# Trend Factor in China*

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# Trend Factor in China


## Abstract

We propose a 4-factor model by adding an additional trend factor to Liu, Stambaugh, and Yuan's (2019; LSY-3) 3-factor model: market, size, and value. Since individual investors contribute about 80% of the trading volume in China, the trend factor captures well the resulting important price and volume trends, and has a monthly Sharpe ratio of 0.48, much greater than those of the market (0.11), size (0.19), and value (0.28). The proposed 4-factor model explains all reported Chinese anomalies, including turnover and reversal that are unexplained previously by LSY-3. Moreover, the model explains well mutual fund returns, working as an analogue of Carhart (1997) 4-factor model in China. It also strongly outperforms the replication of Fama and French (2015) 5-factor model and Hou, Xue, and Zhang (2015) q-factor model in terms of both Sharpe ratio and explanatory power.



*JEL Classification:* G12, G14, G15

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# 1. Introduction

Since China is the world's second largest stock market, it is important to examine how well asset pricing theory developed previously in the US applies in China. The Fama-French 3-factor model (1993, FF-3, henceforth) is one of the most important models for pricing US stocks, but its replication does not work well for Chinese stocks. Accounting for unique features of small stocks in China, Liu, Stambaugh, and Yuan (2019) propose two adjusted size and value factors, and show that these adjusted factors together with the market factor outperform substantially the replication of FF-3 in China. However, Liu, Stambaugh, and Yuan' 3-factor model (LSY-3, henceforth) still fails to explain certain important anomalies.

In this paper, we propose a 4-factor model: the market, size, value and trend, where the first three factors are those of LSY-3. Our motivation is to capture another important future of the Chinese stock market: individual investors contribute about 80% of the trading volume. Because individual investors are more susceptible to herding, we expect there are stronger price trends than the US market. However, typical 6- to 12-month momentum strategies do not perform significantly well in China (see, e.g., Li, Qiu, and Wu, 2010, Cheema and Nartea, 2014, and Cakici, Chan, and Topyan, 2017) due to many individual investors are likely short-term orientated. To capture short-, intermediate- and long-term price trends in China, we construct a China trend factor and let the data determine the weights on both price and volume information across time. Unlike Han, Zhou, and Zhu (2016) whose trend factor depends on only price signals, our trend factor exploits both price and volume data, which makes important difference in China. We also provide a theoretical model that sheds light on why trading volume has a unique role to play in the Chinese stock market.

As a candidate for factor investing, our trend factor is the best. Indeed, it yields the greatest average return of 1.43% per month over the sample period from January 2005 to July 2018, while the average return generated by size factor is 0.97% per month, and by value factor is 1.15%. In terms of Sharpe ratio, the trend factor performs also the best, with a monthly value of 0.48, much greater than those of market (0.11), size (0.19) and value (0.28). Moreover, the trend factor is resilient in recovery. The maximum drawdown (MDD) of the trend factor is only about 13.17%. In contrast, the MDD of market is 69.33%, of the size factor is 25.94%, and of the value factor is 19.65%.

The trend factor earns a significant monthly alpha and 1.17% with respect to LSY-3. The result indicates that the trend factor serves as a legitimate extension of LSY-3. While Liu, Stambaugh, and Yuan (2019) also consider a 4-factor model (LSY-4, henceforth) by adding a turnover factor to capture sentiment, this model, however, has three limitations. First, the turnover factor fails to produce significant alpha in our 4-factor model, whereas the trend factor earns a highly significant alpha of 0.82% per month in LSY-4. Second, the portfolios sorted by exposures to the turnover factor exhibit non-monotonic return pattern. Third, the turnover factor captures investor sentiment in small stocks but not in large ones.

Most importantly, our 4-factor model outperforms LSY-3 and LSY-4 in a number of ways. First, our 4-factor model substantially outperforms LSY-3 and LSY-4 in terms of explaining power. Gibbons, Ross, and Shanken (1989) GRS test of our 4-factor models ability to price the factors in LSY-3 and LSY-4 produces a $p$-value of 0.85 and 0.81, respectively. On the contrary, the GRS $p$-value for LSY-3 and LSY-4 to price the factors in our model are less than $10^{-3}$. In addition, our model explains all reported Chinese pricing anomalies, including those failed to be captured by LSY-3 or LSY-4, such as turnover, reversal, illiquidity, and idiosyncratic volatility and so on. It producing a GRS $p$-value of 0.55 versus the $p$-value of less than $10^{-2}$ and 0.03 for LSY-3 and LSY-4, respectively. Besides, our model also does a better job in explaining mutual fund portfolios. It explains all the fund portfolios sorted by asset under management, and it has smaller aggregate pricing errors compared with LSY-3 and LSY-4. Since there is no traditional momentum factor in China, our 4-factor model serves as an analogue of Carhart (1997) 4-factor model for Chinese mutual funds. Moreover, following Barillas and Shanken (2017), we also compute the Sharpe ratio of the factor models with and without the trend factor. The Sharpe ratio with the trend factor is substantially greater, indicating that our 4-factor model has greater explanatory power in general regardless of the test assets used for model evaluation. Additionally, our 4-factor model also substantially dominates the replication of Fama and French (2015) 5-factor model and Hou, Xue, and Zhang (2015) q-factor model in China, indicating that our 4-factor model outperforms existing popular factor models in terms of explanatory power. Second, Fama-MacBeth regressions show that, after controlling for factors in LSY-3 and LSY-4, our trend measure generates significant risk premia, while the turnover factor of LSY-4 does not once the trend factor is included. Third, the mean-variance spanning test shows that the trend factor lies outside the mean-variance frontier of the LSY-3 and the LSY-4 factors, indicating that existing factor models cannot explain the trend factor.

Why does the trend factor perform well in the Chinese stock market? Theoretically, our model suggests two driving factors behind the trend factor, the market sentiment measured by noise trader demand volatility, and the fundamental economic volatility measured based on dividend growth volatility. Empirically, we use three proxies for volatility: volatility of stock returns, volatility of trading volume, and volatility of earnings. For each proxy, we form trend factors with high, medium and low volatility, and find that the associated trend factor with high volatility earns significantly higher returns. Intuitively, the greater the number of individual investors, the greater the volatility. Hence, the results are consistent with the view that the trend factor perform well in China due to its major market participants being individual investors.

To highlight the role of volume trend, we construct an orthogonal volume trend independent of price trend, and find that it has strong predictive ability, which is consistent with the theoretical implication of Blume, Easley, and O'Hara (1994) that volume can provide predictive information beyond the price statistic. Blume, Easley, and O'Hara (1994) also suggest that the predictability generated by volume decreases with information quality and information quantity about asset fundamentals. We use the volatility of earnings and the participation of institutional investors to measure information quality and information quantity, respectively. Consistent with their theoretical prediction, our empirical results show that volume trend does decrease with information quality and quantity.

Compared with the original trend factor proposed by Han, Zhou, and Zhu (2016) which captures only price trend, our modified trend factor also brings economic gains in the US. An important question is what is the relative importance of volume trend in China and the US? Our results show that the contribution of volume trend to the overall trend is economically and statistically significantly higher in China (42%) than in the US (6%). This result is consistent with the fact that the Chinese stock market is dominated by individual investors, indicating again the important role that the volume trend plays in China.

The rest of the paper is organized as follows. Section 2 discusses the construction of the trend factor and data. Section 3 investigates the trend factor and compares our 4-factor model with both LSY-3 and LSY-4 in various dimensions. Section 4 examines the cross-sectional returns of our trend measure. Section 5 proposes an explanation for the trend factor and examines its predictability by volatility and investigates the role of volume trend. Section 6 compares the trend factor in China and the US. Section 7 examines the robustness. Section 8 concludes.

## 2. Methodology and data

In this section we introduce the methodology and data. First, we provide detailed methodology for our trend factor. Next, we illustrate the factor construction. Finally, we discuss the data used in this paper.

### *2.1. Trend factor*

In this subsection, we construct the trend factor based on price and volume, while the theoretical motivation is provided later in Section 5.1.

To capture short-, intermediate- and long-term price trends in China, we define the moving average (MA) price signals of stock $i$ with lag $L$ in month $t$ as

$$M_{i,L}^{P,t} = \frac{P_{i,d}^{t} + P_{i,d-1}^{t} + \cdots + P_{i,d-L+1}^{t}}{L}, \tag{1}$$

where day $d$ is the last trading day in month $t$, $L$ is the lag length, and $P_{i,d}^{t}$ is the closing price of stock $i$ on day $d$. Following Han, Zhou, and Zhu (2016), we normalize the MA signals by the closing price on the last trading day for stationarity:

$$\widetilde{M}_{i,L}^{P,t} = \frac{M_{i,L}^{P,t}}{P_{i,d}^{t}}. \tag{2}$$

We use the MA signals with several different lag lengths, including 3-, 5-, 10-, 20-, 50-, 100-, 200-, 300-, and 400-days. These MA signals are commonly used in practice and reflect the trend of price and volume over different horizons, including daily, weekly, monthly, quarterly, 1-year and 2-year horizons.

To capture volume trend, we define similarly the MA of volume of stock $i$ with lag $L$ in month $t$ as

$$M_{i,L}^{V,t} = \frac{V_{i,d}^{t} + V_{i,d-1}^{t} + \cdots + V_{i,d-L+1}^{t}}{L}, \tag{3}$$

where $V_{i,d}^t$ is the trading volume of stock $i$ on day $d$. We normalize the MA of volume by the trading volume on day $d$:

$$\widetilde{M}_{i,L}^{V,t} = \frac{M_{i,L}^{V,t}}{V_{i,d}^t}. \tag{4}$$

With signals based on both price and volume, we conduct the following predictive cross-section regression:

$$r_{i,t} = \beta_0 + \sum_j \beta_j^{P,t} \widetilde{M}_{i,L_j}^{P,t-1} + \sum_j \beta_j^{V,t} \widetilde{M}_{i,L_j}^{V,t-1} + \epsilon_i^t, \quad i = 1, ..., n, \tag{5}$$

where $\widetilde{M}_{i,L_j}^{P,t-1}$ ($\widetilde{M}_{i,L_j}^{V,t-1}$) is the MA signal of price (volume) of stock $i$ with lag $L_j$ at the end of month $t-1$, and $\beta_j^{P,t}$ ($\beta_j^{V,t}$) is the coefficient of the MA signal of price (volume) with lag $L_j$ in month $t$. Then, the trend measure for month $t+1$ at month $t$ is

$$ER_{Trend}^{i,t+1} = \sum_j E_t(\beta_j^{P,t+1}) \widetilde{M}_{i,L_j}^{P,t} + \sum_j E_t(\beta_j^{V,t+1}) \widetilde{M}_{i,L_j}^{V,t}, \tag{6}$$

where $E_t(\beta_j^{x,t+1})$ is the forecast coefficient of MA signals of price or volume with lag length $L_j$ for month t+1, and is given by the exponential moving average of the past coefficients,

$$E_t(\beta_j^{x,t+1}) = (1-\lambda) E_{t-1}(\beta_j^{x,t}) + \lambda \beta_j^{x,t}, \quad x = P, V, \tag{7}$$

where $\lambda$ is set to 0.02. In this case, it takes roughly 4 years (50=1/0.02) to get stable forecasts for the coefficients of MA signals. We also set $\lambda$ to different values, such as those in the US, and use alternative methods to forecast the coefficients. Our results are robust.

It is worth noting that only information in month $t$ or prior is used to forecast the trend measure $ER_{Trend}$ in month $t+1$. Hence, our procedure provides real time out-of-sample results.

### *2.2. Factor definition*

We use the trend measure $ER_{Trend}$, along with stock's market capitalization (Size) and earnings-to-price ratio (EP), to construct the trend factor (*Trend*), the size factor (*SMB*), and the value factor (*VMG*) in our 4-factor model by applying a 2×3×3 triple sorting procedure which Hou, Xue, and Zhang (2015) use to construct their $q$-4 factor model.

Following Liu, Stambaugh, and Yuan (2019), we exclude the smallest 30% stocks to avoid the shell-value contamination caused by the IPO constraints in China, and we use the remaining stocks to construct factors. At the end of each month, the remaining 70% stocks are independently sorted into two *Size* groups ($Size_{Small}$ and $Size_{Big}$) by the median of the market capitalization, three *EP* groups ($EP_{Low}$, $EP_{Mid}$ and $EP_{High}$) and three *Trend* groups ($Trend_{Low}$, $Trend_{Mid}$ and $Trend_{High}$) by the 30th and 70th percentiles of EP and $ER_{Trend}$, respectively. As a result, the intersections of those groups produce 18 (2×3×3) *Size-EP-Trend* portfolios, among which there are 9 portfolios in the $Size_{Small}$ ($Size_{Big}$) group, 6 portfolios in the $EP_{Low}$ ($EP_{Mid}$ and $EP_{High}$) group, and 6 portfolios in the $Trend_{Low}$ ($Trend_{Mid}$ and $Trend_{High}$) group.

In our 4-factor model, the trend factor (*Trend*) is defined as the average of VW returns of 6 portfolios in the $Trend_{High}$ group minus that in the $Trend_{Low}$ group. The size factor ($SMB$) is defined as the average of VW returns of 9 portfolios in the $Size_{small}$ group minus that in the $Size_{Big}$ group. The value factor ($VMG$) is defined as the average of VW returns of 6 portfolios in the $EP_{High}$ group minus that in the $EP_{Low}$ group. Our sorting procedure controls jointly for the three factor variables, so the resulting factors are roughly neutral with respect to each other. The market factor ($MKT$) is the return on the VW portfolio of the top 70% stocks, in excess of the one-year deposit interest rate. Following Liu, Stambaugh, and Yuan (2019), when forming VW portfolios, here and throughout the study, we weight each stock by the market capitalization of all its outstanding A shares, including non-tradable shares.

For LSY-3, we simply replicate the Liu, Stambaugh, and Yuan (2019) procedure to construct the size and value factor in a $2 \times 3$ double sorting procedure by market capitalization and EP. In LSY-4, the additional turnover factor $PMO$ (pessimistic minus optimistic) is based on abnormal turnover, which is defined as the past months share turnover divided by the past years turnover. The turnover factor is constructed in the same way as the value factor in LSY-3, except PMO longs the low-turnover stocks and shorts the high-turnover stocks.

### *2.3. Data*

In this subsection, we describe the data used throughout the paper. We include only domestic stocks listed on the Chinese A-Shares in Shanghai Stock Exchange and Shenzhen Stock Exchange. All the stock trading data and firm financial data come from WIND database. The sample period is from January 4, 2000 through July 31, 2018.

We use daily closing price to calculate the MA price signals at the end of each month. The prices are adjusted for splits and stock dividend. During the suspension of trade period, we use the daily closing price right before the suspension to fill in the price during suspension period to calculate the MA price signals. We use the daily RMB trading volume to calculate the MA volume signals. At the end of each month, we calculate the MA signals of volume with a given lag if there are more than half of the days of trading records during the period specified by the given lag and there are trading records in this month. Otherwise, we use the MA volume signals in the last month to fill in the volume signals in this month.

$Size$ of a stock is the market capitalization of all its outstanding A shares, including non-tradable shares. Earnings-to-price ratio ($EP$) is the ratio of the net profit excluding non-recurrent gains/losses in the most recently reported quarterly statement to the market capitalization in the end of last month. Book-to-market ratio ($BM$) is the ratio of the total share holder equity from the most recently reported quarterly statement to the market capitalization in the end of last month. Cash-flow-to-price ($CP$) is the ratio of the net cash flow from operating activities in the most recently reported quarterly statement to the market capitalization in the end of last month. Return-on-equity ($ROE$) is the ratio of the net profit excluding gains/losses to the total share holder equity from the most recently reported quarterly statement. Note that, at the end of a given month, we only use the financial data from the most recent financial reports which have the public release date prior to that month's end to calculate these valuation ratios, so there is no look forward bias.

One-month abnormal turnover ($AbTurn$) is defined as the ratio of the turnover in the last month to the average of monthly turnover in the last twelve months. $R_{-1}$, $R_{-6,-2}$ and $R_{-12,-2}$ is the prior month return, the past six-month cumulative return skipping the last month, and the past twelve-month cumulative return skipping the last month, respectively. $IVOL$ is the idiosyncratic volatility relative to FF-3 estimated from daily returns in the last month. $\beta$ is the market beta estimated from daily returns in the past twelve months. We measure stock illiquidity ($ILLIQ$) in month $t$ as the average daily illiquidity in that month. Following Amihud (2002), the daily illiquidity measure is defined as the ratio of the absolute daily return to the RMB trading volume. Price-to-earnings ratio ($PE$), price-to-cash ratio ($PC$), and price-to-sales ratio ($PS$) is the ratio of the total market capitalization in the end of last month to the earnings, net cash flow from operating activities, and sales in most recent available four quarterly fiscal periods, respectively.

Following Sloan (1996), we define accrual as $Accrual = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep$, where $\Delta CA$ equals the most recent year-to-year change in current assets, $\Delta Cash$ equals the change in cash or cash equivalents, $\Delta CL$ equals the change in current liabilities, $\Delta STD$ equals the change in debt included in current liabilities, $\Delta TP$ equals the change in income taxes payable, and $Dep$ equals the most recent year's depreciation and amortization expenses. Following Fama and French (2015) and Cooper, Gulen, and Schill (2008), we define asset growth as the total assets in the most recent annual report divided by the total assets in the previous annual report.

## 3. Trend factor in China

In this section, we examine the empirical performance of the trend factor in Chinese stock market. We first examine the properties of our trend factor along with other factors. Then, we further compare the performance of our trend factor and the turnover factor in sub-samples controlling for other factor variables. Next, we carry out the spanning tests. Finally, we compare the performance of our 4-factor model with the LSY-3 and LSY-4 in terms of explaining power.

We skip the first 400 days to compute the MA signals and skip the subsequent 38 months to estimate the expected coefficients. So the effective sample period for our study is from January 2005 to July 2018.

### *3.1. Summary statistics*

Panel A of table 1 presents the summary statistics for the trend factor (Trend), in comparison with factors in LSY-3 and LSY-4 factor model, i.e., the market factor (MKT), the size factor (SMB), the value factor (VMG), and the turnover factor (PMO).[1] Among these factors, Trend produces the highest average return of 1.43% per month, while the average return generated by SMB factor is only 0.97% per month and the average monthly return of VMG is 1.15%. Besides, Trend earns the highest Sharpe ratio (0.48), while the highest Sharpe ratio of LSY-3 factors is only 0.28 (VMG). Further more, Trend earns the lowest maximum drawdown (MDD) at 13.17%,

[1]The results using all stocks including the smallest 30% stocks to construct factors are provided in an online appendix. The performance of our trend factor is robust.

while those for the SMB, VMG and PMO are 25.94%, 19.65% and 25.15%, indicating that Trend is resilient in recovery from downside risk and performs well in extreme scenarios.

Panel B of table 1 presents the correlation matrix for the above factors. Note that the trend factor is not highly correlated to LSY-3 factors, but has fairly high correlation (0.52) with PMO factor. Which factor performs better and captures more of the cross-sectional returns will be examined in the next subsection.

