|$, $\frac{A|a_i|}{A|\bar{r}_i|}$ and $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ for the 25 *Size-B/M* portfolios, 25 *Size-Inv* portfolios, 25 *Size*-IO portfolios, and especially for the 25 *Size-OP* portfolios where three-factor model leave 90% of the cross-section average returns unexplained ($\frac{A|a_i|}{A|\bar{r}_i|}$ =0.90) while five factor model reduce it to 70% ($\frac{A|a_i|}{A|\bar{r}_i|}$ =0.70).

Panel A of Table 3.7 shows that adding STR to the three-factor model made improvement for the 25 *Size-B/M* portfolios and a substantial improvement on the 25 *Size*-STR portfolios which three-factor model poorly explained. For example, adding STR reduces $|a_i|$ from 0.072 to 0.039, and reduces $\frac{A|a_i|}{A|\bar{r}_i|}$ from 0.94 to 0.51 for the 25 *Size*-STR portfolios. More interestingly, Panel B shows that adding STR boosts the explanatory power for ALL left-hand-side portfolios, highlighting that STR provides important additional information in explaining the daily expected return of Chinese stock market. It is expected that the improvement is strongest for the 25 *Size*-STR portfolios which five-factor cannot well explain. On the top of the five-factor model, adding STR help reduce the GRS statistics for all portfolios especially on the 25 *Size*-STR portfolios. Regarding $A|a_i|$, STR produce a substantial improvement (3.5 basis point per day, 857 basis point per year) for the 25 *Size*-STR portfolios while some improvement on the other portfolios. Regarding the cross-section average return and variance, adding STR substantially reduced $\frac{A|a_i|}{A|\bar{r}_i|}$ and $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ for the 25 *Size*-STR portfolios and makes decent improvement for the other portfolios compared to the five-factor model.

Panel A and Panel B of Table 3.7 shows that adding SO (and STR) to the three-factor (five-factor) help further boost the explanatory power for almost all 25 VW portfolios, suggesting that SO also provides additional information beyond the three-factor/five-factor model. Finally, Panel A shows that adding IO to the model help better explain 25 *Size-OP* and 25 *Size-Inv* portfolios. However, the improvements made by IO disappear in Panel B when CMA and RMW are added to the model, indicating IO only provides additional information to the three-factor model but not the five-factor one. Nevertheless, adding IO help much better explain 25 *Size*-IO portfolios in both Panel A and Panel B.

Overall, it seems that the five-factor model produces a decent improvement to the conventional three-factor model in explaining the expected return in the Chinese stock market. However, the 25 *Size-STR* portfolios pose a severe challenge to the five-factor model, leaving a substantial proportion of the cross-section returns unexplained. Luckily, adding the STR factor greatly improves the explanatory power not only for the 25 *Size-STR* portfolios but also for the other portfolios. However, note that the average absolute intercepts of 25 *Size-STR* portfolios are still substantial (3.9 basis points per day, 975 basis points per year) even after adding the STR factor. At last, SO also provides additional information to both three-factor and five-factor model.

Table 3.8 presents the regression loadings on the STR, SO and IO factors. The left-hand side presents the loadings of the STR SO and IO factor (*r, g* and *I)* and the right-hand-side (*t(r), t(g)* and *t(*I*))* are the *t-statistics* of the loadings.

The loadings of STR are significant for 8 of the 25 *Size-B/M* portfolios, 9 of the 25 *Size-OP* portfolios, 8 of the 25 *Size-Inv* portfolios, 4 of the 25 *Size*-IO portfolios, and 25 of the 25 *Size-STR* portfolios. The loadings on SO and IO are significant for most portfolios when control the five factors and STR, suggesting they play a critical role in explaining the expected returns in the Chinese stock market[33].

From Table 3.8 we can observe some interesting cross-sectional patterns regarding SO and IO factor. From the result of the 25 *Size-B/M* portfolios, the loadings on IO are *only* significantly negative in the northwest corner of the 25 *Size-B/M* portfolios, suggesting that small companies with low book-to-market ratio (i.e., small growth stocks) are unfavorable to the institutional investors. Meanwhile, the substantial IO loadings in the southwest/northeast suggest the institutional investors prefer large companies with high *B/M* ratio (i.e., large value stocks) and small companies with low *B/M* ratio (i.e., small growth stocks). The negatively significant IO loadings on the west of *Size-OP* portfolios suggest small-to-medium companies with weak profitability is unattractive to institutional investors. In contrast, we can tell that institutional investor prefers profitable companies with large market cap.

From the result of the 25 *Size-B/M*(*OP*) portfolios, the sign of the loadings and the corresponding t-statistics on SO factor describes that small companies tend to have none state ownership while large companies tend to have high state ownership.

The result on the 25 *Size-Inv* portfolios shows that negatively significant SO loadings on the southwest and positively significant loadings on the northeast, revealing that small & aggressive (large & conservative) companies tend to have none (high) state

[33] Among all the portfolios, SO and IO have more significant loadings than STR, although from Table 7 we observe stronger improvement provided by STR. This may due to that STR is daily-rebalancing, incorporating lots of noises into the STR factor return and thus reduce its correlation with the left-hand-side portfolios, most of which rebalance yearly.

ownership, which is an expected outcome. Finally, turn to IO loadings for the 25 *Size-Inv portfolios,* we can see largest *Size* quintile are preferred by institutions who do not show a clear preference to investment style, while small aggressive companies are unfavorable to the institutional investors (negatively significant loadings on the northeast of 25 *Size-Inv* portfolios).

Overall, we observe significant STR loadings, and significant SO and IO loadings on most portfolios controlling for the five-factors, suggesting they might provide useful and additional information in explaining the expected returns of the Chinese stock market on the top of the five-factor model.

7. Mutual fund return

To examine how useful the “new” factors are in explaining the investment performance, we examine them on mutual fund data from CSMAR. To include enough number of observations, we filter out mutual funds which have fewer than 2000 trading days [34]. We obtain a sample of 495 mutual funds. We then compute the daily net asset value (NAV) return using the daily NAV data from CSMAR. Following that, we calculate the model performance measures same as the prior section, treating all mutual funds as a big set of left-hand-side portfolios.

Panel A of Table 3.9 presents the model performance measures based on the 498 mutual funds daily NAV return. First, none of the models can adequately explain the funds’ performance because the *GRS statistics* are all significant. It is surprising that

[34] Our result is qualitatively similar when we choose 1000 days as the filter range.

the five-factor model made an only slight improvement over the three-factor model on *GRS*, $\frac{A|a_i|}{A|\bar{r}_i|}$ and $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ while do not reduce the average absolute intercept. In contrast, adding the STR factor generates a much larger improvement, and it reduces $|a_i|$ from 0.017 to 0.015, reduces $\frac{A|a_i|}{A|\bar{r}_i|}$ from 1.24 to 1.09 and, mostly shockingly, reduces $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ from 0.84 to 0.23, suggesting that STR helps tremendously in explaining the cross-sectional variance of the mutual funds' return. Therefore, the short-term reversal appears to be an important feature of the Chinese mutual funds' return. In contrast, adding SO and IO factor seems to provide no improvement as per the performance measures.

Panel B, Panel C and Panel D present the regression details on the 498 mutual funds based on the three-factor/five-factor/eight-factor model. For all models, only around 5 to 6 percent of the mutual funds have significant intercepts, a small proportion of which are positively significant while the rest are negatively significant. This indicates most of the mutual funds do not generate positive alpha after controlling for only the three factors.

Panel B shows that 36.04% of the funds have significant loadings on the SMB factor and 37.85% of the funds have significant loadings on the HML factor. More interestingly, most of them have positive exposure to SMB (prefer small stocks) while negative exposure to HML (prefer growth stocks). Meanwhile, a smaller proportion of the funds show an opposite investment strategy with a different exposure (7.63% have negatively significant exposure on SMB, and 5.72% have positively significant exposure on HML).

Comparing Panel C to Panel B of Table 3.9, adding RMW and CMA slightly increases the number of negative alphas. The average adjusted R^2 statistic increases from 58.76% to 59.39% in Panel C (63 basis points increase). 30.32% of the funds have significant loading on RMW, while 28.01% of them are positively significant, suggesting a preference for the profitable firm. In contrast, 22.29% of the CMA loadings are negatively significant, while 8.53% of the CMA loadings are positively significant, revealing that more mutual funds prefer firms with aggressive investment style than conservative ones.

Turning to the regression details of the eight-factor model in Panel D of Table 3.9. Firstly, the average adjusted R^2 increases to 59.39% from 60.29% in Panel C, which is a 90-basis-point increase, more than the improvement provided by the five-factor model. Secondly, after adding STR, SO, and IO, the percentage of significant loadings on the SMB, HML, RMW, and CMA all reduced, suggesting that STR, HMN, and ISNT provide additional information in explaining the Chinese mutual fund's performance.

3.57% of funds have significant positive exposure to STR who may have been trading to an STR strategy. Meanwhile, it is puzzling that why 18.57% of the mutual funds trade against (represented by negatively significant exposure) short-term reversal despite its substantial return. One possible explanation is that the short-term reversal may not be profitable to trade in a costly environment. Alternatively, it may be due to their unawareness of the short-term reversal effect. It could also due to the price impact or a herding behavior of mutual funds. We leave this puzzle for future research.

Panel D of Table 3.9 also shows that the proportion of positive and negative significant loadings on SO are balanced (12.65% and 11.04%). Meanwhile, a significant proportion of mutual funds (36.35%) have significant positive loadings on IO, suggesting most of them invest in what everyone (every institution) else invests.

8. Monthly-level result

Since most existing literature examines monthly return, as a robustness check, now we redo the analysis based on the monthly return. All the factors are constructed like our daily analysis. SMB, HML, RMW, CMA and SO are based on 6 (2×3) *Size-BM*, 6 *Size-OP, 6 Size-Inv*, 6 *Size-SO* portfolios that rebalance at the end of every June at year t, using the year-end sorting data at year t-1, and hold until the end of June at year t+1. IO is based on the 6 *Size-IO* portfolios that rebalance twice a year at the end of June of year t (based on the institutional ownership data at the end of December of year t-1) and at the end of December of year t (based on the data at the end of June of year t). Following the convention, MOM is based on the 6 double-sorted portfolios formed on *Size* and past cumulative return from month t-12 to month t-2. Finally, STR is based on the 6 double-sorted portfolios formed on *Size* and past cumulative return of month t-1 only. Note that MOM and STR rebalance end of every month t-1. Also note that the monthly-level STR factor inherently has a longer window than the daily-level one which is based on past return between day t-5 and day t-2, due to the limit of data frequency. At last, a similar methodology to the daily-level analysis also applies to construct the monthly-level playing fields.

Table 3.10 presents the summary statistics for the risk factors based on the monthly return. Mkt, SMB, STR have significant returns, like the daily result in Table 3.4. Note that the monthly-level STR has 1.21% monthly return (14.52% annually) while the daily-level STR has 0.18% daily return (45% annually), as reported in Table 3.4[35]. SO_{NMH} is barely significant but it provides the largest spread among the three SO factors. HML is insignificant suggesting the absence of value effect in the market. Meanwhile, RMW, CMA, MOM and IO return are indistinguishable from zero, similar to our daily-level result.

Table 3.11.1 presents the first factor spanning test. Note that HML is a non-redundant factor although value effect is not significant in Table 3.10. STR, SO_{NMH}, and IO are significant (non-redundant) after controlling for the other factors, suggesting that they provide additional information to the other factors.

The result of the second factor spanning test (adding RMW and CMA) in Table 3.11.2 shows that RMW and CMA are non-redundant. STR is non-redundant with the second highest intercept. However, SO and IO appear to be redundant after adding RMW and CMA.

Table 3.12 presents model performance results based on the monthly-level models. Overall, the monthly return poses less problem to the asset-pricing model than the daily return as the GRS statistics are lower in the monthly-level result than the daily-level one. The 25 *Size-IO* portfolios have insignificant intercepts when explained by the five-

[35] The daily-level STR is based on portfolios that rebalances much frequently than the monthly-level one, so it is unclear which can provide higher return if consider transaction cost.

factor model in Panel B. If comparing the model performance measures in Panel A and Panel B, we can find that the five-factor model can better explain the expected return than the three-factor model for all left-hand-side portfolios, except the 25 *Size-B/M portfolios and 25 Size-STR portfolios.*

We find that adding the monthly-level STR does not provide an improvement in explaining the expected return of most left-hand-side portfolios except for the 25 *Size*-STR portfolios. In contrast, daily model performance in Table 3.7 shows STR deliver decent improvement for most 25 VW portfolios. This difference suggests that daily-level STR may provide more critical information in explaining the expected return than the monthly-level STR. Note that daily-level STR is different from the monthly-level STR because the daily-level one uses information in a much short-term frequency. Nevertheless, as reported in both Panel A and B, the 25 *Size*-STR portfolios still pose a significant challenge to the three-factor/five-factor model which requires the help of the monthly-level STR to explain. We can observe substantial improvement for the 25 *Size*-STR portfolios after adding STR to the model.

Turning to SO, Panel A shows that adding SO provides improvement for all left-hand-side portfolios. Also, Panel B shows that SO provides an improvement to 25 *Size-B/M* portfolios, 25 *Size*-INV portfolios, and 25 *Size*-STR portfolios, suggesting that SO provides a decent level of improvement even to the five-factor model on the monthly-level. However, IO can provide an improvement to three of the five sets of left-hand side portfolios in Panel A but little improvement in Panel B. As a result, IO seems to be redundant in explaining the expected return after control for the five-factor model on the monthly level.

9. Conclusion

We find that the five-factor asset pricing model is an overall better description of the expected return of the Chinese stock market than the three-factor model. We confirm the absence of momentum in China while observe the substantial spread of the *Size-STR* (short-term reversal) double-sorted portfolios, which pose a significant challenge to the three-factor/five-factor model. Adding an STR (factor) not only help explain the *Size-STR* double-sorted portfolios, but also make decent improvement in explaining most of the left-hand-side portfolios. Nevertheless, daily-level STR provides robust improvement while a monthly-level STR do not, suggesting that the STR in a daily frequency provides more useful information in the Chinese stock market. The explanatory power on mutual funds' performance also increase when daily-level STR is added, and daily-level STR help substantially in explaining the cross-sectional variance of Chinese mutual funds' return.

We show that SO (state ownership factor) provides an improvement to the conventional three-factor/five-factor model for most left-hand-side portfolios. SO and IO (institutional ownership factor) can generate significant loadings on most left-hand-side portfolios. Also, adding SO and IO helps further explain the mutual fund's return with significant loadings on these two factors. Overall, our result suggests that ownership structure contain useful information, which is complementary to the five-factor model.

Finally, we are surprised to find that IO is highly correlated with the momentum factor, suggesting that considerable institutional investors in China are momentum follower even though momentum return is insignificant in China. More interestingly, many mutual funds have negatively significant exposure to STR despite the substantial positive spread of the short-term reversal.

Overall, our result suggests five-factor model although made decent improvement compared with the three-factor model, is not a complete description of the Chinese stock market. Our proposed factors, especially STR and SO, capture vast useful information.

10. Tables

Table 3.1
Summary statistics for the sample: 2004-2017.

This table reports the summary statistics for all the A-shares (include Shanghai and Shenzhen Main Board, SMEB and GEM stocks). N is the total number of companies in the sample. Mean (Median) is the average(median) of floatable market capitalization of all the companies in the sample. Total is the total floatable market capitalization of the sample. The unit for market cap is a billion in the Chinese RMB.

Year	N	Mean	Median	Total
2004	1353	0.82	0.47	1103
2005	1355	0.74	0.39	1001
2006	1404	1.68	0.69	2366
2007	1526	5.94	2.26	9068
2008	1601	2.78	0.97	4456
2009	1694	8.83	2.69	14959
2010	2039	9.37	2.92	19108
2011	2318	7.05	1.97	16344
2012	2470	7.28	1.98	17975
2013	2468	8.02	2.70	19794
2014	2590	12.10	3.91	31338
2015	2807	14.77	6.85	41471
2016	3028	12.85	5.79	38917
2017	3346	13.01	4.38	43522

Table 3.2
Difference in average daily percent excess return between the portfolio with high past cumulative return and the portfolio with low past cumulative return (High minus Low spread): 07/01/2004-12/29/2017, 3286 trading days.

This table reports the difference in average percent excess return between portfolio with high past cumulative return and portfolio with low past cumulative return. These portfolios are 25 (5 × 5) value-weighted portfolios formed on *Size* and past cumulative return. The numbers in the parenthesis, (), denotes for the rolling window used to calculate past cumulative return. For example, (251,21) denotes the portfolios which are formed on *Size* and past cumulative return between the day t-251 to day t-21. The t-statistics of the high minus low spread are in the brackets [].