### *3.2. Further comparison with the turnover factor*

In this subsection, we further compare our trend factor (Trend) and the turnover factor (PMO) by using a $2 \times 3 \times 3$ triple sorting procedure to examine their performance in sub-samples controlling for other factor variables.

At the end of each month, stocks are independently sorted into two size groups, three EP groups, and three trend groups by Size, EP, and $ER_{Trend}$, respectively. As a result, there are 18 *Size-EP-Trend* sub-samples, and 6 *Size-EP* sub-samples. In a given *Size-EP* sub-sample, the trend factor is defined as the return spread between the VW portfolios in the two extreme trend groups. *Size-EP-AbTurn* and *Size-Trend-AbTurn* sub-samples, and the associated Trend and PMO factors in these sub-samples are produced in the similar way.

Table 2 shows the resulting average monthly returns for our trend factor (Trend), in comparison with the turnover factor (PMO) in different sub-samples. In Panel A controlling for size and EP, Trend generates persistent positive returns in all these 6 $Size - EP$ sub-samples, producing an average return of 1.43% ($t$-statistic: 6.10) over these sub-samples consequently. PMO, on average, also earns a monthly return of 0.82% ($t$-statistic: 2.82), however, this performance is mainly attributes to small stocks. Specifically, the average return of PMO in small stocks is 1.37% per month, while that in large stocks is only 0.28% ($t$-statistic: 0.83), indicating that the turnover factor captures investor sentiment only in stocks stocks, but not in large stocks. In panel B controlling for size and $ER_{Trend}$ , PMO still seems to be useless in big stocks, producing an average return of -0.28% ($t$-statistic: -0.79) in the big stock groups. Worse still, it also fails to generate significant returns in all these three trend groups, and produces an average return of only 0.30% ($t$-statistic: 1.07) over the 6 *Size-Trend* groups, indicating that the predictability of turnover is partially subsumed by $ER_{Trend}$. On the contrary, in panel C controlling for size and AbTurn, Trend performs remarkably well in two size groups as well as three AbTurn groups, earning an average monthly return up to 1.23% ($t$-statistic: 5.13), indicating that our trend measure provides independent predictability beyond the size and turnover, and can capture the sentiment well in both small and large stocks.

In addition, the portfolios sorted by $ER_{Trend}$ show a great monotonic return pattern with no exception after controlling for size, EP and AbTurn, while the portfolios sorted by AbTurn show a non-monotonic return pattern in large stocks. The detailed results are reported in an online appendix.

Overall, the turnover factor in LSY-4 captures investor sentiment only in small stocks but not in large stocks. On the contrary, our trend factor works well after controlling for size, EP and AbTurn. Besides, it subsumes the predictability of turnover, thus can perform better in the cross-section of stock returns.

### *3.3. Mean-variance spanning tests*

In this subsection, we carry out mean-variance spanning tests to check whether a portfolio of factors in LSY-3 and LSY-4 can mimic the performance of our trend factor. The null hypothesis of the spanning test is that $N$ assets can be spanned in the mean-variance space by a set of $K$ benchmark assets. Following Kan and Zhou (2012), we carry out six spanning tests: Wald test under conditional homoskedasticity, Wald test under independent and identically distributed (I-ID) elliptical distribution, Wald test under conditional heteroskedasticity, Bekerart-Urias spanning test with errors-in-variables (EIV) adjustment, Bekerart-Urias spanning test without the EIV adjustment and DeSantis spanning test. All six tests have asymptotic chi-squared distribution with $2N(N = 1)$ degrees of freedom.

Table 3 shows the results of spanning tests. The hypothesis is strongly rejected that the trend factor lies inside the mean-variance frontier of the LSY-3 factors and the LSY-4 factors, indicating that our trend factor is clearly a unique factor that captures the cross-sectional of stock trends and performs far better than the factors in LSY-3 and LSY-4.

### *3.4. Explaining power*

In this subsection, we investigate the explaining power of our 4-factor model in comparison with LSY-3, and LSY-4. We also replicate Hou, Xue, and Zhang (2015) q-factor model (q-4) and Fama and French (2015) 5-factor model (FF-5) as competitors for our 4-factor model in China.[2] We first examine these models' performance in explaining factors in other models. Then, we compare their pricing ability in explaining stock anomalies and mutual fund portfolios in Chinese stock market. Last, we conduct the Sharpe ratio tests.

We compute the alphas of factors, anomalies and mutual fund portfolios with respect to different benchmark models. The explaining power of the benchmark model is measured in three perspectives. First, we calculate the average absolute alphas and the associated average absolute $t$-statistics for the test assets of factors, anomalies and fund portfolios. Second, to measure further the overall pricing errors, following Shaken (1992), we provide a weighted summary of the alphas,

$$\Delta = \alpha' \Sigma^{-1} \alpha, \tag{8}$$

where $\Sigma$ is the variance-covariance matrix of the residuals across the test portfolios. The smaller the aggregate pricing error $\Delta$, the better performance of the benchmark model. Third, we carry out the GRS test of Gibbons, Ross and Shanken (1989) to examine whether a benchmark model can fully explain the test portfolios in the sense that all the alphas are zero.

#### *3.4.1. Explaining factors in other models*

In this subsection, we compare existing factor models with our 4-factor model in explaining the factors in other models. To do so, we conduct the pairwise comparison of LSY-3, LSY-4, q-4 and FF-5 with our 4-factor model by calculating the alphas of factors (except the market factor) in a given factor model with respect to another benchmark model.

Our trend factor earns highly significant alphas of 1.17%, 0.82%, 1.25% and 1.15% (with corresponding $t$-statistic of 4.04, 3.42, 4.76 and 4.58) with respect to LSY-3, LSY-4, q-4 and FF-5, respectively, indicating that existing factor models cannot explain the performance of the trend

[2] The construction and the summary statistics of the factors in FF-5 and q-4 in China are provided in an online appendix.

factor. On the contrary, no factor in other models earns significant alphas with respect to our 4-factor model. Especially, PMO in LSY-4 generates an insignificant alpha of only 0.26% ($t$-statistic: 0.89) under our 4-factor model.

Table 4 summarizes the results of pairwise comparisons of our 4-factor model with other models in explaining factors. In panel A, our 4-factor model produces overall pricing error $\Delta$ of only 0.003 versus the $\Delta$ of 0.214 for LSY-3. Moreover, the GRS $p$-values of our 4-factor model is 0.85, while that for LSY-3 is less than $10^{-4}$, indicating that our 4-factor model can explain LSY-3, but not vice versa. In Panel B, the average absolute alpha ($t$-statistic) for LSY-4 is 0.40% (2.65), while that for our 4-factor model reduces significantly by three quarters to only 0.11% (0.54). Consistently, the overall pricing error $\Delta$ of our 4-factor model (0.010) is much smaller than that of LSY-4 (0.161). More importantly, in GRS tests, our 4-factor model's $p$-value of 0.81 fails to reject the joint hypothesis that all alphas for LSY-4 factors are zero. In contrast, the $p$-value for LSY-4 is less than $10^{-3}$. The results are similar for q-4 in Panel C and FF-5 in Panel D.

Overall, in terms of explaining the factors in other models, our 4-factor model substantially outperform other models, including LSY-3, LSY-4, q-4 and FF-5. Its overall pricing error is only one tenth of those of other factor models, and $p$-values in the GRS tests indicate that our 4-factor model can fully explain the factors in existing models.

### *3.4.2. Explaining anomalies*

In this subsection, we compare the pricing ability of different factor models in explaining the stock anomalies. We compile 17 anomalies in China that are reported in the literature. These anomalies fall into 10 categories, covering all the anomaly categories examined in Liu, Stambaugh, and Yuan (2019). The anomalies and the corresponding measures are: (1) size anomaly: market capitalization (Size); (2) value anomaly: earnings-to-price ratio (EP), book-to-market ratio (BM) and cash-flow-to-market ratio (CP); (3) turnover anomaly: turnover (Turn); (4) trend anomaly: TrendPV is based on our modified trend measure of price and volume MA ($ER_{Trend}$), while TrendP and TrendV is based on the trend measure of price MA ($ER_{TrendP}$) and of trading volume MA ($ER_{TrendV}$), respectively. (5) illiquidity anomaly: Amihud (2002) illiquidity measure (ILLIQ); (6) past return anomaly: 1-month reversal (REV), and 12-month momentum (MOM); (7) profitability anomaly: return-on-equity (ROE); (8) volatility anomaly: volatility of daily returns in the last month (VOL), idiosyncratic volatility (IVOL), and the maximum daily return in the last month (MAX); (9) accrual anomaly: accrual (Accrual); (10) investment anomaly: asset growth (Invest).

For each anomaly except reversal, we compute a long-short return spread between the extreme decile portfolios sorted by the corresponding anomaly measures in the most recent month-end and rebalance the portfolios monthly. Since the one-month return reversal is a short-term anomaly, stocks are sorted into decile portfolios each day based on the return over the most recent 20 days, and we hold the spread portfolios for five trading days. As a result, there are five portfolios for reversal each day. The daily return of the reversal is defined as the average return of the five portfolios. Then, we use the resulting daily return to calculate the monthly return for reversal. Liu, Stambaugh, and Yuan (2019) use the same procedure to compute the return for the reversal anomaly. We exclude the smallest 30% stocks to form the anomalies. All anomalies are based on the VW decile portfolios using the market capitalization in the most recent month-end as weight.

Although the momentum, accrual and investment produce significant returns in the US, they do not in China.[3] For our later analysis, we include only the remaining 14 anomalies that generate significant returns. LSY factor models fail to explain certain important anomalies. For example, turnover, illiquidity, reversal and idiosyncratic volatility earns an alpha of 1.23%, 0.71%, 1.59% and 1.21% with associated $t$-statistics of 2.31, 3.44, 2.51, and 2.28, respectively, with respect to LSY-3. LSY-4 explains turnover, however, it still fails to explain other three anomalies, leaving a unexplained alpha of 0.47%, 1.23%, and 1.06% with associated $t$-statistics of 1.97, 2.00, and 1.69 for illiquidity, reversal and idiosyncratic volatility, respectively. On the contrary, our 4-factor model explains all these anomalies.

Table 5 summarizes the pricing ability of factor models to explain stock anomalies. The competing models include the "unadjusted" return (i.e., a model with no factors), LSY-3, LSY-4, q-4, FF-5 and our 4-factor model. First, our 4-factor model produces the smallest average absolute alpha of only 0.32%, while that of LSY-3 and LSY-4 is 0.85% and 0.52%, respectively. The average absolute $t$-statistic of our 4-factor model (0.68) is also much lower than those of other models. Second, in terms of the aggregate pricing error ($\Delta$), our 4-factor model also dominates all other factor models. The aggregate pricing error of our 4-factor model is only 0.140, in comparison with

[3] Liu, Stambaugh, and Yuan (2019) also find similar results.

LSY-3 (0.296) and LSY-4 (0.256). Third, in GRS tests, all other factor models strongly reject the joint hypothesis that all 14 anomalies produce zero alphas. In contrast, the GRS $p$-value of our 4-factor model is 0.55, indicating that there is no evidence to reject the hypothesis that our 4-factor model can fully explain the 14 anomalies. Overall, our 4-factor model substantially outperforms existing popular factor models in explaining stock anomalies.

### *3.4.3. Explaining mutual funds*

Carhart (1997) 4-factor model extends Fama and French (1993) 3-factor model by adding a momentum factor to capture the momentum anomaly of Jegadeesh and Titman (1993). Carhart 4-factor model is commonly used to evaluate and explain the mutual fund performance (see, e.g., Daniel, Grinblatt, Titman and Wermers, 1997, Wermers, 2000, and Fama, and French, 2010). However, because of the compound interactions of the various trends, the momentum factor does not work in China (see, e.g., Li, Qiu and Wu, 2010, Cheema and Nartea, 2014, and Cakici, Chan and Topyan, 2017), calling for new factor models to explain mutual fund performance in China. In this subsection, we compare our 4-factor model with LSY-3, LSY-4, q-4 and FF-5 in explaining the mutual fund portfolios.

We include only equity-oriented mutual funds. At the end of each month, we sort mutual funds by the asset under management (AUM) into ten decile portfolios, from Fund1 (small) to Fund10 (big). The mutual fund data comes from the China Stock Market and Accounting Research (CSMAR) database.

Table 6 summarizes the pricing ability of factor models to explain mutual fund returns. Our 4-factor model produces the smallest average absolute alpha, the smallest average absolute $t$-statistic, and the smallest aggregate pricing error, indicating that our 4-factor model outperforms other existing factor models in terms of explaining mutual fund performance, an analogue of Carhart (1997) 4-factor model in China.

### *3.4.4. Sharpe ratio tests*

In the previous subsection, we compare the pricing ability of different factor models by examining their power to explain the test assets of factors, stock anomalies and mutual fund portfolios.

In this subsection, we conduct the Sharpe ratio test of Barillas and Shanken (2017) to compare the explaining power of our 4-factor model and other factor models.

The maximum squared Sharpe ratio ($Sh^2$) of a model based on a vector of factors $f$ is defined as the squared Sharpe ratio of the tangency portfolio spanned by the factors in the model,

$$Sh^2(f) = \mu' C^{-1} \mu, \tag{9}$$

where $\mu$ is the mean vector and $C$ is the variance-covariance matrix of the factors. Assume two factor models based on factor vectors of $f_1$ and $f_2$, respectively, and $Sh^2(f_1) > Sh^2(f_2)$. Then, model $f_1$ with the higher Sharpe ratio performs better in pricing ability in the sense that the Sharpe improvement from exploiting mispricing by $f_1$ is smaller than that by $f_2$, that is,

$$Sh^2(f_1, f_2, R) - Sh^2(f_1) < Sh^2(f_1, f_2, R) - Sh^2(f_1). \tag{10}$$

Hence, the Sharpe ratio test is a stronger method for model comparison as its conclusion is established regardless of the test assets ($R$) used to evaluate model's pricing ability.

Table 7 reports the squared monthly Sharpe ratio for the factor models, including LSY-3, LSY-4, q-4, FF-5 and our 4-factor models. Panel A reports the results for factor models in which we exclude the smallest 30% stocks to form the factors. Among all these five models, our 4-factor model earns the highest squared monthly Sharpe ratio of 0.598 in comparison with LSY-3 (0.387) and LSY-4 (0.446), indicating that our trend factor provides significant economic value beyond the LSY factor models. Besides, our 4-factor model strongly outperforms FF-5 with a $Sh^2$ of 0.404, indicating it does a good job of both explanatory power and model parsimony. Interestingly, q-4 earns the smallest $Sh^2$ of only 0.240. This is partially because that q-4 drops the value factor while the investment factor fails to generate significant return (0.13% per month with a $t$-statistic of 0.85) in China.

Following Ledoit and Wolf (2008), we construct a studentized time-series bootstrap in Panel B to test whether the Sharpe ratio difference among factor models is statistically significant. The results show that LSY-4 fails to generate significant improvement in $Sh^2$ compared with LSY-3. On the contrary, our 4-factor model substantially outperforms all other factor models. Panel C and Panel D report similar results for factor models in which we do not exclude small stocks to construct the factors. Specifically, our 4-factor model strongly dominates all other factor models by earning the highest $Sh^2$ of 0.714, while there is no significant difference among other factor models.

Overall, compared with other factor models, the incremental in $Sh^2$ of our 4-factor model is highly economically and statistically significant, indicating that our 4-factor model substantially dominates existing factor models in terms of explaining power. This result is consistent with the advantage of our 4-factor model in explaining other factors, stock anomalies and mutual funds in previous subsections, and it provides stronger evidence on the superiority of our 4-factor model in explaining power as it holds for any test assets used for model evaluation.

## 4. Cross-sectional returns

In this section, we examine first our trend measure in the cross-section of stock returns in Fama-MacBeth regressions (Fama and MacBeth, 1973). Then, we conduct a double sorting procedure to present the trend quintile portfolios after controlling for various firm characteristics such as size, EP, BM, past returns, idiosyncratic volatility, turnover, etc.

### *4.1. Regression vs portfolio sorting*

The two methods are complementary. Assume a factor model with $F$ factors. The factor exposures are given as $X$, an $N \times F$ matrix with each elements $X_{ij}$ representing the $i$-th security's exposure to the $j$-th factor. The factor exposure can be the firm characteristics measured as fundamentals, technical indicators, or market beta.

Fama-MacBeth regression is given as

$$R = X * \beta + \epsilon, \tag{11}$$

with $\beta$ the factor risk premium (we always include constants as the first column of $X$) and given as

$$\hat{\beta} = P * R, \tag{12}$$

where

$$P = (X'WX)^{-1}X'W, \tag{13}$$

an $F \times N$ matrix, where $W$ is the weighting matrix of the regression. $W = I$ corresponds to OLS. Following Fama (1976, Chapter 9), the slope coefficients ($\beta$) have an interpretation as long-short factor portfolio returns. To see this, the row vectors of $P$ can be interpreted as the portfolio weights of the $F$ factor portfolios. Note that $P * X = I$. This means that each factor portfolio has an exposure of one on itself and has an exposure of zero on all other factors. In particular, each factor portfolio, except for the intercept coefficient, is a self-financing portfolio.

Portfolio sorting is another widely used method to construct factor portfolios. In univariate sorting, the factor portfolio is simply defined as the spread between the extreme portfolios sorted by the exposure to a given factor alone. In independent sorting, stocks are independently sorted into $M$ groups, i.e., three terciles ($M = 3$), and five quintiles ($M = 5$), by the $F$ factor exposures respectively. As a result, the interaction of these $F$ sorts produces $M^F$ portfolios. For a given factor, there are $M^{F-1}$ groups indexed by all other factors, with each group containing $M$ portfolios sorted by the given factor exposure. The factor portfolio is then defined as the average return spread with respect to the given factor over these $M^{F-1}$ groups. Obviously, similar to factor portfolios produced by regressions, factor portfolios produced by portfolio sorting methods are also self-financing portfolios.

So what does a portfolio sorting really do? How is it related to the Fama-MacBeth regression given above? What is the difference between the two portfolio sorting methods? Let's first assume $W = I$, and factor exposures $X$ are divided into three categories, 1, 0, -1 according to the rankings. Obviously, the weights of factor portfolios in univariate sorting are proportional to the corresponding factor exposures. When the factor exposures are independent, the two sorting methods produce the same results. Also since $X'X$ is a diagonal matrix $L$, Equation (13) becomes $P = LX'$, indicating that the weights of factor portfolios produced by regressions are also proportional to the corresponding factor exposures. So in the independent case, the above three methods produce the same results. When the factor exposures are correlated, the independent sorting and the regression generate the similar results in the sense that the resulting factor portfolio only has exposures to itself but has (roughly) no exposures to other factors. However, the factor portfolio generated by univariate sorting still has exposures to other factors. To make it clear, let's consider a two factor model with factor exposure $X_1$ and $X_2$, corresponding to size and value.

**Case 1: Independent case**

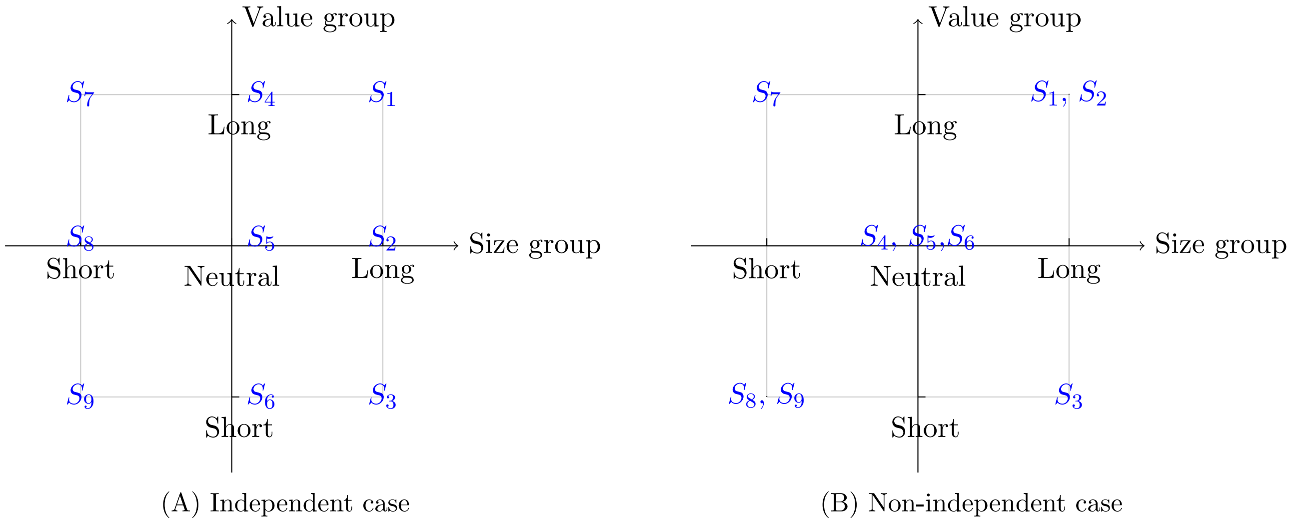


Figure 1: **Independent sorting**. This figure shows the group for each stock in the independent sorting of size and value. Panel A shows the results when the two factor exposures are independent. Panel B shows the results when the two factor exposures are correlated.

Suppose the exposure for size and value are

$$\begin{aligned} X_1 &= [1, 1, 1, 0, 0, 0, -1, -1, -1]', \\ X_2 &= [1, 0, -1, 1, 0, -1, 1, 0, -1]'. \end{aligned}$$

This corresponds to the case in which the factor exposures are independent. We use independent sorting of size and value to sort stocks into three terciles groups respectively. Panel A of Figure 1 shows the group of each stock in this independent sorting. Obviously, the independent sorting and the univariate sorting generate the same factor portfolios:

$$\begin{aligned} P_1 &= [1, 1, 1, 0, 0, 0, -1, -1, -1]/3, \\ P_2 &= [1, 0, -1, 1, 0, -1, 1, 0, -1]/3. \end{aligned}$$

By applying (13), it is easily to show that the factor portfolios generated by OLS regressions are proportional to that generated by the sorting methods. Also, the factor portfolio has zero exposure on each other.

**Case 2: Non-independent case**

Suppose the exposure for size and value are

$$
\begin{aligned}
X_1 &= [1, 1, 1, 0, 0, 0, -1, -1, -1]', \\
X_2 &= [1, 1, -1, 0, 0, 0, 1, -1, -1]'.
\end{aligned}
$$

This corresponds to the case in which the factor exposures are correlated. Panel B of Figure 1 shows the group of each stock in the independent sorting. Obviously, the factor portfolios generated by the independent sorting is

$$
\begin{aligned}
P_1 &= [\frac{1}{2}, \frac{1}{2}, 1, 0, 0, 0, -1, -\frac{1}{2}, -\frac{1}{2}], \\
P_2 &= [\frac{1}{2}, \frac{1}{2}, -1, 0, 0, 0, 1, -\frac{1}{2}, -\frac{1}{2}].
\end{aligned}
$$

By applying (13), it is easily to show the factor portfolio generated by OLS regression is proportional to that generated by independent sorting. However, the factor portfolios generated by the univariate sorting are

$$
\begin{aligned}
P_1 &= [1, 1, 1, 0, 0, 0, -1, -1, -1]/3, \\
P_2 &= [1, 1, -1, 0, 0, 0, 1, -1, -1]/3.
\end{aligned}
$$

It is easily to show that the factor portfolios generated by the independent sorting and regression approach have zero exposure on other factors, which is not true for the univariate sorting. For example, in the univariate sorting, the factor portfolio of size have an exposure of two-thirds on value. Noted that since the independent sorting method only considers relative ranking, the resulting exposure on other factors is not necessarily exactly zero, while that for regression method is exactly zero.

Hence, when using portfolio sorting method to construct factors in multi-factor models, it is important to make sure that factors are controlled for each other. One effective way is to conduct the independent sorting, which is commonly used in academic research (see, e.g., Fama and French, 1993, Fama and French, 2015, Hou, Xue, and Zhang, 2015, and Liu, Stambaugh, and Yuan, 2019). Besides, the multi-factor framework is also popular for equity analysis among practitioners. For example, MSCI Barra uses a procedure similar to the Fama-MacBeth regression to construct factor return for risk modeling (Menchero, Morozov and Shepard, 2008).

### 4.2. Fama-MacBeth regressions

In this subsection, we examine the cross-sectional pricing of our trend measure in comparison with the factor variables in LSY-3 and LSY-4 using Fama-MacBeth regressions.

We use multiple Fama-MacBeth regressions with market-value-weighted least squares (VWLS). Specifically, we standardize factor exposure and assign three categories 1, 0 and -1 according to their rankings. Since the WLS is equivalent to multiply each factor exposure by square root of the weights, this way the factor exposure rankings are kept across the three categories.

Table 8 reports the results of Fama-MacBeth regressions. Controlling for three factor measures in LSY-3, our trend measure ($ER_{Trend}$) generates significant positive premium. In addition, controlling for four factor measures in LSY-4 with an additional turnover factor, $ER_{Trend}$ remains significant. However, AbTurn is not significant in presence of $ER_{Trend}$, which is consistent with failure of PMO in big stocks and $ER_{Trend}$ portfolios in Table 2. Again, our trend factor dominates the turnover factor in capturing cross-sectional returns.

### 4.3. Trend quintile portfolios

In the previous sections, we use a triple sorting procedure and Fama-MacBeth regressions to examine the performance of our trend measure after controlling for other factor variables in LSY-3 and LSY-4. In this subsection, we ask an related important question: what is the performance of the trend measure if we control for other firm characteristics which are known to predict cross-section returns?

Table 9 shows the average return and other firm characteristics of quintile portfolios sorted by our trend measure $ER_{Trend}$. With increasing $ER_{Trend}$, the quintile portfolio returns increase monotonically, with both EW and VW portfolios. This table reports other characteristics of the five quintile portfolios. First, they show roughly flat pattern with size and book-to-market ratio. Second, from bottom to top trend quintile portfolios, the portfolios show a decreasing pattern with past returns, e.g., from 8.49% in the Low group to -1.19% in the High group for $R_{-1}$, indicating that $ER_{Trend}$ captures the reversal effect. Third, they also show decreasing value measured by price-to-earnings, price-to-cash, and price-to-sales.

Table 10 shows the sequentially double sorting result of the VW portfolios sorted by $ER_{Trend}$ after controlling for various firm characteristics, including Size, EP, BM, $R_{-1}$, $R_{-6,-2}$, $R_{-12,-2}$, IVOL , illiquidity and turnover.[4] At the end of each month, we first sort stocks by one of the control variables into five quintile control groups, and then in each control group, stocks are sorted into five trend groups by $ER_{Trend}$. Finally, we average the portfolios across the five quintile portfolios of the control variable to get a new trend quintile portfolio. After controlling for these variables, the returns of the quintile portfolios sorted by $ER_{Trend}$ preserve the monotonic pattern, and the spread portfolios in all controlled groups still earn significant monthly returns of 1.76%, 1.31%, 1.18%, 1.20%, 1.51%, 1.62%, 1.38%, 1.07%, 1.09% after controlling for Size, EP, BM, $R_{-1}$, $R_{-6,-2}$, $R_{-12,-2}$, IVOL, illiquidity and turnover, respectively.

## 5. Explanation

In the previous section, we have shown the superior performance of our trend factor in various aspects. Why does the trend factor perform so well in the Chinese stock market? In this section, we present an explanation for our trend factor and investigate the role of volume. First, we provide a theoretical model that sheds light on the driving factors behind the trend effect and empirically examine the model's implication. We then investigate the relationship between the trend effect and the individual investor participation. Finally, we examine the role of volume with different information environments.

### 5.1. *A theoretical explanation for trend factor in China*

In this subsection, we provide an explanation for the trend factor in China by extending the model of Han, Zhou, and Zhu (2016), which in turn extends Wang (1993).

Assume that there is a risky asset traded in the market with asymmetric information. The risky asset pays out dividend stream

$$dD_t = (\pi_t - \alpha_D D_t)dt + \sigma_D dB_{1t}, \tag{14}$$

[4] The results with EW portfolios are similar and are provided in an online appendix.

where $\pi_t$ measures the long-term mean growth rate of dividend, given by another stochastic process

$$d\pi_t = \alpha_\pi(\bar{\pi} - \pi_t)dt + \sigma_\pi dB_{2t}, \tag{15}$$

where $B_{1t}$ and $B_{2t}$ are independent innovations.

The market is populated with three types of investors, informed, uninformed and noise traders. Informed investors are risk-averse arbitrageurs who face limited arbitrage due to noise traders. Uninformed investors possess limited information about the underlying risky asset and use moving averages of prices to infer more information. The noise traders are those who trade for liquidity reasons, and their liquidity demand impact on the supply of the stock, which is given by an exogenous process $1 + \theta_t$ with

$$d\theta_t = -\alpha_\theta \theta_t dt + \sigma_\theta dB_{3t}, \tag{16}$$

where $B_{3t}$ is another Brownian Motion independent from both $B_{1t}$ and $B_{2t}$.

There exists an equilibrium price given in the following Proposition.

**Proposition:** *In an economy defined above, there exists a stationary rational expectations equilibrium. The equilibrium price function has the following linear form:*

$$P_t = p_0 + p_1 D_t + p_2 \pi_t + p_3 \theta_t + p_4 A_t, \tag{17}$$

*where $p_0, p_1, p_2, p_3$ and $p_4$ are constants determined only by model parameters.*

The proposition says that the equilibrium price is a linear function of the state variables $D_t$, $\pi_t$, $\theta_t$ as well as the moving average $A_t$. We can differentiate the Equation (17), and define the stock return

$$R_{t+1} \equiv \frac{P_{t+\Delta t} - P_t}{\Delta t},$$

then we have the following predictive equation for $R_{t+1}$,

$$R_{t+1} = \gamma_0 + \gamma_1 D_t + \gamma_2 \pi_t + \gamma_3 \theta_t + \gamma_4 A_t + \gamma_5 A_{Dt} + \sigma_P \epsilon_P, \tag{18}$$

where

$$\begin{aligned} \gamma_0 &= p_0 p_4 + p_2 \alpha_\pi \bar{\pi}, \quad \gamma_1 = (p_4 - \alpha_D) p_1, \quad \gamma_2 = p_1 + (p_4 - \alpha_\pi) p_2, \\ \gamma_3 &= (p_4 - \alpha_\theta) p_3, \quad \gamma_4 = (p_4 - \alpha_{p_L}) p_4. \end{aligned} \tag{19}$$

In the predictive equation (18), the only unobservable state variable is the noise trader demand $\theta_t$. To the extent that all investors, including both informed and uninformed investors, can partially observe the noise trader demand through another observable variable $Y_t$, which is exogenous to the model, as follows,

$$E[\theta_t|Y_t] = \xi_0 + \xi_1 Y_t, \tag{20}$$

then we can derive the following corollary.

**Corollary 1.** The stock price return is predictable by the state variables $D_t$, $\pi_t$, $\theta_t$ as well as the moving average $A_t$. If all investors can partially observe the noise trader demand through an exogenous variable $Y_t$ through Equation (20), then we have the predictive equation as

$$R_{t+1} = \gamma_0 + \gamma_3\xi_0 + \gamma_1 D_t + \gamma_2\pi_t + \gamma_3\xi_1 Y_t + \gamma_4 A_t + \gamma_5 A_{Dt} + \sigma'_P\epsilon'_P, \tag{21}$$

where $\sigma'_P\epsilon'_P = \sigma_P\epsilon_P + \gamma_3[\theta_t - (\xi_0 + \xi_1 Y_t)]$.

The corollary indicate that any exogenous variable that is correlated with the noise trader demand will have predictive power to future stock returns. In our empirical study, we propose that noise trader demand is correlated with trading volume. This is especially true to the Chinese stock market since it is populated mainly by retail investors, whose trading volume consists of 80% of the whole market volume. Hence, trading volume can be a strong indicator for noise trader behavior. In our empirical study, since trading volume can be clustered and persistent, we use the trend of volume or a sum of moving averages of trading volume as defined in (4) to predict future returns. Indeed, we find that volume trend can predict future returns even beyond price trend.

**Corollary 2.** The model implies two main driving factors behind the trend effect, one is the information asymmetry, which can be measured by volatility of fundamental variable $\sigma_D$, another is the noise trader behavior, which can be measured by the volatility of noise trader demand $\sigma_\theta$.

In Table 11, we present the impact of $\sigma_\theta$ and $\sigma_D$ on $\gamma_3$ and $\gamma_4$, which are the predictive coefficients of volume trend and price trend. The table shows both predictive coefficients increase with $\sigma_\theta$ and $\sigma_D$.

To confirm our model prediction, in the next subsection, we examine the predictability of trend factor by volatility of stock return, volatility of trading volume and volatility of earnings.

### 5.2. *Trend effect and volatility*

We use three different measures to proxy for volatility: volatility of stock return ($Vol_{Rt}$), volatility of RMB trading volume ($Vol_{Volume}$), and volatility of earnings ($Vol_{Earnings}$).

$Vol_{Rt}$ is defined as the volatility of monthly return in the past 12 months. For the volatility of RMB trading volume , since we want to capture noise trader demand, instead of simply calculating the volatility of trading volume, we regress the monthly RMB trading volume in month $t$ on that in month $t-1$ over the past 12 months, and use the resulting trading volume residual to measure the noise trader demand. The magnitude of the trading volume affects the volatility. For example, stocks with big market capitalization tend to have higher trading volume, leading to a higher volatility of trading volume. To eliminate this magnitude effect, we normalize the trading volume residual by dividing its average in the past 12 months. Then, the volatility of trading volume ( $Vol_{Volume}$) is defined as the volatility of the normalized trading volume residual in the past 12 months.

The volatility of earnings is based on the earnings in the trailing twelve months ($Earnings_{TTM}$). $Earnings_{TTM}$ is defined the sum of the earnings in the most recent four quarterly fiscal periods. The fiscal data is matched with return data by the announcement date, so there is no looking forward bias. Because of the magnitude effect noted before, we first normalize $Earnings_{TTM}$ by its moving average in the past 24 months. The volatility of earnings ($Vol_{Earnings}$) is defined as the volatility of the normalized earnings in the past 24 months.

We also construct a comprehensive volatility proxy ($Vol_{Index}$) to aggregate the above three proxies. First, we normalize each of these three proxies by subtracting its cross-sectional mean, and then dividing by its cross-sectional standard deviation. $Vol_{Index}$ is then defined as the equal-weighted average of these three normalized volatility proxies.

After constructing the proxies for volatility, we use the sequentially double sorting procedure to examine the relationship between the trend effect and the volatility. At the end of each month, stocks are first sorted by the volatility proxy into three tertiles: $Vol_{Low}$, $Vol_{Mid}$ and $Vol_{High}$. In each volatility group, we define the trend factor as the return spread between the two extreme quintile portfolios sorted by $ER_{Trend}$. $\Delta(Trend)$ is defined as the difference of the trend factor between the $Vol_{High}$ and $Vol_{Low}$ group.

Table 12 shows the result of the relationship between the trend effect and volatility in VW portfolios.[5] First, the trend factor earns significantly higher return in the $Vol_{High}$ group than in the $Vol_{Low}$ group. For example, for $Vol_{Rt}$, the trend spread increases from 0.79% in the $Vol_{Low}$ group to 1.54% in the $Vol_{High}$ group. And the difference ($\Delta(Trend)$) is 0.75% with a $t$-statistic of 2.35. The results are similar for $Vol_{Volume}$ and $Vol_{Earnings}$, indicating that the trend factor predictability increases with both the noise trader demand volatility and the fundamental variable volatility, which is consistent with the model prediction in Table 11. Second, the above results become stronger for the simple average of these three volatility proxies. For example, the $\Delta(Trend)$ of $Vol_{Index}$ is 1.27%, which is higher than that of $Vol_{Rt}$ (0.75%), $Vol_{Volume}$ (0.90%) and $Vol_{Earings}$ (0.58%). In conclusion, Table 12 confirms our model prediction that the trend predictability increases with the volatility of noise trader demand and the fundamental economic uncertainty.

### *5.3. Trend effect and individual investor participation*

In the previous sections, we have shown the predictability of our trend measure increases with volatilites. Intuitively, the great participation of the individual investors, the greater the volatilies. This is especially true in China since the major market participants are individual investors. So it is important to examine whether the trend effect increases with individual investors participation.

Different to other developed markets, the Chinese stock market is dominated by individual investors, who are more likely to be driven by sentiment. According to Shanghai Stock Exchange Statistics Annual 2018, at the end of 2017, over 194 million individuals had trading accounts, taking up more than 99% of the whole trading accounts in A-shares in Shanghai stock exchange, and the individual investors contribute about 82% of the trading volume. Individuals also held about 77% shareholdings average across stocks during 2005 to 2018 in Chinese A-Shares stock market. Hence, we use the shareholding ratio of individual investors, which is defined as one minus the shareholding ratio of institutional investors, to proxy for individual participation. The data is from WIND database.

Table 13 reports the results for the trend effect with different individual investor participation in a sequential double sorting procedure. Consistent with our prediction, the trend effect increases with the individual investor participation in both VW and EW portfolios. For example, the VW

[5] The results with EW portfolios are similar and are provided in an online appendix.

trend spread portfolio earns a significant higher return in $Indiv_{High}$ group (1.95%) than in $Indiv_{Low}$ group (1.14%).

### *5.4. The role of volume trend*

In this subsection, we explore the role of volume trend by investigating whether volume trend can predict future returns beyond price trend and examining its performance in different information environments.