	(251, 21)	(251, 2)	(125, 2)	(125, 63)	
Small	-0.02 [-0.93]	-0.13 [-6.02]	-0.18 [-8.94]	-0.01 [-0.66]	
2	-0.02 [-1.36]	-0.10 [-6.36]	-0.13 [-7.71]	0.00 [0.28]	
3	-0.01 [-0.89]	-0.08 [-4.74]	-0.09 [-5.09]	0.00 [0.35]	
4	0.00 [-0.07]	-0.05 [-3.03]	-0.07 [-4.21]	0.01 [0.89]	
Big	-0.01 [-0.55]	-0.04 [-1.86]	-0.07 [-2.78]	-0.03 [-1.35]	
	(63, 2)	(63, 43)	(43, 2)	(43, 21)	
Small	-0.23 [-11.29]	-0.01 [-0.72]	-0.22 [-10.77]	-0.04 [-2.64]	
2	-0.17 [-10.39]	-0.01 [-0.51]	-0.18 [-10.80]	-0.04 [-3.41]	
3	-0.14 [-7.87]	0.00 [-0.36]	-0.15 [-8.60]	-0.05 [-3.96]	
4	-0.10 [-5.53]	0.00 [0.02]	-0.12 [-6.25]	-0.04 [-2.66]	
Big	-0.08 [-2.92]	-0.01 [-0.44]	-0.08 [-3.03]	-0.02 [-0.94]	
	(21, 2)	(21, 10)	(10, 2)	(10, 5)	(5, 2)
Small	-0.20 [-10.26]	-0.06 [-3.89]	-0.20 [-10.25]	-0.09 [-5.57]	-0.23 [-12.20]
2	-0.19 [-10.82]	-0.05 [-3.86]	-0.19 [-11.45]	-0.09 [-6.47]	-0.28 [-16.87]
3	-0.15 [-8.64]	-0.05 [-3.33]	-0.16 [-9.21]	-0.08 [-5.37]	-0.26 [-15.35]
4	-0.13 [-6.62]	-0.02 [-1.60]	-0.14 [-7.34]	-0.08 [-5.19]	-0.21 [-12.03]
Big	-0.07 [-2.55]	0.00 [0.01]	-0.07 [-2.88]	-0.06 [-2.46]	-0.13 [-5.07]

Table 3.3

Averages of daily percent excess return for 25 (5 × 5) value-weighted (VW) portfolios: 07/01/2004-12/29/2017, 3286 trading days.

At the end of each June, all A-shares (include Shanghai and Shenzhen Main Board, SMEB and GEM stocks) are assigned to five Size groups (Small to Big) using the market cap quintiles of all A-shares excluding GEM stocks. Stocks are allocated independently to five *B/M* groups (Low to High) using the *B/M* quintiles of all A-shares excluding GEM stocks. The intersections of these two sorts produce 25 value-weighted *Size-B/M* portfolios. At the end of June of year t, *Size* is the market cap at the end of June of year t. *B/M* is the book equity B at the end of December of year t-1 divided by the market cap M at the end of December of year t-1. The *Size-OP*, *Size-Inv* portfolios are constructed in the same way, except the *OP* and *Inv* variables. The *Size-IO* portfolios are constructed twice every year at the end of each June and December, using the institutional ownership data 6 months prior to the construction. The *Size-STR* portfolios are constructed daily at the end of day t-1, formed on the past cumulative return between day t-5 to day t-2 and Size at the end of day t-1. The column of H-L shows the difference between the average percent returns of High variable portfolios minus average percent returns of Low variable portfolios for each Row. Similarly, the rows S-B show the average percent returns of Small portfolio minus the average returns of Big portfolio for each column. The number in the brackets are t-statistics.

	Low	2	3	4	High	H-L
			Panel A: Size-B/M portfolios			
Small	0.13	0.11	0.13	0.12	0.10	-0.03 [-1.80]
2	0.09	0.10	0.10	0.10	0.08	0.00 [-0.32]
3	0.07	0.07	0.09	0.09	0.07	0.00 [0.00]
4	0.06	0.07	0.07	0.07	0.06	0.00 [0.27]
Big	0.06	0.06	0.06	0.06	0.05	-0.01 [-0.28]
S-B	0.07	0.06	0.07	0.06	0.05	
	[3.74]	[2.87]	[3.09]	[2.47]	[1.82]	
			Panel C: Size-Inv portfolios			
Small	0.13	0.12	0.12	0.11	0.11	-0.01 [-0.87]
2	0.09	0.10	0.10	0.10	0.07	-0.01 [-1.33]
3	0.06	0.08	0.08	0.09	0.08	0.02 [1.65]
4	0.06	0.07	0.07	0.06	0.06	0.00 [0.16]
Big	0.03	0.05	0.05	0.06	0.06	0.02 [1.66]
S-B	0.09	0.08	0.06	0.06	0.05	
	[4.43]	[3.69]	[2.64]	[2.46]	[2.61]	
			Panel E: Size-STR portfolios			
Small	0.22	0.23	0.18	0.08	-0.02	-0.23 [-12.20]
2	0.20	0.19	0.15	0.06	-0.08	-0.28 [-16.87]
3	0.18	0.16	0.11	0.03	-0.08	-0.26 [-15.35]
4	0.15	0.14	0.09	0.03	-0.06	-0.21 [-12.03]
Big	0.11	0.11	0.07	0.02	-0.02	-0.13 [-5.07]
S-B	0.11	0.13	0.11	0.06	0.00	
	[4.48]	[5.83]	[5.18]	[2.54]	[-0.02]	

	Low	2	3	4	High	H-L
			Panel B: Size-OP portfolios			
Small	0.13	0.12	0.10	0.09	0.11	-0.02 [-1.19]
2	0.08	0.10	0.09	0.10	0.08	0.00 [-0.05]
3	0.06	0.07	0.08	0.09	0.07	0.02 [1.43]
4	0.06	0.05	0.07	0.07	0.07	0.01 [1.12]
Big	0.04	0.04	0.05	0.06	0.06	0.02 [0.87]
S-B	0.08	0.09	0.05	0.03	0.05	
	[4.56]	[4.88]	[2.65]	[1.52]	[1.83]	
			Panel D: Size-IO portfolios			
Small	0.12	0.11	0.10	0.09	0.13	0.02 [0.59]
2	0.09	0.10	0.09	0.09	0.10	0.01 [1.03]
3	0.07	0.08	0.08	0.08	0.09	0.02 [1.53]
4	0.07	0.07	0.07	0.07	0.07	0.00 [-0.30]
Big	0.03	0.04	0.05	0.07	0.06	0.03 [1.93]
S-B	0.08	0.07	0.05	0.03	0.07	
	[3.28]	[3.12]	[2.24]	[1.32]	[2.05]	

Table 3.4
Summary statistics of factor daily returns: 07/01/2004-12/29/2017, 3286 trading days.

Mkt is the value-weighted market portfolio return of all A-shares (include Shanghai and Shenzhen Main Board, SMEB and GEM stocks) in excess of risk-free rate. At the end of June, all A-shares are assigned to two *Size* groups using the median market cap of all A-shares excluding GEM stocks as the breakpoint. Stocks are also allocated independently to three *B/M*, *OP* and *Inv* groups (Low, Neutral and High) using the 30th and 70th percentile of all A-shares excluding GEM stocks. The intersections of *Size* and other variable groups produce 6 (2 × 3) value-weighted *Size-B/M, Size-OP, and Size-Inv* portfolios, SL, SN, SH, BL, BN, and BH, where S and B denote for small and big portfolio, and L, N and H indicate low, neutral and high characteristic portfolios. SMB is the average of $SMB_{B/M}$, SMB_{OP}, SMB_{Inv}, and SMB_{IO}, where $SMB_{B/M}$ is the average of the returns on the three small stock portfolios of 6 *Size-B/M* portfolios minus the average returns on the three big stock portfolios of 6 *Size-B/M* portfolios, $SMB_{B/M}$= (SL+SN+SH)/3-(BL+BN+BH)/3. SMB_{OP}, SMB_{Inv}, and SMB_{IO} are constructed in the same way, except for the *OP*, *Inv* and *IO* variables. HML is the average return on the two high *B/M* portfolios of 6 *Size-B/M* portfolios minus the average return of the two low *B/M* portfolios of 6 *Size-B/M* portfolios, HML=(SH+BH)/2-(SL+BL)/2. RMW, CMA and IO are constructed in a same way using 6 *Size-OP, 6 Size-Inv* and 6 *Size-IO* portfolios, except 6 *Size-IO* portfolios are constructed twice a year at the end of June and December. MOM is average return on the two high past cumulative return portfolios of 6 *Size-MOM* portfolios minus the average return of the two low past cumulative return portfolios of 6 *Size-MOM* portfolios. STR is average return on the two low past cumulative return portfolios of 6 *Size-STR* portfolios minus the average return of the two high past cumulative return portfolios 6 *Size-STR* portfolios. *Size-MOM* portfolios (*Size-STR* portfolios) are constructed daily formed on past cumulative return between day t-21 to t-251 (t-2 to t-5) and *Size* at day t-1. SO factors are based on 6 *Size-SO* portfolios formed on state ownership (Zero, Low and High) using the percent state ownership of all A-shares excluding GEM stocks as breakpoints. SO_{NML}=(SZ+BZ)/2-(SL+BL)/2, SO_{LMH}=(SL+BL)/2-(SH+BH)/2, SO_{NMH}=(SZ+BZ)/2-(SH+BH)/2, where Z, L, and H indicate zero, low and high percent state ownership portfolios. Panel A shows average daily percent returns (Mean), the standard deviations of daily returns (Std dev.), the *t-statistics*, and Sharpe Ratio for the average returns. Panel B shows the correlation coefficient between each factor.