The role of trading volume has been examined by a number of studies (see, e.g., Campbell, Grossman and Wang, 1993, Gallant, Rossi and Tauchen, 1992, Wang, 1994, and Lee and Swaminathan, 2000). Theoretically, Blume, Easley, O'Hara (1994) show that in a model in which investors receive signals that are informative of the asset fundamentals, volume can provide information about the signal precision that cannot be deduced from the price. They also show that information quality and information quantity affect the volume-price movement in equilibrium: higher precision reduces the predictability of volume on the price movement; and the volume-price movement relationship disappears as the proportion of the traders with high-precision increases. Their work proposes two testable implications on our volume trend: can volume trend provide any predictability beyond the price trend? And does the predictability of volume trend decrease with information quality or information quantity?

The link between price and volume is complex. To separate out the predictive information of volume trend from that of price trend, we construct an orthogonal volume trend measure ($ER^{\perp}_{TrendV}$) defined as the residuals of the cross-section regression in which the volume trend measure ($ER_{TrendV}$) is regressed on the price trend measure ($ER_{TrendP}$). This orthogonal volume trend measure is uncorrelated with the price trend by construction, thus can be used to examine the predictive information beyond price trend.

We use the volatility of earnings ($Vol_{Earnings}$) defined in previous subsection to proxy for the precision of the information about assets fundamental. Evidently, the higher the volatility of earnings, the lower the information precision. Since institutional investors have advantages over individual investors in acquiring and analyzing information, it is reasonable to use the participation of the institutional investors, defined as the shareholding ratio of the institutional investors, to proxy for the information quantity. Obviously, the greater the institutional investors' participation, the greater the information quantity.

Table 14 shows the average monthly return for the VW volume trend portfolios with different information settings.[6] The predictability of volume trend decreases with the information quality and information quantity. For example, the last column $\Delta Trend$ shows that the volume trend factor in the low information quality (quantity) group earns an average monthly return which is 0.92% (0.47%) higher than that in the high information quality (quantity) group, consistent with the theoretical prediction of Blume, Easley, and O'Hara (1994).

The portfolios sorted by the orthogonal volume trend measure $ER^{\perp}_{TrendV}$ retain the monotonic return pattern, indicating that volume trend provides predictability beyond price trend. In addition, the return pattern of the orthogonal volume trend with different information quality (quantity) is similar to that of volume trend. The detailed results is provided in an online appendix.

## 6. The US evidence

The original trend factor proposed in the US stock market in Han, Zhou and Zhu (2016) captures only price trend, while our modified trend factor captures both price and volume trends. An interesting question is whether our modified trend factor can bring any economic gains in the US. In this section, we explore the performance of trend factors in the US.

### *6.1. Trend factors in the US*

We construct our modified trend factor (TrendPV), the original trend factor of price (TrendP), and the trend factor of trading volume (TrendV) in the US stock market. Our modified TrendPV factor earns the highest average monthly return of 1.51% and the highest Sharpe ratio of 0.34. The return increment between TrendPV and TrendP is 0.15% per month ($t$-statistic: 2.37), indicating that volume can provide incremental predictive information independent to price. The detailed results are provided in an online appendix.

[6]The results with EW portfolios are similar and are provided in an online appendix.

### 6.2. *Comparing volume trend in China and the US*

In the previous subsection, we present evidence that volume trend can provide predictive information beyond price trend in both China and the US. Given the heterogeneous individual investor's participation in China and the US, it is important to compare the relative contribution of volume trend in the two markets.

To this end, we conduct Sharpe (1988) style analysis to examine the contribution of TrendV and TrendP to TrendPV. It turns out that in China, volume trend and price trend seems to be equally important, accounting for 42% and 58% of the overall trend, respectively. However, in the US, the performance of TrendPV is mainly attributed to TrendP, while TrendV contributes only 6%, which is consistent with the explanation that the Chinese stock market is dominated by the individual investors, who contribute 80% of the trading volume. Hence, this result emphasizes again the importance and unique role that volume trend plays in China. The detailed results are provided in an oline appendix.

### 6.3. *Alphas in the US*

In the previous section, we show that existing factor models cannot explain our trend factor in China. Here, we ask a similar question, whether the trend factors can be explained by the factor models in the US. We explore several well-known factor models, including CAPM, Fama and French (1993) 3-factor model (FF-3), Stambaugh and Yuan (2016) 4-factor model (SY-4), and Fama and French (2015) 5-factor model (FF-5). In addition, we also compare the original trend factor and our modified trend factor by comparing their ability to explain each other.

Our results show that TrendP and TrendPV earn significant alphas with respect to CAPM, FF-3, SY-4 and FF-5, indicating that exiting factor models cannot explain the return on trend factors in the US. Moreover, TrendP is explained by TrendPV, producing a monthly alpha of only 0.01% ($t$-statistic: 0.11). In contrast, TrendPV earns a significant monthly alpha of 0.21% ($t$-statistic: 3.20) with respect to CAPM with TrendP, indicating that our modified trend factor substantially outperforms the original one in the US. The detailed results are provided in an online appendix.

We also investigate the explaining power of the analogue of our 4-four factor model, i.e., the trend factor along with the market, size and value factor in FF-3, to explain 11 anomalies in

Stambaugh and Yuan (2016) in the US. While our 4-factor model explains all reported anomalies in China, its analogue fails to explain the anomalies in the US, which may reflect the unique influence of the great individual investors participation in China. The detailed results are provided in an online appendix.

# 7. Robustness

In this section, we show that the superior performance of our trend factor is robust. We first use alternative methods to forecast the coefficients of MA signals. We then explore the issue of transaction costs.

### *7.1. Alternative constructions*

In this subsection, we use two different methods to forecast the coefficient of MA signals as robustness check. In the method of exponential moving average (EMA), at the end of each month, we use the exponential average of all the past coefficients prior to that month to forecast the coefficient in the next month, which is given by Equation (7), $E_t(\beta_j^{t+1}) = (1-\lambda)E_{t-1}(\beta_j^t) + \lambda\beta_j^t$. The parameter ($\lambda$) determines the weight of the coefficients over different horizons. The smaller the $\lambda$, the less the forecast relies on the latest coefficient. In the method of simple moving average (SMA), we simply use the equal-weighted average of coefficients in the last $M$ months as the estimation for coefficients in the next month.

We use various parameters, including those used in Han, Zhou, and Zhu (2016) to examine the alternative constructions. Specifically, we set $\lambda$ to 0.01, 0.03 and 0.05 in EMA, and set $M$ to 12, 24, and 36 in SMA. Under the two methods with various parameters, our trend factor earns persistent significant returns and alphas with respect to CAPM, LSY-3 and LSY-4 factor model. The results are comparable among different construction methods and are provided in an online appendix.

### *7.2. Transaction costs*

In this subsection, we investigate the issue of transaction costs. First, we calculate the turnover rate for our trend factor. Then, following Grundy and Martin (2001), and Barroso and Santa-

Clara(2015), we compute four different types of the break-even transaction costs (BETCs). The first two are the transaction costs that that would completely offset the return or the CAPM risk-adjusted returns. The second two are the costs that make the returns or the risk-adjusted returns insignificant at 5% level. We also calculate the results for the turnover factor for comparison.

Table 15 reports the transaction results for our trend factor (Trend) and the turnover factor (PMO). The turnover rate of our trend factor is 121.96%, and is slightly higher than that of PMO (105.43%). Since our trend factor exploits information over various investment horizons, it is not surprising to that it has higher turnover rates than the PMO to make use of the information. However, in terms of BETCs, our trend factor substantially outperforms PMO. It takes on average 1.35% of transaction costs to offset the return of Trend, while it takes only 0.76% to do the same for PMO. The results are similar for other BETCs. For example, it takes a transaction cost of 0.99% to make the CAPM alpha of our trend factor insignificant. In contrast, it takes only 0.33% to do the same for PMO. Furthermore, we also explore at what level of transaction costs the excess turnover would offset the performance gains of our trend factor relative to the turnover factor. Panel C shows that it takes 5.06% of the transaction costs to offset the return difference and 1.35% to make the return difference insignificant at 5% level. Overall, our trend factor again dominates the turnover factor in terms of the transaction costs.

## 8. Conclusion

In this paper, we propose a 4-factor model for the Chinese stock market, which adds one additional trend factor to Liu, Stambaugh, and Yuan's (2019) 3-factor model. While Liu, Stambaugh, and Yuan's model improves substantially over the replication of Fama-French (1993) 3-factor model in China, ours improves further the performance. Our trend factor exploits both price and volume information of various investment horizons, motivated to account for the about 80% participation of individual investors in stock trading in China.

Our empirical results show that our 4-factor model substantially outperforms existing factor models in terms of explaining power. Our model can explain the factors in other models, including LSY-3, LSY-4, q-4 and FF-5. Moreover, it explains all reported stock anomalies in China including those failed to be captured by LSY-3 and LSY-4, such as turnover, reversal, illiquidity and idiosyncratic volatility and so on. It also explains the mutual fund portfolios sorted by asset under management, serving as Carhart (1997) 4-factor model in China.

The superior performance of trend factor is robust to different constructions and to various firm and market characteristics, including size, market beta, book-to-market equity, earnings-to-price ratio, past returns, idiosyncratic volatility, illiquidity and turnover. Our trend factor also performs remarkably well in the US stock market. However, the contribution of volume trend to the overall trend is economically and statistically significantly higher in China than the US, which emphasizes the important role of volume in China and is consistent with the heterogeneous retail investor trading intensities in these two markets. We provide also a theoretical explanation for the trend factor. Volume trend provides predictability beyond price trend. Our model shows that the usefulness of trading volume is due to the fact that the trading volume driven by noise traders demand is very high in China as compared with other countries like the US.

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**Table 1**

Summary statistics

This table reports the summary statistics for the trend factor (*Trend*), and the LSY-3 factors, including the market factor (*MKT*), the size factor (*SMB*) and the value factor (*VMG*), and the turnover factor (*PMO*). Panel A reports the sample mean, Newey-West (1987) adjusted $t$-statistics, sample standard deviation, Sharpe ratio, skewness and maximum drawdown (MDD) for each factor. Panel B reports the correlation matrix of the factors. The sample period is from January 2005 through July 2018.

| | Trend | MKT | SMB | VMG | PMO |
|---|---|---|---|---|---|
| *Panel A: Summary statistics* | | | | | |
| Mean (%) | 1.43*** | 0.91 | 0.97** | 1.15*** | 0.78*** |
| | (6.10) | (1.20) | (2.37) | (4.11) | (3.12) |
| Std dev (%) | 3.00 | 8.30 | 5.05 | 4.06 | 3.67 |
| Sharpe ratio | 0.48 | 0.11 | 0.19 | 0.28 | 0.21 |
| Skewness | 0.33 | -0.38 | -0.12 | 0.32 | -0.94 |
| MDD (%) | 13.17 | 69.33 | 25.94 | 19.65 | 25.15 |
| *Panel B: Correlation matrix* | | | | | |
| Trend | 1.00 | -0.12 | 0.12 | 0.04 | 0.52 |
| MKT | -0.12 | 1.00 | 0.10 | -0.24 | -0.30 |
| SMB | 0.12 | 0.10 | 1.00 | -0.66 | 0.10 |
| VMG | 0.04 | -0.24 | -0.66 | 1.00 | -0.05 |
| PMO | 0.52 | -0.30 | 0.10 | -0.05 | 1.00 |

**Table 2**

Comparison of PMO and Trend in sub-samples

This table reports the average monthly VW returns for the turnover factor (PMO) and our trend factor (Trend) in sub-samples constructed in 2×3×3 triple independent sortings. At the end of each month, stocks are independently sorted into two *Size* group (Small and Big), three *EP* groups ( *EP*-Low, Mid and *EP*-High) and three *Trend* groups ( *Trend*-Low, Mid and *Trend*-High), by the 30th and 70th percentiles of the EP and $ER_{Trend}$, respectively. As a result, there are 18 (2×3×3) *Size-EP-Trend* portfolios, and 6 (2×3) *Size-EP* sub-samples for $ER_{Trend}$. In a given *Size-EP* sub-sample, the trend factor is defined as the VW return of the *Trend*-High portfolio minus that of the *Trend*-Low portfolio. *Size-EP-AbTurn* portfolios, *Size-Trend-AbTurn* portfolios and the resulting Trend and PMO factors in these sub-samples are produced in the similar way. The Newey-West (1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | PMO | | | Trend | | |
|---|---|---|---|---|---|---|
| *Panel A: Controlling for EP and Size* | | | | | | |
| Size: | Small | Big | Average | Small | Big | Average |
| EP-Low | 1.56*** | 0.51 | 1.04*** | 2.22*** | 1.35*** | 1.78*** |
| | (5.74) | (1.10) | (2.92) | (8.61) | (2.93) | (6.09) |
| Mid | 1.31*** | 0.40 | 0.85** | 1.73*** | 1.14*** | 1.44*** |
| | (3.92) | (0.88) | (2.41) | (6.30) | (3.35) | (5.53) |
| EP-High | 1.23*** | -0.07 | 0.58* | 1.31*** | 0.82* | 1.07*** |
| | (2.99) | (-0.17) | (1.89) | (4.27) | (1.94) | (3.54) |
| Average | 1.37*** | 0.28 | 0.82*** | 1.76*** | 1.10*** | 1.43*** |
| | (4.51) | (0.83) | (2.82) | (7.51) | (3.45) | (6.10) |
| *Panel B: Controlling for $ER_{Trend}$ and Size* | | | | | | |
| Size: | Small | Big | Average | Small | Big | Average |
| Trend-Low | 0.71** | 0.35 | 0.53 | | | |
| | (2.17) | (0.73) | (1.60) | | | |
| Mid | 0.64** | -0.94** | -0.15 | | | |
| | (2.05) | (-2.00) | (-0.47) | | | |
| Trend-High | 1.29*** | -0.25 | 0.52 | | | |
| | (3.15) | (-0.49) | (1.47) | | | |
| Average | 0.88*** | -0.28 | 0.30 | | | |
| | (2.98) | (-0.79) | (1.07) | | | |
| *Panel C: Controlling for AbTurn and Size* | | | | | | |
| Size: | Small | Big | Average | Small | Big | Average |
| AbTurn-Low | | | | 1.89*** | 0.96** | 1.42*** |
| | | | | (4.70) | (2.35) | (4.09) |
| Mid | | | | 1.16*** | 0.51 | 0.83*** |
| | | | | (4.75) | (1.13) | (3.25) |
| AbTurn-High | | | | 1.31*** | 1.55*** | 1.43*** |
| | | | | (4.17) | (2.85) | (4.50) |
| Average | | | | 1.45*** | 1.01*** | 1.23*** |
| | | | | (5.78) | (3.00) | (5.13) |

**Table 3**

Mean-variance spanning tests

This table reports the result of testing whether the trend factor can be spanned by the LSY-3 factors or the LSY-4 factors. $W$ is the Wald test under conditional homoskedasticity, $W_e$ is the Wald test under the IID elliptical, $W_a$ is the Wald test under the conditional heteroskedasticity, $J_1$ is the Bekaert-Urias test with the Errors-in-Variables (EIV) adjustment, $J_2$ is the Bekaert-Urias test without the EIV adjustment, and $J3$ is the DeSantis test. All six tests have an asymptotic chi-squared distribution with $2N(N = 1)$ degrees of freedom. The $p$-values are in brackets. The sample period is from January 2005 through July 2018.

| Model | $W$ | $W_e$ | $W_a$ | $J_1$ | $J_2$ | $J_3$ |
|---|---|---|---|---|---|---|
| LSY-3 | 34.12 | 28.31 | 32.15 | 21.38 | 18.38 | 19.69 |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |
| LSY-4 | 11.78 | 9.60 | 15.14 | 14.13 | 14.36 | 12.93 |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

**Table 4**

Model performance in explaining factors in other models

This table reports the pairwise comparison of the model performance in explaining factors in other models. We calculate the alphas of factors (except the market factor) in a given factor model with respect to another benchmark model. We report the average absolute monthly alpha (%), the average absolute $t$-statistics, the aggregate pricing error $\Delta = \alpha' \Sigma^{-1} \alpha$, and the Gibbons, Ross, and Shaken (1898) "GRS" $F$-statistics with associated $p$-values in the brackets. Panel A, Panel B, Panel C and Panel D reports the result for LSY-3, LSY-4, q-4 and FF-5 in comparison with our-4 factor model, respectively. The sample period is from January 2005 through July 2018.

| | *Panel A: LSY-3 VS Our-4* | | *Panel B: LSY-4 VS Our-4* | |
|---|---|---|---|---|
| Meausre | LSY-3 | Our-4 | LSY-4 | Our-4 |
| Average $\lvert\alpha\rvert$ | 0.49 | 0.05 | 0.40 | 0.11 |
| Average $\lvert t\rvert$ | 2.63 | 0.50 | 2.65 | 0.54 |
| $\Delta$ | 0.214 | 0.003 | 0.161 | 0.010 |
| GRS | 8.11*** | 0.16 | 5.82*** | 0.32 |
| | [ $<10^{-4}$] | [0.85] | [$<10^{-3}$] | [0.81] |
| | *Panel C: q-4 VS Our-4* | | *Panel D: FF-5 VS Our-4* | |
| Meausre | q-4 | Our-4 | FF-5 | Our-4 |
| Average $\lvert\alpha\rvert$ | 0.80 | 0.11 | 0.58 | 0.12 |
| Average $\lvert t\rvert$ | 3.86 | 0.67 | 3.03 | 0.30 |
| $\Delta$ | 0.393 | 0.039 | 0.221 | 0.028 |
| GRS | 16.55*** | 1.28 | 8.17*** | 0.67 |
| | [$<10^{-8}$] | [0.28] | [$<10^{-4}$] | [0.61] |

**Table 5**

Model performance in explaining anomalies

This table compares the pricing ability of different factor models, including Liu, Stambaugh, and Yuan (2019) 3-factor (LSY-3) and 4-factor (LSY-4), Hou, Xue, and Zhang (2015) q-factor (q-4), Fama and French (2015) 5-factor (FF-5), and our 4-factor model, in explaining anomalies. Also reported are results for "unadjusted" return spread (i.e., for a model with no factors). For each model, the table reports the average absolute monthly alpha (%), the average absolute $t$-statistics, the aggregate pricing error $\Delta = \alpha' \Sigma^{-1} \alpha$, and the Gibbons, Ross, and Shaken (1898) "GRS" $F$-statistics with associated $p$-values in the brackets. The sample period is from January 2005 through July 2018.

| Measure | Unadjusted | LSY-3 | LSY-4 | q-4 | FF-5 | Our-4 |
|---|---|---|---|---|---|---|
| Average $\|\alpha\|$ | 1.33 | 0.85 | 0.52 | 1.48 | 0.73 | 0.32 |
| Average $\|t\|$ | 2.72 | 2.01 | 1.25 | 2.98 | 1.77 | 0.68 |
| $\Delta$ | 0.527 | 0.296 | 0.256 | 0.479 | 0.257 | 0.140 |
| GRS | 5.60*** | 2.24*** | 1.84** | 4.01*** | 1.89** | 0.91 |
| | [0.00] | [0.00] | [0.03] | [0.00] | [0.03] | [0.55] |

**Table 6**

Model performance in explaining mutual funds

This table compares the pricing ability of different factor models, including Liu, Stambaugh, and Yuan (2019) 3-factor (LSY-3) and 4-factor (LSY-4), Hou, Xue, and Zhang (2015) q-factor (q-4), Fama and French (2015) 5-factor (FF-5), and our 4-factor model, in explaining mutual funds portfolios. Also reported are results for "unadjusted" return spread (i.e., for a model with no factors). For each model, the table reports the average absolute monthly alpha (%), the average absolute $t$-statistics, the aggregate pricing error $\Delta = \alpha'\Sigma^{-1}\alpha$, and the Gibbons, Ross, and Shaken (1898) "GRS" $F$-statistics with associated $p$-values in the brackets. The sample period is from January 2005 through July 2018.

| Measure | Unadjusted | LSY-3 | LSY-4 | q-4 | FF-5 | Our-4 |
|---|---|---|---|---|---|---|
| Average $\|\alpha\|$ | 1.47 | 0.35 | 0.30 | 0.48 | 0.55 | 0.26 |
| Average $\|t\|$ | 1.81 | 1.38 | 1.05 | 1.02 | 1.22 | 0.88 |
| $\Delta$ | 0.109 | 0.045 | 0.034 | 0.040 | 0.052 | 0.025 |
| GRS | 1.67* | 0.49 | 0.35 | 0.48 | 0.55 | 0.24 |
| | [0.09] | [0.89] | [0.96] | [0.89] | [0.85] | [0.99] |

**Table 7**

Sharpe ratio tests

This table reports the results of the Sharpe ratio tests for the factor models in China, including Liu, Stambaugh, and Yuan (2019) 3-factor (LSY-3) and 4-factor (LSY-4), Hou, Xue, and Zhang (2015) q-factor (q-4), Fama and French (2015) 5-factor (FF-5), and our 4-factor model. Following Barillas and Shanken (2017), Panel A reports the squared monthly Sharpe ratios ($Sh^2$) for these models. Panel B reports the $Sh^2$ difference between the model in the corresponding column and the model in the corresponding row. Following Ledoit and Wolf (2008), we construct a studentized time-series bootstrap to examine whether the $Sh^2$ difference is statistically significant. The bootstrap $p$-value for the null hypothesis that the difference is zero is reported in brackets. The number of bootstrap repetitions is 4999. Panel A and Panel B report the results where we exclude the smallest 30% stocks to form the factors. Panel C and Panel D report the results for all stocks. Statistics are calculated over January 2005 and July 2018.

| | LSY-3 | LSY-4 | q-4 | FF-5 | Our-4 |
|---|---|---|---|---|---|
| *Panel A: All but the smallest 30% stocks, $Sh^2$* | | | | | |
| $Sh^2$ | 0.387 | 0.446 | 0.240 | 0.404 | 0.598 |
| *Panel B: All but the smallest 30% stocks, $Sh^2$ difference* | | | | | |
| LSY-3 | | 0.059 | -0.147* | 0.017 | 0.211** |
| | | [0.320] | [0.054] | [0.849] | [0.035] |
| LSY-4 | -0.059 | | -0.206*** | -0.042 | 0.152** |
| | [0.320] | | [0.004] | [0.611] | [0.047] |
| q-4 | 0.147* | 0.206*** | | 0.164* | 0.358*** |
| | [0.054] | [0.004] | | [0.062] | [0.000] |
| FF-5 | -0.017 | 0.042 | -0.164* | | 0.194** |
| | [0.849] | [0.611] | [0.062] | | [0.038] |
| Our-4 | -0.211** | -0.152** | -0.358*** | -0.194** | |
| | [0.035] | [0.047] | [0.000] | [0.038] | |
| *Panel C: All stocks, $Sh^2$* | | | | | |
| $Sh^2$ | 0.470 | 0.499 | 0.362 | 0.448 | 0.714 |
| *Panel D: All stocks, $Sh^2$ difference* | | | | | |
| LSY-3 | | 0.029 | -0.108 | -0.022 | 0.244*** |
| | | [0.634] | [0.280] | [0.834] | [0.007] |
| LSY-4 | -0.029 | | -0.137 | -0.051 | 0.215** |
| | [0.634] | | [0.240] | [0.621] | [0.022] |
| q-4 | 0.108 | 0.137 | | 0.086 | 0.352*** |
| | [0.280] | [0.240] | | [0.382] | [0.003] |
| FF-5 | 0.022 | 0.051 | -0.086 | | 0.266** |
| | [0.834] | [0.621] | [0.382] | | [0.018] |
| Our-4 | -0.244*** | -0.215** | -0.352*** | -0.266** | |
| | [0.007] | [0.022] | [0.003] | [0.018] | |

**Table 8**

Fama-MacBeth regressions

This table reports the average slope coefficients from month-by-month Fama-MacBeth regressions. At the end of each month, stocks are sorted into three terciles by the characteristics. For stocks in the bottom group, the label of the related characteristics is -1; for stocks in the medium group, the label of the related characteristics is 0; for stocks in the top group, the label of the related characteristics is 1. Then, individual stock returns are regressed cross-sectionally on the characteristic labels in the previous month, including the trend measure ($ER_{Trend}$), the market beta ($\beta$), the market capitalization (Size), the earnings-to-price ratio (EP), and the abnormal turnover (AbTurn). The regression is a modified cross-section regression with market-value-weighted least squares (VWLS) in the first step. The Newey-West (1987) adjusted $t$-statistics are reported in parentheses, and the $p$-values are reported in brackets. The sample period is from January 2005 through July 2018.

| | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| Intercept | Coeff | 0.015* | 0.015* | 0.015* | 0.015* |
| | $t$-stat | (1.721) | (1.712) | (1.723) | (1.715) |
| | $p$-value | [0.087] | [0.089] | [0.087] | [0.088] |
| $ER_{Trend}$ | Coeff | | 0.005*** | | 0.005*** |
| | $t$-stat | | (3.301) | | (3.350) |
| | $p$-value | | [0.001] | | [0.001] |
| $\beta$ | Coeff | -0.001 | -0.001 | -0.001 | -0.001 |
| | $t$-stat | (-0.237) | (-0.225) | (-0.175) | (-0.217) |
| | $p$-value | [0.813] | [0.822] | [0.861] | [0.828] |
| Size | Coeff | -0.006** | -0.005** | -0.005** | -0.005** |
| | $t$-stat | (-2.382) | (-2.255) | (-2.299) | (-2.193) |
| | $p$-value | [0.018] | [0.026] | [0.023] | [0.029] |
| EP | Coeff | 0.005*** | 0.004** | 0.005*** | 0.004*** |
| | $t$-stat | (2.633) | (2.410) | (2.872) | (2.618) |
| | $p$-value | [0.009] | [0.017] | [0.005] | [0.009] |
| AbTurn | Coeff | | | -0.002 | -0.001 |
| | $t$-stat | | | (-1.467) | (-0.999) |
| | $p$-value | | | [0.144] | [0.319] |

**Table 9**

Average return and other characteristics of the trend quintile portfolios

This table reports the EW and VW average monthly return and other characteristics of the quintile portfolios sorted by the trend measure ($ER_{Trend}$). $R_{EW}$ (%) is the EW average monthly return. $R_{VW}$ (%) is the VW average monthly return. Size is the market capitalization and is in ten-thousand of RMB. BM is the book-to-market ratio. $R_{-1}$ (%), $R_{-6,-2}$ (%) and $R_{-12,-2}$ (%) are the prior month return, the past six-month cumulative return skipping the last month, and the past twelve-month cumulative return skipping the last month, respectively. IVOL (%) is the idiosyncratic volatility relative to the Fama-French three factor model estimated from daily returns in the last month. ILLIQ is the average of daily illiquidity, which is defined as the ratio of the absolute daily return to its daily RMB trading volume, in that month. The RMB trading volume is in thousand of RMB and ILLIQ is rescaled by timing one million. Turn (%) is the monthly turnover. PC, PE, and PS are the price-to-cash ratio, price-to-earnings ratio and price-to-sales ratio, respectively. The sample period is from January 2005 through July 2018.

| Rank | $R_{EW}$ | $R_{VW}$ | Size | BM | $R_{-1}$ | $R_{-6,-2}$ | $R_{-12,-2}$ | IVOL | ILLIQ | Turn | PC | PE | PS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 0.56 | 0.44 | 1820105 | 0.37 | 8.49 | 20.28 | 38.9 | 2.44 | 0.17 | 61.08 | 22.62 | 53.75 | 5.98 |
| 2 | 1.41 | 1.14 | 1727557 | 0.39 | 3.4 | 16.04 | 36.76 | 1.97 | 0.18 | 49.05 | 20.43 | 49.87 | 5.34 |
| 3 | 1.75 | 1.38 | 1732769 | 0.42 | 1.21 | 13.16 | 33.6 | 1.76 | 0.19 | 43.76 | 19.19 | 45.97 | 4.99 |
| 4 | 2.15 | 1.65 | 1636636 | 0.44 | -0.10 | 10.78 | 30.63 | 1.62 | 0.20 | 40.01 | 18.46 | 44.49 | 4.84 |
| High | 2.30 | 1.86 | 1733243 | 0.44 | -1.19 | 8.19 | 28.85 | 1.50 | 0.22 | 35.72 | 16.44 | 41.78 | 4.84 |

**Table 10**

Performance after controlling for firm characteristics

This table reports the VW average monthly return of the double sorting portfolios after controlling for various firm characteristics. First, we sort stocks by one of the control variables into five quintile groups, and then in each quintile, stocks are sorted into five groups by the trend measure return ($ER_{Trend}$). As a result, there are 25 (5 × 5) portfolios. Finally, we average the portfolios across the five quintile portfolios of the control variable to get a new trend quintile portfolio, all of which should have similar levels of the control variable. Panel A reports the results of the 5 × 5 quintile portfolios and the five new trend quintile portfolios after controlling for the market size. In Panel B, we report the results of only the new trend quintile portfolios after controlling for one of the firm characteristics. Newey-West (1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| Control:Size | *Panel A: Control For Market Size* | | | | | |
| Small | 0.88 | 2.00** | 2.42** | 2.63*** | 3.27*** | 2.39*** |
| | (0.88) | (2.11) | (2.60) | (2.71) | (3.35) | (6.41) |
| 2 | 0.54 | 1.57 | 1.98** | 2.46** | 2.67*** | 2.13*** |
| | (0.59) | (1.55) | (2.13) | (2.49) | (2.80) | (6.37) |
| 3 | 0.67 | 1.28 | 1.63* | 2.08** | 2.17** | 1.51*** |
| | (0.70) | (1.41) | (1.71) | (2.13) | (2.38) | (5.39) |
| 4 | 0.39 | 1.40 | 1.55* | 1.95** | 1.95** | 1.56*** |
| | (0.44) | (1.47) | (1.70) | (2.16) | (2.30) | (4.78) |
| Big | 0.42 | 0.93 | 1.34 | 1.46* | 1.62* | 1.20*** |
| | (0.49) | (1.06) | (1.61) | (1.90) | (1.90) | (2.64) |
| Average Over Size | 0.58 | 1.44 | 1.78** | 2.12** | 2.33*** | 1.76*** |
| | (0.65) | (1.58) | (2.03) | (2.38) | (2.67) | (6.59) |
| | *Panel B: Control For Other Variables* | | | | | |
| Average Over EP | 0.46 | 1.06 | 1.27 | 1.71** | 1.78** | 1.31*** |
| | (0.55) | (1.22) | (1.50) | (2.03) | (2.11) | (4.17) |
| Average Over BM | 0.69 | 1.15 | 1.30 | 1.68** | 1.87** | 1.18*** |
| | (0.84) | (1.33) | (1.54) | (2.00) | (2.20) | (3.49) |
| Average Over $R_{-1}$ | 0.71 | 1.28 | 1.55* | 1.85** | 1.94** | 1.20*** |
| | (0.86) | (1.41) | (1.83) | (2.12) | (2.24) | (3.46) |
| Average Over $R_{-6,-2}$ | 0.55 | 1.24 | 1.44* | 1.66* | 2.03** | 1.51*** |
| | (0.63) | (1.44) | (1.69) | (1.96) | (2.41) | (4.10) |
| Average Over $R_{-12,-2}$ | 0.33 | 1.17 | 1.32 | 1.71** | 1.96** | 1.62*** |
| | (0.39) | (1.33) | (1.54) | (2.10) | (2.33) | (4.69) |
| Average Over IVOL | 0.47 | 1.20 | 1.45* | 1.78** | 1.86** | 1.38*** |
| | (0.57) | (1.34) | (1.69) | (2.10) | (2.19) | (3.60) |
| Average Over ILLIQ | 0.87 | 1.53* | 1.69* | 1.93** | 1.95** | 1.07*** |
| | (1.03) | (1.74) | (1.97) | (2.28) | (2.38) | (3.41) |
| Average Over Turn | 0.64 | 1.12 | 1.46 | 1.53* | 1.74* | 1.09*** |
| | (0.75) | (1.24) | (1.64) | (1.71) | (1.93) | (2.98) |

**Table 11**

Price trend predictability v.s. volatility

This table presents the model implied trend predictability for various $\sigma_\theta$ and $\sigma_D$, the noise trader demand volatility and the fundamental variable volatility. The model implies that the stock return predictability equation is

$$R_{t+1} = \gamma_0 + \gamma_3\xi_0 + \gamma_1 D_t + \gamma_2\pi_t + \gamma_3\xi_1 Y_t + \gamma_4 A_t + \gamma_5 A_{Dt} + \sigma'_P\epsilon'_P,$$

where $Y_t$ and $A_t$ are volume trend and price trend, and $\gamma_3$ and $\gamma_4$ are their predictive coefficients, respectively. The model parameters are $r = 0.05, \rho = 0.2, \bar{\pi} = 0.85, \sigma_D = 1.0, \sigma_\pi = 0.6, \sigma_\theta = 3.0, \alpha_\theta = 0.4, \alpha_D = 1.0, \alpha = 1, \alpha_2 = 1, \sigma_u = 1, w = 0.9$.

| *Panel A:* $\gamma_3$ | | | | | | | |
|---|---|---|---|---|---|---|---|
| $\sigma_D\backslash\sigma_\theta$ | 1.0 | 1.5 | 2.0 | 2.5 | 3.0 | 3.5 | 4.0 |
| 0.50 | 0.10 | 0.10 | 0.11 | 0.11 | 0.11 | 0.12 | 0.12 |
| 0.75 | 0.13 | 0.13 | 0.14 | 0.14 | 0.15 | 0.15 | 0.16 |
| 1.00 | 0.17 | 0.18 | 0.18 | 0.19 | 0.20 | 0.21 | 0.22 |
| 1.25 | 0.23 | 0.23 | 0.24 | 0.25 | 0.26 | 0.29 | 0.32 |
| 1.50 | 0.29 | 0.30 | 0.31 | 0.33 | 0.36 | 0.40 | 0.47 |
| *Panel B:* $\gamma_4$ | | | | | | | |
| $\sigma_D\backslash\sigma_\theta$ | 1.0 | 1.5 | 2.0 | 2.5 | 3.0 | 3.5 | 4.0 |
| 0.50 | 0.76 | 0.77 | 0.78 | 0.79 | 0.81 | 0.82 | 0.84 |
| 0.75 | 0.84 | 0.84 | 0.85 | 0.86 | 0.87 | 0.89 | 0.90 |
| 1.00 | 0.89 | 0.90 | 0.90 | 0.91 | 0.92 | 0.93 | 0.94 |
| 1.25 | 0.92 | 0.93 | 0.93 | 0.94 | 0.94 | 0.95 | 0.96 |
| 1.50 | 0.94 | 0.95 | 0.95 | 0.95 | 0.96 | 0.96 | 0.97 |

**Table 12**

Trend and volatility

This table reports the VW average monthly return of the trend quintile portfolios in different volatility groups. Stocks are first sorted by the volatility proxy into three groups: $Vol_{Low}$, $Vol_{Mid}$ and $Vol_{High}$. Then, in each group, stocks are sorted by the $ER_{Trend}$ into five quintile portfolios, and the trend spread is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend spread in $Vol_{High}$ and $Vol_{Low}$ group. We use four measures to proxy for volatility. $Vol_{Rt}$ is the volatility of stock return, $Vol_{Volume}$ is the volatility of trading volume, and $Vol_{Earnings}$ is the volatility of earnings. $Vol_{Index}$ is the equal-weighted average of the above three normalized volatility proxies. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A:* $Vol_{Rt}$ | | | | | | | |
| $Vol_{Low}$ | 1.26 | 1.28 | 1.92** | 2.00** | 2.05** | 0.79** | 0.75** |
| | (1.45) | (1.50) | (2.19) | (2.31) | (2.27) | (2.05) | (2.35) |
| $Vol_{Mid}$ | 0.83 | 1.26 | 1.63* | 1.75* | 1.92** | 1.08*** | |
| | (0.95) | (1.39) | (1.82) | (1.89) | (2.14) | (2.96) | |
| $Vol_{High}$ | 0.30 | 0.96 | 1.33 | 1.61* | 1.84* | 1.54*** | |
| | (0.33) | (1.02) | (1.39) | (1.69) | (1.91) | (3.96) | |
| *Panel B:* $Vol_{Volume}$ | | | | | | | |
| $Vol_{Low}$ | 0.98 | 1.24 | 1.70* | 1.88** | 1.80* | 0.81** | 0.90** |
| | (1.09) | (1.39) | (1.88) | (2.04) | (1.96) | (2.44) | (2.51) |
| $Vol_{Mid}$ | 0.80 | 1.20 | 1.82** | 2.11** | 1.92** | 1.12*** | |
| | (0.89) | (1.32) | (2.05) | (2.27) | (2.11) | (2.92) | |
| $Vol_{High}$ | 0.30 | 1.01 | 1.38 | 1.77* | 2.01** | 1.71*** | |
| | (0.34) | (1.11) | (1.57) | (1.92) | (2.22) | (4.04) | |
| *Panel C:* $Vol_{Earnings}$ | | | | | | | |
| $Vol_{Low}$ | 0.92 | 1.43* | 1.73** | 2.04** | 2.00** | 1.08** | 0.58** |
| | (1.16) | (1.68) | (2.08) | (2.49) | (2.48) | (2.57) | (2.43) |
| $Vol_{Mid}$ | 0.83 | 1.08 | 1.63* | 1.86** | 1.94** | 1.11*** | |
| | (0.88) | (1.18) | (1.82) | (1.99) | (2.01) | (2.80) | |
| $Vol_{High}$ | 0.31 | 0.91 | 1.60 | 1.60 | 1.97** | 1.66*** | |
| | (0.33) | (0.93) | (1.62) | (1.59) | (2.04) | (5.13) | |
| *Panel D:* $Vol_{Index}$ | | | | | | | |
| $Vol_{Low}$ | 1.26 | 1.30 | 1.77** | 2.12** | 1.82** | 0.56 | 1.27*** |
| | (1.51) | (1.51) | (2.03) | (2.45) | (2.14) | (1.56) | (4.22) |
| $Vol_{Mid}$ | 0.70 | 1.35 | 1.65* | 1.97** | 2.04** | 1.34*** | |
| | (0.78) | (1.41) | (1.84) | (2.13) | (2.24) | (3.65) | |
| $Vol_{High}$ | 0.13 | 0.81 | 1.22 | 1.52 | 1.97** | 1.84*** | |
| | (0.14) | (0.84) | (1.31) | (1.57) | (2.03) | (4.63) | |