Panel A, Averages, standard deviations, t-statistics and Sharpe ratio for daily factor return

	Mkt	SMB	HML	RMW	CMA	MOM	STR	SO_{LMH}	SO_{NMH}	SO_{NML}	IO
Mean	0.06	0.04	0.00	0.01	0.00	-0.02	0.18	0.00	0.01	0.01	0.01
Std Dev.	1.73	0.81	0.55	0.59	0.40	0.74	0.87	0.35	0.36	0.29	0.45
t-Statistic	1.91	2.80	0.13	0.74	0.26	-1.33	11.97	0.37	1.80	1.78	1.57
Sharpe Ratio	0.03	0.04	-0.01	0.00	-0.01	-0.03	0.20	-0.01	0.01	0.01	0.01

Panel B, Correlation between factors

	Mkt	SMB	HML	RMW	CMA	MOM	STR	SO_{LMH}	SO_{NMH}	SO_{NML}	IO
Mkt	1.00										
SMB	0.09	1.00									
HML	0.06	-0.53	1.00								
RMW	-0.10	-0.71	0.35	1.00							
CMA	-0.32	0.27	-0.04	-0.51	1.00						
MOM	0.03	0.10	-0.23	0.08	-0.14	1.00					
STR	0.16	0.12	-0.07	-0.14	0.00	0.07	1.00				
SO_{LMH}	-0.12	0.07	-0.06	-0.01	0.14	-0.11	-0.02	1.00			
SO_{NMH}	-0.17	0.26	-0.20	-0.03	0.17	0.02	-0.05	0.66	1.00		
SO_{NML}	-0.06	0.23	-0.17	-0.03	0.03	0.16	-0.03	-0.38	0.45	1.00	
IO	-0.05	0.01	-0.36	0.26	-0.32	0.36	-0.03	-0.05	0.10	0.18	1.00

Table 3.5

Explain each factor using the three-factor model: 07/01/2004-12/29/2017, 3286 trading days.

This table reports the results of regressions of a selected factor on Mkt, SMB and HML. The construction of factors is in Table 4. The t-statistics are in the brackets.

	Int	Mkt	SMB	HML	R^2
RMW	0.03	-0.01	-0.53	-0.03	0.51
	[4.02]	[-2.34]	[-49.49]	[-2.09]	
CMA	0.00	-0.09	0.20	0.15	0.22
	[-0.24]	[-23.97]	[22.44]	[11.20]	
MOM	-0.02	0.02	-0.03	-0.34	0.06
	[-1.33]	[2.76]	[-1.69]	[-12.42]	
STR	0.17	0.08	0.09	-0.05	0.04
	[11.62]	[8.76]	[4.29]	[-1.49]	
SO_{LMH}	0.00	-0.03	0.04	-0.01	0.02
	[0.40]	[-7.49]	[3.94]	[-0.39]	
SO_{NMH}	0.01	-0.04	0.11	-0.04	0.10
	[1.56]	[-10.97]	[12.31]	[-2.95]	
SO_{NML}	0.01	-0.01	0.07	-0.03	0.06
	[1.39]	[-4.09]	[10.01]	[-3.08]	
IO	0.02	0.00	-0.14	-0.40	0.17
	[2.57]	[-0.09]	[-13.28]	[-26.00]	

Table 3.6.1

Factor spanning regression: 07/01/2004-12/29/2017, 3286 trading days.

This table reports the results of regressions of a selected factor on all the other factors. The construction of factors is in Table 4. The t-statistics are in the brackets.

	Int	Mkt	SMB	HML	STR	SO_{NMH}	IO	R^2
Mkt	0.00		0.43	0.46	0.27	-0.88	0.07	0.08
	[0.00]		[9.53]	[6.67]	[8.08]	[-10.45]	[0.99]	
SMB	0.03	0.06		-0.85	0.06	0.42	-0.37	0.37
	[2.32]	[9.53]		[-37.84]	[4.22]	[13.17]	[-13.71]	
HML	0.02	0.03	-0.36		-0.02	-0.02	-0.42	0.42
	[3.06]	[6.67]	[-37.84]		[-2.33]	[-1.03]	[-25.87]	
STR	0.18	0.07	0.10	-0.08		-0.12	-0.07	0.04
	[11.80]	[8.08]	[4.22]	[-2.33]		[-2.85]	[-2.04]	
SO_{NMH}	0.01	-0.04	0.12	-0.01	-0.02		0.06	0.11
	[1.91]	[-10.45]	[13.17]	[-1.03]	[-2.85]		[4.19]	
IO	0.02	0.00	-0.15	-0.40	-0.02	0.09		0.18
	[2.82]	[0.99]	[-13.71]	[-25.87]	[-2.04]	[4.19]		

Table 3.6.2
Factor spanning regression including RMW and CMA: 07/01/2004-12/29/2017, 3286 trading days.
This table reports the results of regressions of a selected factor on all the other factors. The construction of factors is in Table 4. The t-statistics are in the brackets.

	Int	Mkt	SMB	HML	RMW	CMA	STR	SO_{NMH}	IO	R^2
Mkt	0.03		0.23	0.57	-0.92	-2.22	0.22	-0.34	-0.25	0.25
	[0.96]		[4.20]	[9.00]	[-11.85]	[-27.46]	[7.24]	[-4.21]	[-3.56]	
SMB	0.04	0.02		-0.36	-0.91	-0.15	0.01	0.46	0.09	0.64
	[4.26]	[4.20]		[-18.34]	[-44.62]	[-5.32]	[1.37]	[18.59]	[4.10]	
HML	0.02	0.04	-0.26		0.23	0.17	-0.02	-0.09	-0.44	0.44
	[2.21]	[9.00]	[-18.34]		[10.74]	[7.10]	[-1.88]	[-3.96]	[-25.00]	
RMW	0.02	-0.04	-0.42	0.15		-0.53	-0.02	0.27	0.23	0.69
	[4.19]	[-11.85]	[-44.62]	[10.74]		[-30.72]	[-2.48]	[15.73]	[15.02]	
CMA	0.01	-0.08	-0.06	0.09	-0.42		0.00	0.17	-0.14	0.47
	[2.25]	[-27.46]	[-5.32]	[7.10]	[-30.72]		[-0.05]	[11.16]	[-10.15]	
STR	0.18	0.07	0.04	-0.07	-0.11	0.00		-0.10	-0.03	0.04
	[11.93]	[7.24]	[1.37]	[-1.88]	[-2.48]	[-0.05]		[-2.17]	[-0.79]	
SO_{NMH}	0.00	-0.02	0.21	-0.05	0.26	0.21	-0.01		0.02	0.18
	[0.70]	[-4.21]	[18.59]	[-3.96]	[15.73]	[11.16]	[-2.17]		[1.23]	
IO	0.01	-0.02	0.05	-0.36	0.29	-0.22	-0.01	0.02		0.32
	[1.59]	[-3.56]	[4.10]	[-25.00]	[15.02]	[-10.15]	[-0.79]	[1.23]		

Table 3.7

Summary test statistics of three-, five-factor models, and the models with added factors for 25 (5 × 5) VW portfolios: 07/01/2004-12/29/2017, 3286 trading days.

This table reports the ability of the three-, five-factor models, and the models with added factors to explain daily excess returns on the 25 (5 × 5) VW portfolios. The three-factor model is Fama and French (1993) three-factor model including Mkt, SMB and HML, and the five-factor model is Fama and French (2015) five-factor model including Mkt, SMB, HML, RMW and CMA. Panel A(B) reports the test summary statistics when three-factor model (five-factor model) is the bassline model; STR indicates the model where STR is added to the three-factor (five-factor) model; STR SO indicates the model where STR and SO are added to the three-factor (five-factor) model; STR SO IO indicates the model where STR, SO and IO are added to the three-factor (five-factor) model. The *GRS* statistic tests whether the expected values of all 25 intercept estimates are zero. $A|a_i|$ indicates the average absolute regression intercept. $\frac{A|a_i|}{A|\bar{r}_i|}$ denotes for the ratio of average absolute value of regression intercept a_i over average absolute value of return deviations from the cross-sectional average $\bar{r}_i$. $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ is the average squared intercept over the over the average squared value of $\bar{r}_i$, corrected for sampling error in the numerator and denominator.

Panel A, Three-factor model as the baseline model					*Panel B, Five-factor model as the baseline model*				
Model	GRS	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$	Model	GRS	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$
					25 Size-B/M portfolios				
Three-factor	3.29***	0.015	0.76	0.75	Five-factor	3.28***	0.014	0.70	0.73
STR	3.06***	0.015	0.74	0.68	STR	2.87***	0.012	0.63	0.61
STR SO	2.91***	0.014	0.70	0.59	STR SO	2.85***	0.012	0.62	0.59
STR SO IO	2.81***	0.014	0.69	0.62	STR SO IO	2.88***	0.012	0.63	0.62
					25 Size-OP portfolios				
Three-factor	4.31***	0.018	0.90	1.05	Five-factor	3.67***	0.014	0.70	0.67
STR	4.33***	0.019	0.95	1.16	STR	3.45***	0.013	0.68	0.62
STR SO	4.17***	0.017	0.89	0.98	STR SO	3.44***	0.013	0.67	0.60
STR SO IO	3.86***	0.016	0.82	0.79	STR SO IO	3.34***	0.013	0.67	0.59
					25 Size-Inv portfolios				
Three-factor	3.50***	0.017	0.78	0.71	Five-factor	3.66***	0.015	0.70	0.64
STR	3.58***	0.017	0.81	0.76	STR	3.44***	0.014	0.68	0.62
STR SO	3.44***	0.016	0.76	0.68	STR SO	3.42***	0.014	0.67	0.60
STR SO IO	3.17***	0.015	0.72	0.61	STR SO IO	3.33***	0.014	0.67	0.59
					25 Size-IO portfolios				
Three-factor	1.92***	0.014	0.79	0.55	Five-factor	1.56**	0.012	0.68	0.31
STR	1.97***	0.014	0.80	0.59	STR	1.49*	0.012	0.66	0.28
STR SO	1.88***	0.013	0.76	0.48	STR SO	1.50*	0.011	0.65	0.27
STR SO IO	1.74**	0.011	0.60	0.21	STR SO IO	1.53**	0.010	0.57	0.17
					25 Size-STR portfolios				
Three-factor	23.05***	0.072	0.94	1.27	Five-factor	22.57***	0.074	0.97	1.30
STR	17.07***	0.039	0.51	0.43	STR	16.33***	0.039	0.50	0.40
STR SO	16.89***	0.039	0.50	0.41	STR SO	16.30***	0.039	0.50	0.40
STR SO IO	16.86***	0.039	0.51	0.42	STR SO IO	16.39***	0.039	0.51	0.41

Table 3.8

Factor loadings for 25 (5 × 5) VW portfolios: 07/01/2004-12/29/2017, 3286 trading days. This table reports the regression coefficient estimates on STR, SO, and IO factor for all the 25 (5 × 5) VW double-sorted portfolios. r, g and I are coefficient estimates on STR, SO and IO factor, respectively. t(r), t(g) and t(I) are t-statistics of the corresponding loadings. The regression equation is the eight-factor model,

$$R(t) - R_F(t) = a + b[R_M(t) - R_F(t)] + sSMB(t) + hHML(t) + rRMW(t) + cCMA(t) + rSTR(t) + gSO(t) + I * IO(t) + e(t).$$

	Low	2	3	4	High	Low	2	3	4	High
Panel A: Size - B/M portfolios										
	r					t(r)				
Small	0.04	0.02	0.00	-0.02	-0.01	2.85	1.75	-0.28	-2.36	-1.11
2	0.01	0.02	0.00	0.00	-0.01	1.36	2.86	-0.37	0.62	-0.88
3	0.00	0.00	-0.01	0.00	0.00	-0.33	0.59	-1.45	-0.10	0.15
4	0.00	-0.02	-0.01	-0.01	-0.01	0.20	-2.70	-0.88	-1.18	-1.05
Big	-0.01	0.02	0.02	0.00	0.02	-1.64	2.84	2.33	-0.42	2.80
	g					t(g)				
Small	0.10	0.06	0.04	0.10	0.08	2.81	1.95	1.37	4.42	2.69
2	-0.01	-0.03	0.11	-0.01	-0.13	-0.39	-1.58	6.17	-0.76	-6.40
3	0.00	-0.08	-0.08	-0.14	-0.12	-0.17	-3.74	-4.23	-8.01	-5.14
4	-0.09	-0.08	-0.08	-0.14	-0.34	-4.18	-4.12	-3.69	-6.77	-13.03
Big	0.01	-0.16	-0.13	-0.16	-0.12	0.74	-7.74	-5.61	-6.58	-5.78
	I					t(I)				
Small	-0.11	-0.24	0.06	0.14	0.13	-3.52	-8.35	2.38	7.23	4.98
2	-0.09	-0.19	-0.04	0.07	0.05	-4.42	-11.45	-2.48	5.08	2.69
3	-0.03	-0.03	-0.04	0.04	-0.03	-1.73	-1.41	-2.43	2.42	-1.46
4	0.09	0.06	-0.01	-0.02	0.02	4.59	3.53	-0.61	-0.83	0.71
Big	0.19	0.23	0.16	0.03	-0.03	11.25	12.29	7.70	1.26	-1.42
Panel B: Size - OP portfolios										
	r					t(r)				
Small	0.02	0.00	-0.01	-0.01	-0.01	2.44	0.22	-1.15	-0.47	-1.02
2	0.02	0.01	-0.01	-0.01	0.03	3.24	0.76	-1.30	-0.77	2.67
3	0.01	0.01	0.01	-0.02	-0.01	0.90	1.78	0.80	-2.25	-0.70
4	0.00	0.00	-0.02	-0.01	-0.01	-0.24	0.41	-2.18	-1.68	-1.58
Big	-0.03	-0.02	0.01	0.00	0.00	-2.65	-1.76	0.91	-0.05	0.81
	g					t(g)				
Small	0.09	0.11	0.16	0.01	0.10	3.38	4.88	6.67	0.39	2.66
2	0.02	0.02	0.00	0.03	-0.10	1.29	1.34	-0.05	1.53	-3.51
3	-0.05	0.00	-0.06	-0.16	-0.16	-2.43	-0.09	-3.11	-8.02	-7.10
4	-0.07	-0.06	-0.04	-0.19	-0.27	-3.34	-2.81	-1.96	-9.05	-11.63
Big	-0.15	-0.13	-0.12	-0.19	0.11	-4.80	-4.86	-4.62	-8.15	7.84
	I					t(I)				
Small	0.07	0.01	0.05	-0.02	0.03	2.90	0.62	2.51	-0.90	0.81
2	-0.07	-0.13	0.05	-0.01	0.02	-4.66	-8.43	2.96	-0.61	0.64
3	-0.03	-0.07	-0.02	0.03	0.05	-1.61	-4.81	-1.31	1.83	2.26
4	0.03	-0.06	-0.02	0.07	0.11	1.81	-3.09	-1.24	3.98	5.58
Big	0.11	0.00	0.16	0.11	0.11	4.10	0.16	6.92	5.37	9.06
Panel C: Size - Inv portfolios										
	r					t(r)				
Small	0.02	0.00	0.01	0.02	0.01	1.62	-0.06	0.59	1.86	0.80
2	0.03	0.00	0.00	0.00	0.03	3.82	0.26	-0.44	-0.13	4.29
3	0.00	0.00	0.01	-0.01	-0.01	0.38	0.68	1.70	-1.26	-0.96
4	0.00	0.00	-0.01	-0.01	-0.02	0.39	-0.34	-1.20	-1.71	-2.76
Big	0.02	-0.01	-0.01	0.02	0.00	1.79	-0.65	-1.51	2.40	0.09
	g					t(g)				
Small	-0.03	0.01	0.09	0.09	0.21	-1.14	0.22	3.44	2.81	6.97
2	-0.02	0.02	-0.02	-0.02	0.01	-1.29	1.15	-0.87	-1.00	0.71
3	-0.12	-0.10	-0.03	-0.05	-0.12	-5.62	-5.72	-1.51	-2.83	-5.85