**Table 13**

Trend and individual investor participation

This table reports the VW and EW average monthly return of the trend quintile portfolios in stock groups with different individual investor participation. Stocks are first sorted by the shareholding ratio of individual investors into three groups, $Indiv_{Low}$, $Indiv_{Mid}$ and $Indiv_{High}$. Then, in each group, stocks are sorted by the $ER_{Trend}$ into five quintile portfolios, and the trend spread is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend spread in $Indiv_{High}$ and $Indiv_{Low}$ group. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A: Value-weighted* | | | | | | | |
| $Indiv_{Low}$ | 1.09 | 1.63* | 1.75** | 2.10*** | 2.23*** | 1.14** | 0.81* |
| | (1.37) | (1.83) | (2.02) | (2.67) | (2.69) | (2.52) | (1.77) |
| $Indiv_{Mid}$ | 0.44 | 0.93 | 1.22 | 1.73** | 1.85* | 1.42*** | |
| | (0.52) | (1.04) | (1.56) | (1.98) | (1.96) | (3.19) | |
| $Indiv_{High}$ | -0.78 | 0.35 | 0.98 | 0.94 | 1.17 | 1.95*** | |
| | (-0.86) | (0.38) | (1.07) | (0.95) | (1.24) | (4.13) | |
| *Panel B: Equal-weighted* | | | | | | | |
| $Indiv_{Low}$ | 1.72* | 2.23** | 2.31*** | 2.92*** | 2.92*** | 1.20*** | 0.94*** |
| | (1.97) | (2.42) | (2.63) | (3.27) | (3.31) | (3.69) | (3.03) |
| $Indiv_{Mid}$ | 0.77 | 1.22 | 1.68* | 2.10** | 2.35** | 1.58*** | |
| | (0.84) | (1.32) | (1.88) | (2.25) | (2.43) | (4.99) | |
| $Indiv_{High}$ | -0.47 | 0.56 | 1.22 | 1.41 | 1.66* | 2.13*** | |
| | (-0.52) | (0.60) | (1.30) | (1.42) | (1.73) | (7.11) | |

**Table 14**

Volume trend, information quality and information quantity

This table reports the VW average monthly return of the volume trend quintile portfolios in stock groups with different information quality and information quantity. The volume trend quintile portfolios are formed on $ER_{TrendV}$. The information quality is measured by the volatility of the normalized earnings. The information quantity is measured by the shareholding ratios of the institutional investors. Stocks are first sorted by the information quality or information quantity into three groups, Low Quality (Quantity) , Mid Quality (Quantity) and High Quality (Quantity). Then, in each group, stocks are sorted by the $ER^{\perp}_{TrendV}$ into five quintile portfolios, and the trend spread is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend spread in Low Quality (Quantity) and High Quality (Quantity) group. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A: Information quality* | | | | | | | |
| Low | 0.81 | 1.46 | 1.33 | 1.73* | 2.28** | 1.47*** | -0.92** |
| | (0.83) | (1.44) | (1.33) | (1.79) | (2.37) | (4.75) | (-2.61) |
| Mid | 0.96 | 1.49 | 1.68* | 1.71* | 2.02** | 1.06*** | |
| | (1.04) | (1.57) | (1.82) | (1.91) | (2.14) | (3.35) | |
| High | 1.41* | 1.54* | 1.71** | 1.91** | 1.96** | 0.56 | |
| | (1.67) | (1.92) | (2.05) | (2.26) | (2.30) | (1.52) | |
| *Panel B: Information quantity* | | | | | | | |
| Low | -0.03 | 0.83 | 0.72 | 1.21 | 1.47 | 1.50*** | -0.47* |
| | (-0.04) | (0.84) | (0.74) | (1.29) | (1.59) | (4.06) | (-1.67) |
| Mid | 0.85 | 1.40 | 1.52* | 1.66* | 2.14** | 1.29*** | |
| | (0.95) | (1.53) | (1.67) | (1.86) | (2.23) | (4.26) | |
| High | 1.93** | 2.10** | 2.36*** | 2.67*** | 2.96*** | 1.03*** | |
| | (2.17) | (2.48) | (2.65) | (3.06) | (3.23) | (3.27) | |

**Table 15**

Transaction costs

This table reports the turnover rate and the corresponding break-even transaction costs (BETCs) of the trend factor ($Trend$) and the turnover factor ($PMO$). *Zero return:* BETCs that would completely offset the returns or the risk-adjusted returns (CAPM alpha); *5% Insignificant*: BETCs that make the returns or the risk-adjusted returns insignificant at the 5% level. Panel A and B reports the results for the trend factor and the PMO factor, respectively. Panel C reports the excess turnover rate of the trend factor relative to the PMO factor and the BETCs to offset the extra returns (risk-adjusted returns) of the trend factor relative to the PMO factor. The sample period is from January 2005 through July 2018.

| | Turnover(%) | Break-even costs(%) | |
|---|---|---|---|
| | Mean | Zero return | 5% Insignificant |
| *Panel A: Trend factor* | | | |
| Return | 121.96 | 1.35 | 0.93 |
| CAPM Alpha | 121.96 | 1.39 | 0.99 |
| *Panel B: PMO factor* | | | |
| Return | 105.43 | 0.76 | 0.14 |
| CAPM Alpha | 105.43 | 0.94 | 0.39 |
| *Panel C: Trend - PMO* | | | |
| Return | 16.53 | 5.06 | 1.35 |
| CAPM Alpha | 16.53 | 4.32 | 0.91 |

# Online Appendix

This appendix provides supplementary results in the paper. Section A.1 provides the factor summary statistics, in which we use all stocks including the smallest 30% to construct factors. Section A.2 discusses the replication of Hou, Xue, and Zhang (2015) q-factor model (q-4) and Fama and French (2015) 5-factor model (FF-5) in China. Section A.3 provides the detailed results for the portfolios constructed in triple sorting procedures. Section A.4 constructs orthogonal volume trend independent of price trend. Section A.5 presents results for EW trend portfolios in various perspectives. Section A.6 examines the trend factor under alternative construction. Section A.7 investigates the trend factor in the US. Section A.8 compares the moving average (MA) signals and the return signals.

### *A.1. Factors using all stocks*

In this section, we construct factors using all stocks without excluding the smallest 30%. Table A1 presents the associated summary statistics for our trend factor (Trend), factors in LSY-3, i.e., the market factor (MKT), the size factor (SMB), and the value factor (VMG), and the turnover factor (PMO) in LSY-4.

SMB earns the largest average month return of 1.68%, indicating that the size effect is more stronger among small stocks. Trend generates the second largest average month return of 1.64% per month, while that for VMG is 1.05% and for PMO is 0.89%. Besides, Trend produces the highest Sharpe ratio of 0.54, while the highest Sharpe ratio of LSY-3 factors is only 0.31 (SMB). Moreover, Trend earns the lowest maximum drawdown (MDD) at only 9.41%, versus the MDD of SMB (22.47%), VMG (23.04%) and PMO (32.63%).

### *A.2. Replication of q-4 and FF-5 in China*

We replicate q-4 and FF-5 in China. We report the results for factors constructed in two universes. The first one covers the biggest 70% stocks but not the smallest 30% stocks, while the second one covers all stock including the smallest 30% stocks. The market factor (MKT) in q-4 and FF-5 is the return on the VW portfolio of all stocks in the universe, in excess of the one-year deposit interest rate.

Following Hou, Xue, and Zhang (2015), we construct the q-factors, including SMB, ROE, and I/A, from a triple $2 \times 3 \times 3$ sorting procedure on size, ROE, and asset growth. Size of a stock is the market capitalization of all its outstanding A shares, including non-tradable shares. ROE is the ratio of the net profit excluding gains/losses to the total share holder equity from the most recently reported quarterly statement. Asset growth is defines as the total assets in the most recent annual report divided by the total assets in the previous annual report. Specifically, the asset growth is updated annually, and the asset growth in the end of June in year $t$ is defined as the total assets in the financial report in fiscal year ending in calendar year $t$-1 divided by the total assets in the financial report in fiscal year ending in calendar year $t$-2.

At the end of each month, we independently we sort stocks into 2 size groups by the median of the market capitalization, 3 ROE groups by the 30th and 70th percentiles of ROE, and 3 I/A groups by the 30th and 70th percentiles of asset growth. As a result, the intersections of those groups produce 18 portfolios. The size factor (SMB) is defined as the simple average of the VW returns of the 9 small size portfolios minus that of the 9 big size portfolios. The ROE factor (ROE) is defined as the simple average of the VW returns of the 6 high ROE portfolios minus that of the 6 low ROE portfolios. The investment factor (I/A) is defined as the simple average of the VW returns of the 6 low asset growth portfolios minus that of the 6 high asset growth portfolios.

Following Fama and French (2015), we construct the FF-5 factors, including SMB, HML, RMW and CMA, from independent $2 \times 3$ sorting procedures on size, book-to-market ratio, ROE, and asset growth. Size, ROE, and asset growth is defined in the same way as in q-4. Book-to-market ratio (BM) is the ratio of the total share holder equity from the most recently reported quarterly statement to the market capitalization in the end of last month.

At the end of each month, we independently sort stocks into two size groups by the median of the size, and three value groups by the 30th and 70th percentiles of BM. The size factor ($SMB_{BM}$) is defined as the simple average of the VW returns of the 3 small size portfolios minus that of the 3 big size portfolios. The value factor (HML) is defined as the simple average of the VW returns of the 2 high BM portfolios minus that of the 2 low BM portfolios. The profitability factor (RMW) and investment factor (CMA) are constructed in the same way as HML, except that the second sort is on either ROE or asset growth. The procedures used to construct RMW and CMA produce two additional size factors, $SMB_{ROE}$ and $SMB_{Inv}$. The size factor (SMB) in FF-5 is defined as the average of $SMB_{BM}$, $SMB_{ROE}$, and $SMB_{Inv}$.

Table A2 reports the summary statistics for the q-4 factors. Although the investment factor (I/A) works well in the US, it seems to be useless in China. Specifically, I/A produces an average monthly return of only 0.13% ($t$-statistic: 1.06) in the largest 70% stocks, and 0.12% ($t$-statistic: 1.13) in all stocks. Besides, the ROE factor earns an average monthly return of 0.65% ($t$-statistic: 3.00) in the largest 70% stocks, and 0.43% ($t$-statistic: 2.16) in all stocks.

Table A3 shows the summary statistics for the FF-5 factors. Similar to the performance of I/A in q-4, the investment factor (CMA) in FF-5 also performs poorly in China, producing a slightly negative average return of -0.15% in the largest 70% stocks, and -0.08% in all stocks.

### *A.3. Triple sorting portfolios*

Here we report the detailed results for the portfolios in sub-samples by constructing 2×3×3 triple sorting procedures on size, EP, AbTurn, and $ER_{Trend}$. At the end of each month, stocks are independently sorted into two size groups by the median of size, three EP groups by the 30th and 70th percentiles of EP, and three trend groups by the 30th and 70th percentiles $ER_{Trend}$, respectively. As a result, there are 18 *Size-EP-Trend* sub-samples. *Size-EP-AbTurn* sub-samples and *Size-Trend-AbTurn* sub-samples are constructed in the same way.

Table A4 shows the VW average monthly returns for portfolios formed in the above independent sorting procedure. In Panel A, after controlling for size and EP, the returns of portfolios increase with $ER_{Trend}$ with no exception. Similarly, after controlling for size and AbTurn in Panel C, the portfolios sorted by $ER_{Trend}$ still show a great monotonic return pattern with no exception. On the contrary, the portfolios sorted by AbTurn, the exposure to PMO, shows a non-monotonic return pattern in large stocks. For example, in the *BigSize-MidEP* group in Panel B, the return increases from 1.00% in the *LowAbTurn* portfolio to 1.28% in the *MidAbTurn* portfolio and then drops to 0.60% in the *HighAbTurn* portfolio. Worse still, in the *BigSize-Mid*$ER_{Trend}$ group in Panel C, after controlling for size and $ER_{Trend}$, the returns of portfolios increase with AbTurn, which is contradict to the motivation of PMO, that the turnover captures the investor sentiment, so the low-turnover stocks, about which investors are relatively pessimistic, will have higher return.

Overall, our trend measure works well after controlling for factor variables in LSY-3 and LSY-4. On the contrary, the turnover factor captures investor sentiment only in small stocks but not in large stocks.

### *A.4. Orthogonal volume trend*

In this section, we investigate whether volume trend can provide additional predictability independent of price trend. The link between price and volume is complex. To separate out the predictability of volume trend from that of price trend, we construct an orthogonal volume trend measure ($ER^{\perp}_{TrendV}$) defined as the residuals of the cross-section regression in which volume trend measure ($ER_{TrendV}$) is regressed on price trend measure ($ER_{TrendP}$). This orthogonal volume trend measure is uncorrelated with the price trend by construction, thus can be used to examine the predictive information beyond price trend.

Table A5 reports the VW quintile portfolios sorted by $ER^{\perp}_{TrendV}$ with different information quality and information quantity. We use the volatility of earnings ($Vol_{Earnings}$) and the shareholding ratios of institutional investors to measure information quality and information quantity, respectively. Evidently, the portfolio return increases with $ER^{\perp}_{TrendV}$, and produces positive return spread in each information quality and quantity group, indicating that volume trend can provide independent predictability beyond price trend. Besides, the return on the spread portfolio deceases with information quality and information quantity, which is consistent with the theoretical prediction of Blume, Easley, and O'Hara (1994) that the predictability of volume signal decreases with information quality and information quantity.

### *A.5. Results for EW portfolios*

In this section, we report the results for EW trend portfolios in various perspective. The results are similar and comparable to those in VW portfolios.

Table A6 shows the performance of EW trend portfolios after controlling various firm characteristics in a sequentially double sorting procedure. After controlling for these variables, the returns of the quintile portfolios sorted by $ER_{Trend}$ preserve the monotonic pattern, and the spread portfolios in all controlled groups still earn significant monthly returns of 1.73%, 1.63%, 1.53%, 1.55%, 1.75%, 1.73%, 1.56%, 1.27%, 1.17% after controlling for Size, EP, BM, $R_{-1}$, $R_{-6,-2}$, $R_{-12,-2}$, IVol, illiquidity and turnover, respectively.

Table A7 examines the trend effect with different volatility in EW portfolios. The trend effect increases in the volatility of return ($Vol_{Rt}$), volatility of trading volume ($Vol_{Volume}$), volatility of earnings ($Vol_{Earnings}$), and the volatility index ($Vol_{Index}$). Specifically, the last column ($\Delta Trend$) shows that the difference of the trend factor between the low volatility and high volatility group is 0.67%, 0.87%, 0.66%, and 1.15% for $Vol_{Rt}$, $Vol_{Volume}$, $Vol_{Earnings}$, and $Vol_{Index}$, respectively.

Table A8 reports the performance of volume trend with different information quality and information quantity in EW portfolios. We use the volatility of earnings ($Vol_{Earnings}$) and the ratio of the shareholding ratio of institutional investors to proxy for information quality and information quantity, respectively. The results show that volume trend decreases with information quality as well as information quantity. The difference of the volume trend factor between the low and high information quality (quantity) group is 0.51% (0.58%).

Table A9 reports the EW quintile portfolios sorted by $ER^{\perp}_{TrendV}$ with different information quality and information quantity. The results are similar to those in Table A5 with VW portfolios. First, the $ER^{\perp}_{TrendV}$ portfolios show an increasing return pattern and generate significant positive spread returns in each information quality and quantity group. Second, the trend effect decreases with information quality and quantity.

### *A.6. Alternative constructions*

In this section, we use two different methods to forecast the coefficient of MA signals to check the robustness of our trend measure. In the method of exponential moving average (EMA), at the end of each month, we use the exponential average of all the past coefficients prior to that month to forecast the coefficient in the next month, which is given by $E_t(\beta_j^{t+1}) = (1-\lambda)E_{t-1}(\beta_j^t)+\lambda\beta_j^t$. In the method of simple moving average (SMA), we simply use the equal-weighted average of coefficients in the last $M$ months as the estimation for coefficients in the next month.

We use various parameters, including those used in Han, Zhou, and Zhu (2016) to examine the alternative constructions. Table A10 shows that our trend factor generates persistent and comparable performance under alternative coefficient forecasts. Specifically, in EMA with $\lambda$ being

0.01, 0.03, and 0.05, our trend factor earns an average return of 1.31%, 1.36%, and 1.20% per month, respectively. In SMA with $M$ being 12, 24, and 36, our trend factor earns an average return of 0.91%, 1.10%, and 1.16% per month, respectively. Besides, it also earns significant alphas with respect to CAPM, LSY-3, and LSY-4 factor model.

### *A.7. Detailed evidence in the US*

In this section, we provide detailed results of our modified trend factor in the US. We first present the summary statistics of the trend factors. Then, we compares the role of trend volume in China and the US by conducting Sharpe (1988) style regressions. Last, we examine whether existing factor models can explain the performance of our trend factor in the US.

#### *A.7.1. Summary statistics in the US*

Since there are more stocks and longer sample period in the US, following Han, Zhou, and Zhu (2016), we use MAs of lag lengths 3-, 5-, 10-, 20-, 50-, 100-, 200-, 400-, 600-, 800-, and 1000- days to construct the trend measures. We construct three trend factors, including our modified trend factor of price and volume (TrendPV), the trend factor of price (TrendP), and the trend factor of volume (TrendV). The trend factor is the return spread between the extreme VW quintile portfolios sorted by the associated trend measures.

Table A11 reports the summary statistics for the three trend factors in the US. First, our modified TrendPV factor earns the highest average monthly return of 1.51%, while the TrendP earns 1.36%. The increment is 0.15% per monthly with a $t$-statistic of 2.37, indicating that volume can provide incremental predictive information independent to price, which is consistent with results in China and the theoretical implication of Blume, Easley and O'Hara (1994). TrendV also produces a significant return, but in a smaller magnitude (0.35%) compared with TrendPV and TrendP.

#### *A.7.2. Sharpe style regressions*

In the previous section, we show that volume trend can provide predictability beyond price trend in both China and US. In this section, we ask two questions: what is the relative contribution of volume trend and price trend to the overall trend in China and the US? And is there any difference between the two markets?

The stock markets in China and the US have essentially different information environment. It is reasonable to propose that information quality and information quantity in the US stock market is higher than that in the Chinese stock market. This is because that first, the US stock market is dominated by institutional investors while the Chinese stock market is dominated by individual investors. Institutional investors have advantage over individual investors in acquiring and analyzing information, which improves information precision. Second, the US stock market has a much longer history than the Chinese stock market does. As a result, investors in the US are more experienced in processing information. Third, the US stock market is more open. Although the Chinese stock market is becoming increasingly open to international investors, there are still some regulations for foreign investors. On the contrary, the global investor can access the US stock market easily, flourishing the information set in the US stock market.