4	-0.14	-0.13	-0.21	-0.12	-0.08	-6.47	-6.00	-10.30	-5.75	-3.56
Big	-0.18	-0.01	0.32	-0.16	-0.18	-6.08	-0.54	14.11	-8.68	-10.11
	I					t(I)				
Small	0.14	0.07	0.09	-0.05	-0.13	5.49	3.49	3.75	-1.69	-4.74
2	-0.03	-0.01	-0.06	-0.03	-0.11	-1.61	-0.83	-3.45	-1.72	-6.02
3	-0.05	-0.01	-0.01	0.04	-0.05	-2.67	-0.70	-0.77	2.54	-2.53
4	-0.01	0.03	0.06	0.01	0.02	-0.42	1.57	3.53	0.50	1.17
Big	0.24	0.14	-0.08	0.22	0.16	9.35	6.12	-4.17	13.38	10.24
Panel D: Size - IO portfolios										
	r					t(r)				
Small	-0.02	0.00	0.01	0.01	0.01	-2.11	-0.32	0.50	0.82	0.38
2	0.01	0.01	0.01	0.00	0.00	1.00	1.46	1.23	0.21	0.06
3	0.00	0.00	-0.01	0.00	-0.02	-0.62	-0.32	-1.20	0.12	-2.42
4	-0.01	0.00	-0.03	0.00	-0.01	-0.92	-0.36	-3.49	-0.56	-1.32
Big	0.01	0.00	0.01	0.01	0.01	0.67	0.22	0.74	0.87	1.79
	g					t(g)				
Small	0.16	0.03	0.12	0.12	0.01	5.52	0.97	3.53	3.66	0.09
2	-0.12	0.03	0.03	0.09	0.01	-5.89	1.52	1.26	3.69	0.55
3	-0.21	-0.12	-0.05	0.05	-0.07	-10.96	-5.68	-2.24	2.08	-3.01
4	-0.21	-0.18	-0.27	-0.03	-0.04	-8.97	-8.30	-12.28	-1.34	-1.97
Big	0.02	0.13	-0.34	-0.05	0.13	0.87	5.79	-15.95	-2.92	7.36
	I					t(I)				
Small	-0.02	0.09	0.23	0.25	0.75	-0.66	3.58	7.77	8.46	11.68
2	-0.36	-0.21	0.03	0.18	0.39	-19.53	-11.66	1.91	8.22	17.16
3	-0.25	-0.10	0.02	0.23	0.23	-14.30	-5.58	1.00	11.32	11.63
4	-0.22	-0.10	0.03	0.12	0.23	-10.50	-5.48	1.37	6.18	11.68
Big	-0.86	-0.30	0.12	0.40	0.55	-36.77	-14.67	6.23	27.14	35.27
Panel E: Size - STR portfolios										
	r					t(r)				
Small	0.39	0.22	0.07	-0.10	-0.34	29.58	20.17	6.21	-8.59	-20.81
2	0.42	0.21	0.07	-0.12	-0.40	48.59	25.28	7.54	-14.55	-37.60
3	0.42	0.21	0.06	-0.13	-0.43	50.44	25.36	6.71	-15.55	-41.39
4	0.44	0.24	0.05	-0.17	-0.46	47.70	27.52	5.57	-18.75	-41.54
Big	0.70	0.37	0.06	-0.25	-0.74	65.03	36.12	5.39	-22.71	-70.34
	g					t(g)				
Small	-0.05	-0.14	-0.18	-0.17	-0.15	-1.57	-5.03	-6.25	-5.71	-3.63
2	-0.16	-0.22	-0.25	-0.20	-0.23	-7.05	-10.20	-10.69	-9.12	-8.14
3	-0.18	-0.29	-0.31	-0.27	-0.29	-8.28	-13.51	-13.55	-11.82	-10.66
4	-0.21	-0.28	-0.33	-0.28	-0.35	-8.58	-12.51	-13.95	-11.79	-11.86
Big	-0.18	-0.36	-0.35	-0.32	-0.15	-6.49	-13.40	-11.60	-11.04	-5.47
	I					t(I)				
Small	0.07	-0.04	-0.07	0.02	0.05	2.26	-1.54	-2.70	0.93	1.44
2	-0.01	-0.11	-0.14	-0.09	-0.02	-0.59	-5.93	-6.59	-4.76	-0.99
3	-0.02	-0.09	-0.08	-0.06	0.00	-0.80	-4.91	-3.99	-3.09	-0.01
4	0.06	-0.04	-0.04	0.00	0.09	2.62	-2.26	-1.78	0.10	3.45
Big	0.24	0.06	0.07	0.15	0.19	9.72	2.41	2.56	5.89	7.67

Table 3.9

Summary test statistics of three-, five-factor models, and the models with added factors for 498 mutual funds' return: 10/14/2009-12/29/2017, 2000 trading days.

This table reports the ability of three-, five-factor models, and models with added STR, SO and IO factor to explain the mutual fund's performance. Thee three-factor model is Fama and French (1993) three-factor model including Mkt, SMB and HML, and the five-factor model is Fama and French (2015) five-factor model including Mkt, SMB, HML, RMW and CMA.

Panel A reports the summary test statistics of the model performance. STR indicates the model where STR is added to the five-factor model; STR SO indicates the model where STR and SO are added to the five-factor model; STR SO IO indicates the model where STR, SO and IO are added to the five-factor model. The *GRS* statistic tests whether the expected values of all 25 intercept estimates are zero. $A|a_i|$ indicates the average absolute regression intercept. $\frac{A|a_i|}{A|\bar{r}_i|}$ denotes for the ratio of average absolute value of regression intercept a_i over average absolute value of return deviations from the cross-sectional average $\bar{r}_i$. $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ is the average squared intercept over the over the average squared value of $\bar{r}_i$, corrected for sampling error in the numerator and denominator.

Panel B, C, D, and E reports the summary of the factor loadings for the mutual funds' return. sig.(%) indicates the percentage of funds have significant loadings on the factors. positive sig. (%) denotes the percentage of funds which have positively significant loadings on the factors. negative sig. (%) indicates the percentage of funds which have negatively significant loadings on the factors. Mean(Adj R^2) is the average adjusted *R-squared* statistics.

Panel A, Model performance measures

Model	GRS	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$
Three-factor	2.64***	0.017	1.25	0.91
Five-factor	2.61***	0.017	1.24	0.84
STR	2.65***	0.015	1.09	0.23
STR SO	2.64***	0.015	1.10	0.34
STR SO IO	2.66***	0.016	1.17	0.59

Panel B, Summary factor loadings of the three-factor model

	Int	Mkt	SMB	HML	RMW	CMA	STR	SO	IO	Mean(Adj R^2)
Mean	-0.01	0.67	0.10	-0.23						58.76%
Mean (t-statistics)	-0.61	65.94	2.32	-4.93						
positive sig. (%)	2.01	50.00	28.41	5.72						
negative sig. (%)	4.72	0.00	7.63	32.13						
sig. (%)	6.73	50.00	36.04	37.85						

Panel C, Summary factor loadings of the five-factor model

	Int	Mkt	SMB	HML	RMW	CMA	STR	SO	IO	Mean(Adj R^2)
Mean	-0.01	0.67	0.15	-0.25	0.15	-0.15				59.39%
Mean (t-statistics)	-0.68	60.80	3.85	-5.51	3.32	-2.43				
positive sig. (%)	1.51	49.90	31.93	4.32	29.82	6.22				
negative sig. (%)	5.12	0.00	5.92	33.33	1.91	27.81				
sig. (%)	6.63	49.90	37.85	37.65	31.73	34.04				

Panel D, Summary factor loadings of the eight-factor model

	Int	Mkt	SMB	HML	RMW	CMA	STR	SO	IO	Mean(Adj R^2)
Mean	-0.01	0.65	0.10	-0.20	0.06	-0.10	-0.02	0.00	0.26	60.29%
Mean (t-statistics)	-0.57	58.65	2.01	-4.09	1.09	-1.53	-1.40	0.15	6.26	
positive sig. (%)	1.61	49.90	26.51	5.92	13.96	7.03	3.51	12.65	36.35	
negative sig. (%)	5.22	0.00	6.33	30.72	3.61	22.49	18.57	11.04	2.51	
sig. (%)	6.83	49.90	32.83	36.65	17.57	29.52	22.09	23.69	38.86	

Table 3.10

Summary statistics of factor monthly returns: 07/2004-12/2017, 162 months.