In the previous section, we have shown the predictability of volume trend decreases with information quality and information quantity. Given the great difference of the information environment between China and the US noted above, it is natural to hypothesize that the contribution of volume trend to the overall trend should be greater in China than in the US. To this end, we conduct Sharpe (1988) style analysis to examine the contribution of volume trend to the overall trend in China and the US.

Sharp (1988) style regression is commonly used in fund performance analysis to identify the contribution of different style portfolios to a given fund. In our cases, we regress the trend factor of price and volume (TrendPV) on the trend factor of price (TrendP) and trend factor of volume (TrendV), with the constraints that the coefficient is non-negative and the sum of the coefficients is one. Hence, the style regression examines the contribution of the volume trend and the price trend on the overall trend.

Table A12 shows the results of style regressions in China and the US.[7] In China, volume trend and price trend seem to be equally important, accounting for 42% and 58% of the overall trend, respectively. However, in the US, the economic importance of price trend is substantially higher than volume trend. Specifically, price trend contributes 94% to the overall trend, while volume trend contributes only 6%. In addition, the *p*-value indicates that the contribution difference of

[7] If the trend factors were constructed controlling for size and EP, the results are similar.

volume trend between China and the US is statistically significant. The results are consistent with the explanation that the Chinese stock market is dominated by individual investors, who contribute 80% of the trading volume. Hence, the results emphasize again the importance of volume trend in China.

### *A.7.3. Alphas in the US*

The previous section shows that the existing factor models can not explain our trend factor in China. Here, we answer a similar question that whether the trend factors can be explained by factor models in the US. We explore several well-known factor models, including CAPM, Fama and French (1993) 3-factor model (FF-3), Stambaugh and Yuan (2016) 4-factor model (SY-4), and Fama and French (2015) 5-factor model (FF-5).[8]

As shown in Table A13, TrendPV earns significant alphas of 1.46%, 1.43%, 1.27%, and 1.45%, with respect to CAPM, FF-3, SY-4, and FF-5, respectively. Similarly, TrendP generates significant alphas of 1.32%, 1.31%, 1.17%, and 1.32%, with respect to CAPM, FF-3, SY-4, and FF-5, respectively, indicating that the factor models cannot explain neither TrendPV nor TrendP. In addition, we also compare TrendPV and TrendP by regressing one on the market factor with the other one. The results show TrendP is explained by TrendPV, producing a monthly alpha of only 0.01% ($t$-statistic: 0.10). In contrast, TrendPV earns a significant monthly alpha of 0.21% ($t$-statistic: 3.20) with respect to CAPM with TrendP. Overall, exiting factor models cannot explain the return on the trend factors, and our modified trend factor substantially outperforms the original one in the US.

In Table Table A14, we also investigate the explaining power of analogue of our 4-four factor model, i.e., the trend factor along with the market, size and value factor in FF-3, to explain 11 anomalies in Stambaugh and Yuan (2016) in the US. While our 4-factor model explains all the anomalies in China, its analogue fails to explains the anomalies in the US, which may reflect the unique influence of the great individual investors participation in China.

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[8]The factor data of FF-3 and FF-5 is from the Kenneth R. French Data Library. The factor data of SY-4 is from Robert F. Stambaugh's website.

### A.8. MA signals VS return signals

In this section, we compare the return signals and moving average (MA) signals. To do so, we form an additional $MOM_{All}$ factor that is constructed in the same way as the trend factor of price (TrendP), except that TrendP is based on the MA price signals, while $MOM_{All}$ is based on the return signals over the same horizons as those of MA prices signals in TrendP.

Table A15 reports the performance of two MA-based factors, i.e., our trend factor of price and volume (TrendPV), and the trend factor of price (TrendP), in comparison with a return-based factor ($MOM_{All}$). Panel A shows the summary statistics of these factors. TrendPV earns the highest average return of 1.43% and the highest Sharpe ratio of 0.48, while $MOM_{All}$ produces the lowest average return of 0.99% and the lowest Sharpe ratio of 0.27.

Panel B shows the alphas of these factors under different benchmark models. TrendPV and TrendP earns significant alpha of 0.82% and 0.63% with respect to LSY-4, respectively. However, $MOM_{All}$ is explained by LSY-4, producing a insignificant alpha of 0.39 ($t$-statistic: 1.29). Furthermore, we investigate their pricing ability to explain each other. Based on TrendP and $MOM_{All}$, we form two associated 4-factor models, denoted as TrendP-4 and $MOM_{All}$-4, respectively, which are constructed in the same way as our 4-factor model. TrendPV is not explained by neither TrendP-4 nor $MOM_{All}$-4. TrendP is captured by our 4-factor model, but not by $MOM_{All}$-4. In contrast, $MOM_{All}$ is explained by both our 4-factor model and TrendP-4. Overall, the factor of MA signals substantially outperforms that of return signals in terms of Sharpe ratio and explaining power.

**Table A1**

Summary statistics for the trend factor and LSY factors: formed on all stocks

This table reports the summary statistics for the trend factor (*Trend*), and the LSY-3 factors, including the market factor (*MKT*), the size factor (*SMB*) and the value factor (*VMG*), and the turnover factor (*PMO*). The factors are formed using all stocks including the smallest 30%. For each factor, we report the sample mean, Newey-West (1987) adjusted $t$-statistics, sample standard deviation, Sharpe ratio, skewness and maximum drawdown (MDD). The sample period is from January 2005 through July 2018.

| | Trend | MKT | SMB | VMG | PMO |
|---|---|---|---|---|---|
| Mean (%) | 1.64*** | 0.93 | 1.68*** | 1.05*** | 0.89** |
| | (6.89) | (1.08) | (3.86) | (4.45) | (2.59) |
| Std. dev (%) | 3.02 | 8.32 | 5.37 | 3.62 | 4.29 |
| Sharpe ratio | 0.54 | 0.11 | 0.31 | 0.29 | 0.21 |
| Skewness | 0.57 | -0.30 | 0.19 | 0.33 | 0.30 |
| MDD (%) | 9.41 | 70.60 | 22.47 | 23.04 | 32.63 |

**Table A2**

Summary statistics for q-4 factors

This table reports the summary statistics for Hou, Xue, and Zhang (2015) q-4 factors, including the the market factor ($MKT$), the size factor ($SMB$), the profitability factor ($ROE$), and the investment factor ($I/A$). Panel A reports the result in which we exclude the smallest 30% stocks to construct factors. Panel B reports the result in which the factors are formed using all stocks. For each factor, we report the sample mean, Newey-West (1987) adjusted $t$-statistics, sample standard deviation, Sharpe ratio, skewness and maximum drawdown (MDD). The sample period is from January 2005 through July 2018.

| | MKT | SMB | ROE | I/A |
|---|---|---|---|---|
| *Panel A: All stocks but the smallest 30%* | | | | |
| Mean (%) | 0.91 | 0.84** | 0.65*** | 0.13 |
| | (1.06) | (2.43) | (3.00) | (1.06) |
| Std. dev (%) | 8.30 | 4.53 | 3.50 | 1.96 |
| Sharpe Ratio | 0.11 | 0.19 | 0.18 | 0.07 |
| Skewness | -0.38 | -0.36 | -0.22 | -0.25 |
| MDD (%) | 69.33 | 27.39 | 28.65 | 14.35 |
| *Panel B: All stocks* | | | | |
| Mean (%) | 0.93 | 1.34*** | 0.43** | 0.12 |
| | (1.08) | (3.41) | (2.16) | (1.13) |
| Std. dev (%) | 8.32 | 4.81 | 3.24 | 1.76 |
| Sharpe Ratio | 0.11 | 0.28 | 0.13 | 0.07 |
| Skewness | -0.30 | -0.27 | -0.06 | -0.43 |
| MDD (%) | 70.60 | 26.77 | 24.81 | 11.68 |

**Table A3**

Summary statistics for FF-5 factors

This table reports the summary statistics for Fama and French (2015) 5-factors , including the the market factor ($MKT$), the size factor ($SMB$), the value factor ($HML$) the profitability factor ($RMW$), and the investment factor ($CMA$). Panel A reports the result in which in which we exclude the smallest 30% stocks to construct factors. Panel B reports the result in which the factors are formed using all stocks. For each factor, we report the sample mean, Newey-West (1987) adjusted $t$-statistics, sample standard deviation, Sharpe ratio, skewness and maximum drawdown (MDD). The sample period is from January 2005 through July 2018.

| | MKT | SMB | HML | RMW | CMA |
|---|---|---|---|---|---|
| *Panel A: All stocks but the smallest 30%* | | | | | |
| Mean (%) | 0.91 | 0.74* | 0.85*** | 0.68*** | -0.15 |
| | (1.06) | (1.87) | (2.62) | (2.86) | (-0.93) |
| Std. dev (%) | 8.30 | 5.51 | 4.38 | 3.79 | 2.33 |
| Sharpe ratio | 0.11 | 0.13 | 0.19 | 0.18 | -0.06 |
| Skewness | -0.38 | -0.32 | 0.40 | -0.09 | -0.22 |
| MDD (%) | 69.33 | 33.33 | 20.40 | 32.03 | 31.82 |
| *Panel B: All stocks* | | | | | |
| Mean (%) | 0.93 | 1.29*** | 0.87*** | 0.45** | -0.08 |
| | (1.08) | (2.88) | (2.83) | (2.07) | (-0.60) |
| Std. dev (%) | 8.32 | 5.81 | 3.96 | 3.60 | 2.20 |
| Sharpe ratio | 0.11 | 0.22 | 0.22 | 0.13 | -0.04 |
| Skewness | -0.30 | -0.27 | 0.53 | 0.07 | -0.13 |
| MDD (%) | 70.60 | 31.78 | 16.13 | 29.77 | 22.69 |

**Table A4**

Average returns of triple sorting portfolios

This table reports the VW average monthly percent returns for the portfolios formed in a 2×3×3 triple independent sorting by *Size* and other two characteristics among *EP*, $ER_{Trend}$ and *AbTurn*. At the end of each month, stocks are independently sorted into two *Size* group (Small and Big), three *EP* groups (Low *EP*, Mid and High *EP*) and three *Trend* groups (Low $ER_{Trend}$, Mid and High $ER_{Trend}$), by the 30th and 70th percentiles of the EP and $ER_{Trend}$, respectively. As a result, there are 18 (2×3×3) *Size-EP-*$ER_{Trend}$ portfolios. *Size-EP-AbTurn* portfolios and *Size-*$ER_{Trend}$*-AbTurn* portfolios are produced in the same way. This tale reports the average monthly VW percent returns of these portfolios. The sample period is from January 2005 through July 2018.

| | Small | | | Big | | |
|---|---|---|---|---|---|---|
| *Panel A: Sorted by Size, EP and* $ER_{Trend}$ | | | | | | |
| EP: | Low | Mid | High | Low | Mid | High |
| Low $ER_{Trend}$ | 0.12 | 0.82 | 1.94 | -0.36 | 0.42 | 1.16 |
| Mid | 1.27 | 2.08 | 2.69 | 0.45 | 1.22 | 1.52 |
| High $ER_{Trend}$ | 2.34 | 2.55 | 3.26 | 0.99 | 1.56 | 1.98 |
| *Panel B: Sorted by Size, EP and AbTurn* | | | | | | |
| AbTurn: | Low | Mid | High | Low | Mid | High |
| Low EP | 1.88 | 1.60 | 0.31 | 0.34 | 0.69 | -0.16 |
| Mid | 2.32 | 1.85 | 1.01 | 1.00 | 1.28 | 0.60 |
| High EP | 3.45 | 2.59 | 2.22 | 1.55 | 1.44 | 1.62 |
| *Panel C: Sorted by Size,* $ER_{Trend}$ *and AbTurn* | | | | | | |
| AbTurn: | Low | Mid | High | Low | Mid | High |
| Low $ER_{Trend}$ | 1.14 | 1.24 | 0.43 | 0.77 | 1.15 | 0.43 |
| Mid | 2.15 | 2.11 | 1.51 | 0.81 | 1.35 | 1.76 |
| High $ER_{Trend}$ | 3.03 | 2.40 | 1.74 | 1.73 | 1.66 | 1.98 |

**Table A5**

Orthogonal volume trend, information quality and information quantity

This table reports the VW average monthly return of the orthogonal volume trend quintile portfolios in stock groups with different information quality and information quantity. The orthogonal volume trend quintile portfolio is formed on $ER^{\perp}_{TrendV}$, which is defined as the average of the residuals regressing $ER_{Trend}$ on $ER_{TrendP}$ and the residuals regressing $ER_{TrendV}$ on $ER_{TrendP}$ cross-sectionally. The information quality is measured by the volatility of the normalized earnings. The information quantity is measured by the shareholding ratios of the institutional investors. Stocks are first sorted by the information quality or information quantity into three groups, Low Quality (Quantity) , Mid Quality (Quantity) and High Quality (Quantity). Then, in each group, stocks are sorted by the $ER^{\perp}_{TrendV}$ into five quintile portfolios, and the trend spread is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend spread in Low Quality (Quantity) and High Quality (Quantity) group. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A: Information quality* | | | | | | | |
| Low | 1.32 | 1.37 | 1.34 | 1.41 | 2.13** | 0.81** | -0.55 |
| | (1.34) | (1.35) | (1.32) | (1.48) | (2.14) | (2.39) | (-1.58) |
| Mid | 1.26 | 1.49 | 1.52 | 1.62* | 1.93** | 0.67** | |
| | (1.36) | (1.53) | (1.64) | (1.75) | (2.13) | (2.53) | |
| High | 1.61* | 1.78** | 1.48* | 1.81** | 1.87** | 0.26 | |
| | (1.96) | (2.18) | (1.78) | (2.18) | (2.26) | (0.78) | |
| *Panel B: Information quantity* | | | | | | | |
| Low | 0.41 | 1.05 | 0.71 | 0.92 | 1.39 | 0.98** | -0.29 |
| | (0.42) | (1.07) | (0.72) | (1.00) | (1.52) | (2.57) | (-1.03) |
| Mid | 1.26 | 1.45 | 1.36 | 1.56* | 1.95** | 0.69*** | |
| | (1.36) | (1.57) | (1.50) | (1.77) | (2.08) | (2.71) | |
| High | 2.14** | 2.34*** | 2.24** | 2.40*** | 2.83*** | 0.69** | |
| | (2.44) | (2.66) | (2.55) | (2.64) | (3.27) | (2.28) | |

**Table A6**

Performance after controlling firm characteristics: EW portfolios

This table reports the EW average monthly return of the double sorting portfolios after controlling for various firm characteristics. First, we sort stocks by one of the control variables into five quintile groups, and then in each quintile, stocks are sorted into five groups by the trend-expected return ($ER_{Trend}$). As a result, there are 25 (5 $\times$ 5) portfolios. Finally, we average the portfolios across the five quintile portfolios of the control variable to get a new trend quintile portfolio, all of which should have similar levels of the control variable. Panel A reports the results of the 5 $\times$ 5 quintile portfolios and the five new trend quintile portfolios after controlling for the market size. In Panel B, we report the results of only the new trend quintile portfolios after controlling for one of the firm characteristics. Newey-West (1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | TrendLow | Trend2 | Trend3 | Trend4 | TrendHigh | High-Low |
|---|---|---|---|---|---|---|
| Control:Size | *Panel A: Control For Market Size* | | | | | |
| Small | 0.91 | 2.00** | 2.41** | 2.64*** | 3.31*** | 2.40*** |
| | (0.91) | (2.12) | (2.60) | (2.71) | (3.37) | (6.26) |
| 2 | 0.55 | 1.58 | 1.97** | 2.46** | 2.68*** | 2.13*** |
| | (0.60) | (1.56) | (2.13) | (2.49) | (2.81) | (6.42) |
| 3 | 0.66 | 1.26 | 1.63* | 2.07** | 2.18** | 1.52*** |
| | (0.70) | (1.38) | (1.71) | (2.13) | (2.38) | (5.40) |
| 4 | 0.42 | 1.42 | 1.56* | 1.98** | 1.95** | 1.53*** |
| | (0.47) | (1.49) | (1.72) | (2.19) | (2.30) | (4.82) |
| Big | 0.57 | 1.11 | 1.52* | 1.62* | 1.62* | 1.05*** |
| | (0.63) | (1.22) | (1.76) | (1.94) | (1.86) | (3.00) |
| Average Over Size | 0.62 | 1.47 | 1.82** | 2.16** | 2.35*** | 1.73*** |
| | (0.68) | (1.59) | (2.02) | (2.35) | (2.63) | (6.66) |
| | *Panel B: Control For Other Variables* | | | | | |
| Average Over EP | 0.71 | 1.43 | 1.69* | 2.14** | 2.33*** | 1.63*** |
| | (0.80) | (1.56) | (1.85) | (2.32) | (2.64) | (6.45) |
| Average Over BM | 0.76 | 1.40 | 1.71* | 2.01** | 2.27** | 1.53*** |
| | (0.85) | (1.55) | (1.88) | (2.21) | (2.55) | (6.73) |
| Average Over $R_{-1}$ | 0.71 | 1.42 | 1.80** | 2.08** | 2.25** | 1.55*** |
| | (0.78) | (1.54) | (2.01) | (2.23) | (2.49) | (6.33) |
| Average Over $R_{-6,-2}$ | 0.59 | 1.40 | 1.70* | 2.12** | 2.34*** | 1.75*** |
| | (0.65) | (1.53) | (1.89) | (2.31) | (2.61) | (6.62) |
| Average Over $R_{-12,-2}$ | 0.56 | 1.42 | 1.72* | 2.14** | 2.29** | 1.73*** |
| | (0.62) | (1.56) | (1.89) | (2.34) | (2.57) | (6.80) |
| Average Over IVOL | 0.68 | 1.45 | 1.66* | 2.20** | 2.25** | 1.56*** |
| | (0.76) | (1.57) | (1.81) | (2.39) | (2.51) | (5.84) |
| Average Over ILLIQ | 0.83 | 1.58* | 1.82** | 2.07** | 2.09** | 1.27*** |
| | (0.92) | (1.72) | (2.01) | (2.27) | (2.39) | (5.34) |
| Average Over Turn | 0.90 | 1.39 | 1.74* | 1.93** | 2.08** | 1.17*** |
| | (1.02) | (1.54) | (1.90) | (2.08) | (2.26) | (4.41) |