Mkt is the value-weighted market portfolio return of all A-shares (include Shanghai and Shenzhen Main Board, SMEB and GEM stocks) in excess of risk-free rate. At the end of June, all A-shares are assigned to two *Size* groups using the median market cap of all A-shares excluding GEM stocks as the breakpoint. Stocks are also allocated independently to three *B/M*, *OP* and *Inv* groups (Low, Neutral and High) using the 30th and 70th percentile of all A-shares excluding GEM stocks. The intersections of *Size* and other variable groups produce 6 (2 × 3) value-weighted *Size-B/M, Size-OP, and Size-Inv* portfolios, SL, SN, SH, BL, BN, and BH, where S and B denote for small and big portfolio, and L, N and H indicate low, neutral and high characteristic portfolios. SMB is the average of $SMB_{B/M}$, SMB_{OP}, SMB_{Inv}, and SMB_{IO}, where $SMB_{B/M}$ is the average of the returns on the three small stock portfolios of 6 *Size-B/M* portfolios minus the average returns on the three big stock portfolios of 6 *Size-B/M* portfolios, $SMB_{B/M}$= (SL+SN+SH)/3-(BL+BN+BH)/3. SMB_{OP}, SMB_{Inv}, and SMB_{IO} are constructed in the same way, except for the *OP*, *Inv* and *IO* variables. HML is the average return on the two high *B/M* portfolios of 6 *Size-B/M* portfolios minus the average return of the two low *B/M* portfolios of 6 *Size-B/M* portfolios, HML=(SH+BH)/2-(SL+BL)/2. RMW, CMA and IO are constructed in a same way using 6 *Size-OP, 6 Size-Inv* and 6 *Size-IO* portfolios, except 6 *Size-IO* portfolios are constructed twice a year at the end of June and December. MOM is average return on the two high past cumulative return portfolios of 6 *Size-MOM* portfolios minus the average return of the two low past cumulative return portfolios of 6 *Size-MOM* portfolios. STR is average return on the two low past cumulative return portfolios of 6 Size-STR portfolios minus the average return of the two high past cumulative return portfolios 6 Size-STR portfolios. *Size-MOM* portfolios (*Size-STR* portfolios) are constructed monthly formed on past cumulative return between month t-12 to t-2 (t-1 to t-1) and *Size* at month t-1. SO factors are based on 6 *Size-SO* portfolios formed on state ownership (Zero, Low and High) using the 30th and 70^{th} percentile of percent state ownership of all A-shares excluding GEM stocks as breakpoints. SO_{NML}=(SZ+BZ)/2-(SL+BL)/2, SO_{LMH}=(SL+BL)/2-(SH+BH)/2, SO_{NMH}=(SZ+BZ)/2-(SH+BH)/2, where Z, L, and H indicate zero, low and high percent state ownership portfolios. Panel A shows average monthly percent returns (Mean), the standard deviations of monthly returns (Std dev.), the *t-statistics* and Sharpe Ratio for the average returns. Panel B shows the correlation between each factor.

Panel A, Averages, standard deviations, t-statistics and Sharpe ratio for daily factor return

	Mkt	SMB	HML	RMW	CMA	MOM	STR	SO_{LMH}	SO_{NMH}	SO_{NML}	IO
Mean	1.18	0.89	0.02	0.06	0.10	-0.29	1.21	0.08	0.24	0.16	0.19
Std Dev.	8.72	5.12	3.07	3.50	2.22	3.75	4.06	1.55	1.91	1.45	2.06
t-Statistic	1.72	2.20	0.08	0.23	0.60	-0.99	3.80	0.66	1.61	1.41	1.17
Sharpe Ratio	0.11	0.13	-0.06	-0.04	-0.05	-0.13	0.25	-0.09	0.01	-0.04	-0.01

Panel B, Correlation between factors

	Mkt	SMB	HML	RMW	CMA	MOM	STR	SO_{LMH}	SO_{NMH}	SO_{NML}	IO
Mkt	1.00										
SMB	0.12	1.00									
HML	0.05	-0.54	1.00								
RMW	-0.35	-0.74	0.21	1.00							
CMA	0.09	0.44	0.08	-0.72	1.00						
MOM	-0.17	-0.06	-0.17	0.29	-0.20	1.00					
STR	0.01	0.31	-0.21	-0.23	0.06	-0.25	1.00				
SO_{LMH}	-0.06	0.26	-0.18	-0.19	0.18	-0.06	0.06	1.00			
SO_{NMH}	-0.15	0.50	-0.40	-0.23	0.18	0.09	0.00	0.67	1.00		
SO_{NML}	-0.13	0.38	-0.33	-0.10	0.04	0.17	-0.06	-0.19	0.60	1.00	
IO	-0.08	-0.14	-0.34	0.43	-0.43	0.40	-0.19	-0.20	0.05	0.28	1.00

Table 3.11.1

Factor spanning regression: 07/2004-12/2017, 162 months.

This table reports the results of regressions of a selected factor on all the other factors. The construction of factors is in Table 10. The t-statistics are in brackets.

	Int	Mkt	SMB	HML	STR	SO_{NMH}	IO	R^2
Mkt	1.15		0.58	0.30	-0.15	-1.27	0.03	0.09
	[1.57]		[3.14]	[0.99]	[-0.86]	[-3.02]	[0.08]	
SMB	0.44	0.10		-0.77	0.20	0.96	-0.68	0.53
	[1.43]	[3.14]		[-6.83]	[2.68]	[5.83]	[-4.48]	
HML	0.55	0.02	-0.30		-0.10	-0.19	-0.63	0.49
	[2.94]	[0.99]	[-6.83]		[-2.22]	[-1.71]	[-7.19]	
STR	1.25	-0.03	0.22	-0.29		-0.48	-0.42	0.17
	[4.05]	[-0.86]	[2.68]	[-2.22]		[-2.55]	[-2.52]	
SO_{NMH}	0.23	-0.04	0.19	-0.10	-0.08		0.02	0.34
	[1.68]	[-3.02]	[5.83]	[-1.71]	[-2.55]		[0.31]	
IO	0.45	0.00	-0.17	-0.39	-0.09	0.03		0.29
	[3.03]	[0.08]	[-4.48]	[-7.19]	[-2.52]	[0.31]		

Table 3.11.2

Factor spanning regression including CMA and RMW: 07/2004-12/2017, 162 months.

This table reports the results of regressions of a selected factor on all the other factors. The construction of factors is in Table 10. The t-statistics are in brackets.

	Int	Mkt	SMB	HML	RMW	CMA	STR	SO_{NMH}	IO	R2
Mkt	1.93		-0.32	0.46	-2.34	-1.63	-0.12	-0.64	0.72	0.28
	[2.93]		[-1.37]	[1.65]	[-6.46]	[-3.89]	[-0.73]	[-1.65]	[1.92]	
SMB	0.67	-0.04		-0.42	-1.01	-0.14	0.14	0.65	0.11	0.76
	[2.98]	[-1.37]		[-4.59]	[-8.95]	[-0.96]	[2.55]	[5.26]	[0.88]	
HML	0.42	0.04	-0.29		0.19	0.43	-0.08	-0.21	-0.55	0.53
	[2.22]	[1.65]	[-4.59]		[1.67]	[3.59]	[-1.70]	[-1.92]	[-5.57]	
RMW	0.44	-0.09	-0.34	0.09		-0.67	0.00	0.15	0.30	0.83
	[3.41]	[-6.46]	[-8.95]	[1.67]		[-9.93]	[0.09]	[2.00]	[4.31]	
CMA	0.26	-0.05	-0.04	0.18	-0.58		-0.03	0.10	0.00	0.63
	[2.11]	[-3.89]	[-0.96]	[3.59]	[-9.93]		[-1.17]	[1.37]	[-0.06]	
STR	1.23	-0.03	0.29	-0.24	0.02	-0.26		-0.47	-0.50	0.19
	[3.81]	[-0.73]	[2.55]	[-1.70]	[0.09]	[-1.17]		[-2.48]	[-2.72]	
SO_{NMH}	0.15	-0.03	0.24	-0.11	0.17	0.12	-0.08		-0.03	0.36
	[1.05]	[-1.65]	[5.26]	[-1.92]	[2.00]	[1.37]	[-2.48]		[-0.33]	
IO	0.21	0.03	0.04	-0.31	0.35	-0.01	-0.09	-0.03		0.42
	[1.49]	[1.92]	[0.88]	[-5.57]	[4.31]	[-0.06]	[-2.72]	[-0.33]		

Table 3.12
Summary test statistics of three-, five-factor models, and the models with added factors for 25 (5 × 5) VW portfolios: 07/2004-12/2017, 162 months.