**Table A7**

Trend and volatility: EW portfolios

This table reports the EW average monthly return of the trend quintile portfolios in different volatility groups. At the end of each month, stocks are first sorted by the volatility proxy into three groups: VolLow, VolMid and VolHigh. Then, in each group, stocks are sorted by the $ER_{Trend}$ into five quintile portfolios, and the return for the trend factor is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend factor in VolHigh and VolLow group. We use four measures to proxy for volatility. $Vol_{Rt}$ is the volatility of stock return, $Vol_{Volume}$ is the volatility of trading volume, and $Vol_{Earnings}$ is the volatility of earnings. $Vol_{Index}$ is the equal-weighted average of the above three normalized volatility proxies. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A:* $Vol_{Rt}$ | | | | | | | |
| Vol Low | 1.13 | 1.47* | 1.95** | 2.07** | 2.35** | 1.22*** | 0.67*** |
| | (1.27) | (1.69) | (2.22) | (2.41) | (2.59) | (3.75) | (2.63) |
| Vol Mid | 0.89 | 1.43 | 1.76* | 2.05** | 2.26** | 1.37*** | |
| | (0.99) | (1.58) | (1.92) | (2.13) | (2.48) | (4.49) | |
| Vol High | 0.39 | 1.02 | 1.58 | 1.96** | 2.28** | 1.89*** | |
| | (0.42) | (1.08) | (1.64) | (2.01) | (2.40) | (5.81) | |
| *Panel B:* $Vol_{Volume}$ | | | | | | | |
| Vol Low | 0.90 | 1.30 | 1.82** | 2.00** | 2.08** | 1.18*** | 0.87*** |
| | (0.99) | (1.45) | (1.98) | (2.15) | (2.30) | (3.99) | (3.21) |
| Vol Mid | 0.83 | 1.39 | 1.95** | 2.26** | 2.22** | 1.39*** | |
| | (0.90) | (1.50) | (2.17) | (2.42) | (2.41) | (4.00) | |
| Vol High | 0.47 | 1.15 | 1.57* | 2.07** | 2.52*** | 2.05*** | |
| | (0.53) | (1.25) | (1.76) | (2.20) | (2.71) | (5.84) | |
| *Panel C:* $Vol_{Earnings}$ | | | | | | | |
| Vol Low | 0.98 | 1.53* | 1.89** | 2.25*** | 2.25*** | 1.27*** | 0.66*** |
| | (1.22) | (1.77) | (2.23) | (2.62) | (2.71) | (4.04) | (3.19) |
| Vol Mid | 0.80 | 1.31 | 1.80** | 2.13** | 2.38** | 1.57*** | |
| | (0.85) | (1.43) | (2.00) | (2.28) | (2.48) | (4.43) | |
| Vol High | 0.41 | 1.01 | 1.74* | 1.79* | 2.34** | 1.93*** | |
| | (0.43) | (1.03) | (1.78) | (1.79) | (2.44) | (6.52) | |
| *Panel D:* $Vol_{Index}$ | | | | | | | |
| Vol Low | 1.19 | 1.51* | 1.79** | 2.18** | 2.15** | 0.96*** | 1.15*** |
| | (1.39) | (1.76) | (2.03) | (2.48) | (2.50) | (3.12) | (4.83) |
| Vol Mid | 0.89 | 1.49 | 1.82** | 2.18** | 2.44*** | 1.54*** | |
| | (0.97) | (1.56) | (2.00) | (2.32) | (2.62) | (4.81) | |
| Vol High | 0.24 | 0.89 | 1.45 | 1.91* | 2.35** | 2.12*** | |
| | (0.25) | (0.93) | (1.55) | (1.93) | (2.46) | (6.14) | |

**Table A8**

Volume trend, information quality and information quantity: EW portfolios

This table reports the VW average monthly return of the volume trend quintile portfolios in stock groups with different information quality and information quantity. The volume trend quintile portfolios are formed on $ER_{TrendV}$. The information quality is measured by the volatility of the normalized earnings. The information quantity is measured by the shareholding ratios of the institutional investors. Stocks are first sorted by the information quality or information quantity into three groups, Low Quality (Quantity) , Mid Quality (Quantity) and High Quality (Quantity). Then, in each group, stocks are sorted by the $ER^{\perp}_{TrendV}$ into five quintile portfolios, and the trend spread is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend spread in Low Quality (Quantity) and High Quality (Quantity) group. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A: Information quality* | | | | | | | |
| Low | 0.76 | 1.41 | 1.39 | 1.73* | 2.30** | 1.54*** | -0.51* |
| | (0.79) | (1.40) | (1.42) | (1.85) | (2.39) | (5.96) | (-1.86) |
| Mid | 0.94 | 1.62* | 1.74* | 1.89** | 2.23** | 1.29*** | |
| | (1.01) | (1.71) | (1.88) | (2.09) | (2.39) | (4.45) | |
| High | 1.12 | 1.54* | 1.82** | 1.94** | 2.14** | 1.02*** | |
| | (1.31) | (1.89) | (2.14) | (2.37) | (2.55) | (3.42) | |
| *Panel B: Information quantity* | | | | | | | |
| Low | -0.13 | 0.83 | 0.85 | 1.15 | 1.56* | 1.69*** | -0.58** |
| | (-0.14) | (0.84) | (0.88) | (1.25) | (1.66) | (5.99) | (-2.39) |
| Mid | 0.86 | 1.51 | 1.66* | 1.78** | 2.35** | 1.49*** | |
| | (0.94) | (1.63) | (1.82) | (1.98) | (2.44) | (5.47) | |
| High | 1.80** | 2.20** | 2.30** | 2.75*** | 2.91*** | 1.11*** | |
| | (2.00) | (2.54) | (2.56) | (3.14) | (3.23) | (4.16) | |

**Table A9**

Orthogonal volume trend, information quality and information quantity: EW portfolios

This table reports the VW average monthly return of the orthogonal volume trend quintile portfolios in stock groups with different information quality and information quantity. The orthogonal volume trend quintile portfolio is formed on $ER^{\perp}_{TrendV}$, which is defined as the average of the residuals regressing $ER_{Trend}$ on $ER_{TrendP}$ and the residuals regressing $ER_{TrendV}$ on $ER_{TrendP}$ cross-sectionally. The information quality is measured by the volatility of the normalized earnings. The information quantity is measured by the shareholding ratios of the institutional investors. Stocks are first sorted by the information quality or information quantity into three groups, Low Quality (Quantity) , Mid Quality (Quantity) and High Quality (Quantity). Then, in each group, stocks are sorted by the $ER^{\perp}_{TrendV}$ into five quintile portfolios, and the trend spread is the return spread between the extreme quintile portfolios. $\Delta(Trend)$ is the difference between the trend spread in Low Quality (Quantity) and High Quality (Quantity) group. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | Low | 2 | 3 | 4 | High | Trend | $\Delta Trend$ |
|---|---|---|---|---|---|---|---|
| *Panel A: Information quality* | | | | | | | |
| Low | 1.24 | 1.38 | 1.34 | 1.46 | 2.12** | 0.88*** | -0.33 |
| | (1.27) | (1.38) | (1.36) | (1.57) | (2.26) | (3.16) | (-1.18) |
| Mid | 1.34 | 1.59 | 1.64* | 1.73* | 2.10** | 0.76*** | |
| | (1.42) | (1.64) | (1.76) | (1.87) | (2.34) | (2.94) | |
| High | 1.50* | 1.79** | 1.57* | 1.83** | 2.05** | 0.55* | |
| | (1.80) | (2.16) | (1.90) | (2.22) | (2.53) | (1.96) | |
| *Panel B: Information quantity* | | | | | | | |
| Low | 0.37 | 0.92 | 0.81 | 0.93 | 1.39 | 1.02*** | -0.38* |
| | (0.39) | (0.94) | (0.83) | (1.01) | (1.52) | (3.75) | (-1.87) |
| Mid | 1.36 | 1.53 | 1.47 | 1.62* | 2.17** | 0.81*** | |
| | (1.44) | (1.65) | (1.63) | (1.79) | (2.30) | (3.12) | |
| High | 2.15** | 2.41*** | 2.26** | 2.40*** | 2.79*** | 0.64** | |
| | (2.42) | (2.74) | (2.54) | (2.67) | (3.27) | (2.51) | |

**Table A10**

Performance of the trend factor under alternative coefficient forecasts

This table reports the result for the trend factor under two different methods for coefficient forecast. Exponential moving average (EMA) uses the exponential average of all the past coefficients to forecast the coefficient in the next month and the parameter $\lambda$ determines the weight of the coefficients over different horizons. Simple moving average (SMA) uses the equal-weighted average of the past coefficients in the last $M$ months to forecast the coefficient in the next month. Panel A reports the average month return, Panel B reports the alphas with respect to CAPM, Panel C reports the alphas with respect to LSY-3 factor model, and Panel D reports the alphas with respect to LSY-4 factor model. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

| | $\lambda$ for EMA | | | $M$ for SMA | | |
|---|---|---|---|---|---|---|
| | 0.01 | 0.03 | 0.05 | 12 | 24 | 36 |
| *Panel A: Mean return (%)* | | | | | | |
| Mean | 1.31*** | 1.36*** | 1.20*** | 0.91*** | 1.10*** | 1.16*** |
| | (6.04) | (5.56) | (4.87) | (3.37) | (4.70) | (4.60) |
| *Panel B: Alpha (%) w.r.t. CAPM* | | | | | | |
| $\alpha$ | 1.33*** | 1.40*** | 1.24*** | 0.92*** | 1.13*** | 1.20*** |
| | (6.08) | (5.90) | (5.32) | (3.71) | (5.07) | (4.99) |
| *Panel C: Alpha (%) w.r.t. LSY-3 factor model* | | | | | | |
| $\alpha$ | 1.02*** | 1.13*** | 1.06*** | 0.87** | 1.12*** | 0.88*** |
| | (4.18) | (3.55) | (3.17) | (2.20) | (3.77) | (2.69) |
| *Panel D: Alpha (%) w.r.t. LSY-4 factor model* | | | | | | |
| $\alpha$ | 0.69*** | 0.82*** | 0.86*** | 0.66** | 1.00*** | 0.64** |
| | (3.06) | (2.95) | (2.70) | (2.12) | (3.22) | (2.07) |

**Table A11**

Summary statistics of trend factors in the US

This table reports the summary statistics of the trend factors in US. $TrendPV$ is our modified trend factor which captures both price and volume trend. $TrendP$ is the original trend factor of Han, Zhou, and Zhu (2016) which only captures price trend. $TrendV$ is the trend factor based on the trading volume. $\Delta^{TrendPV}_{TrendP}$ is the difference between $TrendPV$ and $TrendP$. $\Delta^{TrendPV}_{TrendV}$ is the difference between $TrendPV$ and $TrendV$. Newey-West(1987) adjusted t-statistics are reported in parentheses. The sample period is from January 1963 through December 2016.

| | TrendPV | TrendP | TrendV | $\Delta^{TrendPV}_{TrendP}$ | $\Delta^{TrendPV}_{TrendV}$ |
|---|---|---|---|---|---|
| Mean (%) | 1.51*** | 1.36*** | 0.35*** | 0.15** | 1.16*** |
| | (8.71) | (8.23) | (2.61) | (2.37) | (6.01) |
| Std dev (%) | 4.42 | 4.31 | 4.15 | 1.72 | 4.75 |
| Sharpe Ratio | 0.34 | 0.32 | 0.08 | 0.09 | 0.24 |

**Table A12**

Sharpe style regressions in China and the US

This table reports the Sharpe style regression results regressing the return of the trend factor of price and volume ($TrendPV$) on the returns of trend factor of price ($TrendP$) and trend factor of volume ($TrendV$). The slope coefficients are restricted to be non-negative and their sum is restricted to 1. Regression results are reported for China and US. The $t$-statistics are in parentheses. We test the difference of the coefficients between China and US. The $p$-value for the null hypothesis that the coefficients are equal for China and the US are reported in the bracket. The sample period is from January 2005 through December 2016.

| | China | U.S. | Difference |
|---|---|---|---|
| TrendV | 0.42*** | 0.06*** | 0.36*** |
| | (5.90) | (2.71) | [0.00] |
| TrendP | 0.58*** | 0.94*** | |
| | (8.14) | (39.18) | |

**Table A13**

Alphas of trend factors in the US

This table reports the alphas of two trend factors under different factor models. *TrendP* is the original trend factor of Han, Zhou, and Zhu (2016) which only captures price trend. *TrendPV* is our modified trend factor which captures both price and volume trend. FF-3 is the Fama and French (1993) 3-factor model. SY-4 is the Stambaugh and Yuan (2016) 4-factor model, which consists of two mispricing factors, i.e., MGMT and PERF, in addition to market and size factor. FF-5 is the Fama and French (2015) 5-factor model. We also compares the two trend factors by regressing one on the market factor with the other one. Newey-West(1987) adjusted t-statistics are reported in parentheses. The sample period is from July 1963 through December 2016.

| | *Panel A: TrendPV* | | | | | *Panel B: TrendP* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CAPM | FF-3 | SY-4 | FF-5 | TrendP | CAPM | FF-3 | SY-4 | FF-5 | TrendPV |
| $\alpha(\%)$ | 1.46*** | 1.43*** | 1.27*** | 1.45*** | 0.21*** | 1.32*** | 1.31*** | 1.17*** | 1.32*** | 0.01 |
| | (8.47) | (8.18) | (5.89) | (7.11) | (3.20) | (8.07) | (7.77) | (5.30) | (6.61) | (0.10) |
| $\beta_{MKT}$ | 0.06 | 0.04 | 0.10 | 0.06 | 0.01 | 0.05 | 0.02 | 0.06 | 0.04 | -0.00 |
| | (1.15) | (0.61) | (1.59) | (0.78) | (0.56) | (1.15) | (0.24) | (1.08) | (0.55) | (-0.21) |
| $\beta_{SMB}$ | | 0.12 | 0.11 | 0.07 | | | 0.16 | 0.15 | 0.10 | |
| | | (0.76) | (0.80) | (0.62) | | | (1.06) | (1.09) | (0.93) | |
| $\beta_{HML}$ | | 0.03 | | -0.08 | | | -0.02 | | -0.18 | |
| | | (0.31) | | (-0.54) | | | (-0.18) | | (-1.29) | |
| $\beta_{MGMT}$ | | | 0.11 | | | | | 0.08 | | |
| | | | (1.06) | | | | | (0.87) | | |
| $\beta_{PERF}$ | | | 0.08 | | | | | 0.04 | | |
| | | | (0.96) | | | | | (0.45) | | |
| $\beta_{RMW}$ | | | | -0.14 | | | | | -0.18 | |
| | | | | (-0.74) | | | | | (-1.00) | |
| $\beta_{CMA}$ | | | | 0.22 | | | | | 0.31 | |
| | | | | (1.02) | | | | | (1.53) | |
| $\beta_{TrendPV}$ | | | | | | | | | | 0.90*** |
| | | | | | | | | | | (29.86) |
| $\beta_{TrendP}$ | | | | | 0.95*** | | | | | |
| | | | | | (42.51) | | | | | |

**Table A14**

Alphas of anomalies in the US

This table reports the alphas for the 11 anomalies of Stambaugh and Yuan (2016) with respect to the Fama-French three factor model along with our modified trend factor in the US. The anomaly data is from Robert F. Stambaugh's website. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from October 1973 through December 2014.

| | Coefficient | | | | | $t$-statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Alpha | MKT | SMB | HML | TrendPV | Alpha | MKT | SMB | HML | TrendPV |
| Accruals | 0.38** | -0.05 | -0.22*** | 0.13* | -0.01 | 2.41 | -1.14 | -3.20 | 1.87 | -0.12 |
| Asset growth | 0.23* | -0.14*** | 0.15** | 0.61*** | 0.08 | 1.74 | -3.17 | 2.25 | 7.00 | 1.56 |
| Composite equity issue | 0.49*** | -0.23*** | -0.20*** | 0.51*** | -0.00 | 3.61 | -5.87 | -3.63 | 6.36 | -0.04 |
| Distress | 0.93*** | -0.71*** | -0.54*** | -0.56** | 0.17 | 3.45 | -7.71 | -3.91 | -2.43 | 1.35 |
| Gross profitability | 0.61*** | -0.29*** | -0.09* | -0.69*** | 0.04 | 4.30 | -5.77 | -1.90 | -6.86 | 0.78 |
| Investment to asset | 0.54*** | -0.10** | 0.11 | 0.30*** | -0.03 | 3.89 | -2.46 | 1.43 | 4.16 | -0.78 |
| Momentum | 1.32*** | -0.28*** | 0.13 | -0.51** | 0.10 | 3.31 | -2.75 | 0.62 | -2.32 | 0.54 |
| Net operating assets | 0.46*** | 0.04 | -0.05 | 0.18** | -0.01 | 3.10 | 0.88 | -0.58 | 2.05 | -0.15 |
| O-score | 0.44*** | -0.18*** | -0.71*** | -0.38*** | -0.02 | 2.93 | -5.37 | -13.38 | -5.69 | -0.53 |
| ROA | 0.92*** | -0.21*** | -0.58*** | -0.33** | 0.02 | 4.87 | -3.23 | -6.68 | -2.55 | 0.33 |
| Net stock issue | 0.60*** | -0.18*** | -0.25*** | 0.11 | 0.03 | 5.11 | -4.58 | -5.22 | 1.46 | 1.00 |

**Table A15**

Moving-average signals VS return signals

This table compares the performance of factors based on returns and moving average (MA) signals. $TrendPV$ is our modified trend factor based on price MAs and trading volume MAs. $TrendP$ is the original trend factor based on price MAs only. $MOM_{All}$ is constructed in the similar way as $TrendP$, except that it is based on return signals over the same horizons as those of price MA signals used in $TrendP$. $TrendPV$ and the resulting 4-factor model is constructed using the $2 \times 3 \times 3$ sorting procedure introduced in subsection 2.2. Similarly, $TrendP$, $MOM_{All}$, and the two resulting 4-factor models are constructed in the same manner. We exclude the smallest 30% stocks to construct all these factors. Panel A reports the summary statistics for the three factors, i.e., $TrendPV$, $TrendP$ and $MOM_{All}$. Panel B reports the alphas for these three factors under different factor models. LSY-4 is Liu, Stambaugh and Yuan (2019) 4-factor model. Our-4, TrendP-4 and $MOM_{All}$-4 is the 4-factor model of $TrendPV$, $TrendP$, and $MOM_{All}$, respectively. Newey-West(1987) adjusted $t$-statistics are reported in parentheses. The sample period is from January 2006 through July 2018.

| | $TrendPV$ | $TrendP$ | $MOM_{All}$ |
|---|---|---|---|
| *Panel A: Summary statistics* | | | |
| Mean(%) | 1.43*** | 1.29*** | 0.99*** |
| | (6.10) | (4.89) | (3.26) |
| Std. dev(%) | 3.00 | 3.46 | 3.72 |
| Sharp | 0.48 | 0.37 | 0.27 |
| *Panel B: Alphas (%) with respect to different models* | | | |
| LSY-4 | 0.82*** | 0.63** | 0.39 |
| | (3.42) | (2.02) | (1.29) |
| Our-4 | | -0.21 | -0.26 |
| | | (-1.06) | (-0.97) |
| TrendP-4 | 0.51*** | | -0.15 |
| | (2.83) | | (-0.59) |
| $MOM_{All}$-4 | 0.94*** | 0.58** | |
| | (3.38) | (2.12) | |