This table reports the ability of the three-, five-factor models, and the models with added factors to explain monthly excess returns on the 25 (5 × 5) VW portfolios. Thee three-factor model is Fama and French (1993) three-factor model including Mkt, SMB and HML, and the five-factor model is Fama and French (2015) five-factor model including Mkt, SMB, HML, RMW and CMA. Panel A(B) reports the test summary statistics when three-factor model (five-factor model) is the bassline model; STR indicates the model where STR is added to the three-factor (five-factor) model; STR SO indicates the model where STR and SO are added to the three-factor (five-factor) model; STR SO IO indicates the model where STR, SO and IO are added to the three-factor (five-factor) model. The *GRS* statistic tests whether the expected values of all 25 intercept estimates are zero. $A|a_i|$ indicates the average absolute regression intercept. $\frac{A|a_i|}{A|\bar{r}_i|}$ denotes for the ratio of average absolute value of regression intercept a_i over average absolute value of return deviations from the cross-sectional average $\bar{r}_i$. $\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$ is the average squared intercept over the over the average squared value of $\bar{r}_i$, corrected for sampling error in the numerator and denominator.

Panel A, Three-factor model as the baseline model					*Panel B, Five-factor model as the baseline model*				
Model	GRS	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$	Model	GRS	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{A(\hat{a}_i^2)}{A(\hat{u}_i^2)}$
					25 Size-B/M portfolios				
Three-factor	2.09***	0.275	0.61	0.42	Five-factor	1.91**	0.264	0.59	0.48
STR	2.31***	0.276	0.61	0.41	STR	2.03***	0.272	0.61	0.47
STR SO	2.26***	0.265	0.59	0.36	STR SO	2.05***	0.268	0.60	0.45
STR SO IO	2.01***	0.267	0.59	0.40	STR SO IO	2.00***	0.272	0.60	0.47
					25 Size-OP portfolios				
Three-factor	3.18***	0.349	0.82	0.79	Five-factor	2.80***	0.281	0.66	0.49
STR	3.20***	0.346	0.81	0.81	STR	2.72***	0.280	0.65	0.47
STR SO	3.26***	0.331	0.77	0.73	STR SO	2.88***	0.284	0.66	0.47
STR SO IO	2.78***	0.303	0.71	0.55	STR SO IO	2.78***	0.292	0.68	0.49
					25 Size-Inv portfolios				
Three-factor	2.37***	0.312	0.66	0.47	Five-factor	2.29***	0.281	0.60	0.40
STR	2.37***	0.316	0.67	0.46	STR	2.19***	0.282	0.60	0.40
STR SO	2.46***	0.294	0.62	0.39	STR SO	2.31***	0.272	0.58	0.37
STR SO IO	2.18***	0.279	0.59	0.34	STR SO IO	2.23***	0.273	0.58	0.36
					25 Size-IO portfolios				
Three-factor	1.47*	0.261	0.65	0.35	Five-factor	1.21	0.206	0.52	0.16
STR	1.60**	0.273	0.69	0.42	STR	1.19	0.218	0.55	0.22
STR SO	1.67**	0.261	0.65	0.40	STR SO	1.30	0.218	0.55	0.23
STR SO IO	1.34	0.225	0.56	0.18	STR SO IO	1.25	0.214	0.54	0.18
					25 Size-STR portfolios				
Three-factor	3.57***	0.530	0.76	0.83	Five-factor	3.15***	0.548	0.78	0.89
STR	2.98***	0.374	0.53	0.36	STR	2.54***	0.365	0.52	0.32
STR SO	2.82***	0.361	0.52	0.33	STR SO	2.48***	0.358	0.51	0.31
STR SO IO	2.52***	0.363	0.52	0.32	STR SO IO	2.39***	0.363	0.52	0.31

11. Appendices

Appendix 3.1

Summary statistics of the institutional ownership data.

This table reports the summary statistics of the institutional ownership data. N indicates the number of A-shares which have institutional ownership data; Mean is the average percent institutional ownership of the sample; Median is the median percent institutional ownership of the sample; Min and Max are the minimum and maximum percent institutional ownership of the sample.

Year/month	N	Mean	Median	Min	Max
2003/06	918	6.85%	2.18%	0.03%	86.71%
2003/12	921	7.34%	2.47%	0.03%	88.90%
2004/06	997	7.79%	2.79%	0.03%	88.01%
2004/12	955	8.85%	3.17%	0.03%	88.37%
2005/06	954	9.04%	3.30%	0.04%	87.16%
2005/12	961	9.32%	4.03%	0.04%	87.40%
2006/06	1012	9.06%	4.45%	0.03%	85.94%
2006/12	1061	9.51%	4.71%	0.09%	86.77%
2007/06	1140	9.53%	5.02%	0.00%	85.64%
2007/12	1149	9.77%	5.54%	0.00%	85.77%
2008/06	1156	9.49%	5.24%	0.07%	84.91%
2008/12	1120	9.63%	5.42%	0.00%	83.29%
2009/06	1183	8.99%	5.08%	0.06%	83.91%
2009/12	1357	8.44%	5.03%	0.05%	84.76%
2010/06	1569	8.32%	5.12%	0.05%	85.31%
2010/12	1730	8.08%	5.14%	0.07%	85.66%
2011/06	1934	7.16%	4.32%	0.02%	84.76%
2011/12	2039	7.09%	4.34%	0.00%	86.62%
2012/06	2118	6.47%	3.61%	0.03%	88.34%
2012/12	2160	6.37%	3.28%	0.05%	87.89%
2013/06	2004	6.86%	3.77%	0.04%	87.56%
2013/12	2024	6.96%	3.93%	0.05%	86.62%
2014/06	2107	6.77%	3.70%	0.05%	86.31%
2014/12	2340	6.53%	3.78%	0.03%	85.95%
2015/06	2600	6.37%	4.17%	0.03%	83.16%
2015/12	2596	6.38%	4.24%	0.03%	87.48%
2016/06	2642	6.40%	4.06%	0.05%	88.13%
2016/12	2765	6.60%	4.37%	0.00%	86.13%
2017/06	2839	6.22%	3.90%	0.02%	84.63%

Appendix 3.2
Summary statistics of the state ownership data.
This table reports the summary statistics of the companies which have state ownership (SO) data. N denotes the number of firm which have SO data. N(=0) and N(>0) indicates the number of firms have SO equal or larger than zero. Mean, Median, Min and Max indicate the average, median, minimum and maximum value, respectively, of the percent state ownership of the firms with non-zero SO. Note that 0.00% indicates it is close but not equal to zero.

Year/month	*N*	*N(=0)*	*N(>0)*	*Mean*	*Median*	*Min*	*Max*
				Among stocks with SO>0			
2003/12	1263	258	1005	45.33%	49.18%	0.12%	85.00%
2004/12	1353	293	1060	44.17%	47.75%	0.00%	85.00%
2005/12	1351	307	1044	42.93%	46.02%	0.09%	84.99%
2006/12	1432	345	1087	37.68%	40.18%	0.02%	84.44%
2007/12	1548	469	1079	36.04%	36.94%	0.02%	91.48%
2008/12	1602	581	1021	34.33%	34.34%	0.02%	97.12%
2009/12	1751	1060	691	32.36%	31.39%	0.01%	89.78%
2010/12	2107	1449	658	28.80%	24.16%	0.01%	89.78%
2011/12	2341	1773	568	25.77%	18.55%	0.00%	84.71%
2012/12	2470	1986	484	26.60%	19.94%	0.00%	85.68%
2013/12	2514	2063	451	21.51%	13.39%	0.00%	92.19%
2014/12	2631	2135	496	19.79%	9.89%	0.00%	92.19%
2015/12	2823	2289	534	17.41%	8.62%	0.00%	81.39%
2016/12	3116	2481	635	18.12%	9.08%	0.00%	87.46%

Appendix 3.3

Comparison of our five factors with CSMAR's five factor, 07/01/1994 to 12/29/2017, 5714 trading days.

This table reports a comparison between our five-factors and those available from China Stock Market & Accounting Research database (CSMAR). The construction of our factors is in Table 4. Mean is the average percent daily return of the factors. Median is the median of the percent daily return of the factors. Std dev. is the daily standard deviation of the factors. Correlation is the correlation coefficient between our factors and those retrieved from CSMAR.

	Mkt		SMB		HML		RMW		CMA	
	CSMAR	Ours	CSMAR	Ours	CSMAR	Ours	CSMAR	Ours	CSMAR	Ours
Mean	0.122	0.059	0.046	0.036	0.022	0.006	-0.005	0.000	0.012	0.007
Median	0.095	0.098	0.077	0.070	-0.003	-0.022	-0.027	-0.014	0.006	0.008
Std dev.	2.098	2.001	0.770	0.722	0.618	0.605	0.658	0.761	0.594	0.532
Correlation	96%		94%		84%		82%		83%	

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