Trend Factor in China*

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Abstract

We propose a 4-factor model for the Chinese stock market by adding the trend factor to Liu, Stambaugh, and Yuan's (2019; LSY-3) 3-factor model, which consists of the market, size, and value. Since individual investors contribute about 80% of total trading volume in China, the trend factor works by capturing the highly relevant price and volume trends, earning a monthly Sharpe ratio of 0.48 – much greater than that of the market (0.11), size (0.19), and value (0.28). Our 4-factor model explains all reported Chinese anomalies – including turnover and reversal – that other existing models like LSY-3 fail to explain. It also strongly outperforms the replication of Fama and French's (2015) 5-factor model and Hou, Xue, and Zhang's (2015) q-factor model in terms of both Sharpe ratio and explanatory power. Moreover, our model excels in explaining mutual fund returns and works as an analogue of Carhart's (1997) 4-factor model in China.

JEL Classification: G12, G14, G15

Keywords: China Stocks, Trends, Predictability, Factor Model, Anomalies

1. Introduction

China is the home to the world's second largest stock market after the US, so it is important to examine how well existing asset pricing theories developed for the US market applies in China. The Fama-French 3-factor model (1993, FF-3, henceforth), for instance, is one of the most prominent 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 factor, and show that together with the market factor, they substantially outperform 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 consisting of the market, size, value and trend, where the first three factors are those of LSY-3. Our motivation is to capture another critical feature of the Chinese stock market, which is that individual investors contribute about 80% of total trading volume. As retail investors are more susceptible to herding, we expect there to be 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 the fact that many individual investors are likely short-term orientated. Hence to capture short-, intermediate-, and long-term price trends, we construct a trend factor specific to China by letting the data determine the weights on both price and volume information across time. By utilizing price as well as volume data - both crucial elements to explaining the Chinese stock market - our trend factor serves as an extension to the original trend factor developed for the US market by Han, Zhou, and Zhu (2016), which relies solely on price signals. In this paper, we also provide a theoretical model that sheds light on why trading volume plays such a unique and indispensable role in the Chinese stock market.

As a candidate for factor investing, our trend factor easily beats out its competition by yielding an average return of 1.43% per month over the sample period from January 2005 to July 2018, while the size factor generated 0.97% per month, and the value factor earned 1.15%. In terms of Sharpe ratio, the trend factor also outperforms others with a monthly value of 0.48, much greater than that of market (0.11), size (0.19) and value (0.28). Moreover, the trend factor is resilient in recovery with the maximum drawdown (MDD) of only 13.17%, compared with 69.33% for the market factor, 25.94% for the size factor, and 19.65% for the value factor.

With a significant monthly alpha 1.17% with respect to LSY-3, 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 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. Secondly, the portfolios sorted by exposures to the turnover factor exhibit a non-monotonic return pattern. Thirdly, the turnover factor captures investor sentiment in small stocks but not in larger ones.

As a financial model, our 4-factor model outperforms LSY-3 and LSY-4 in a number of ways. First is explaining power. The Gibbons, Ross, and Shanken (1989) GRS test of our 4-factor model's ability to price the factors in LSY-3 and LSY-4 produces p-values of 0.85 and 0.81, respectively. On the contrary, the GRS p-values for LSY-3's and LSY-4's ability to price the factors in our model are less than 10^{-3}. In addition, our model is able to explain 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 produces a GRS p-value of 0.55 versus the p-values of less than 10^{-2} and 0.03 for LSY-3 and LSY-4, respectively. Our model also excels in explaining mutual fund portfolios returns with smaller aggregate pricing errors than LSY-3 and LSY-4. Since there is no traditional momentum factor in China, our 4-factor model is suited to serve as an analogue of Carhart's (1997) 4-factor model for Chinese mutual funds. Moreover, we compute the Sharpe ratios of the various factor models with and without the trend factor using the Barillas and Shanken (2017) method, and find that Sharpe ratio with the trend factor is substantially greater, indicating that our 4-factor model has greater explanatory power regardless of the test assets used for model evaluation. Additionally, our 4-factor model far outperforms the replication of Fama and French's (2015) 5-factor model and Hou, Xue, and Zhang's (2015) q-factor model in China, again proving its superior explanatory power against existing factor models.

Secondly, beyond explaining power, Fama-MacBeth regressions show that after controlling for factors in LSY-3 and LSY-4, our trend factor generates significant risk premia, while the turnover factor of LSY-4 does not once the trend factor is included. Thirdly, 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 forces 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 performs 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 predictive power generated by volume decreases with information quality and information quantity on asset fundamentals. To verify this, 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.

Similar to 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. What is the relative importance of volume trend in China vs the US? Our results show that the contribution of volume trend to the overall trend is economically and statistically much higher in China (42%) than in the US (6%), consistent with the fact that the Chinese stock market is dominated by individual investors.

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 time horizons, including: daily, weekly, monthly, quarterly, 1-year and 2-year horizons.

To capture volume trend, we similarly define 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 λ 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 λ 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 the 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. We do so by applying a 2×3×3 triple sorting procedure that Hou, Xue, and Zhang (2015) use to construct their q-4 factor model.

Following Liu, Stambaugh, and Yuan (2019), we exclude the smallest 30% of stocks to avoid the shell-value contamination caused by IPO constraints in China when we construct the factors. At the end of each month, the remaining 70% of 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% of 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 weigh 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 2×3 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 month's share turnover divided by the past year's 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 the daily closing price to calculate the MA price signals at the end of each month. The prices are adjusted for stock splits and dividends. During the suspension of trade period, we use the daily closing price right before the suspension to fill in the price during the 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 more than half of the days in the month consist of trading records specified by the given tag, and if there are trading records in this month. Otherwise, we use the MA volume signals in the previous month to fill in the volume signals for 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 at the end of the past month. Book-to-market ratio (BM) is the ratio of the total shareholder equity from the most recently reported quarterly statement to the market capitalization at the end of the past 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 at the end of the past month. Return-on-equity (ROE) is the ratio of the net profit excluding gains/losses to the total shareholder 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 that have public release dates prior to that month's end to calculate these valuation ratios, so that there is no look forward bias.

One-month abnormal turnover ($AbTurn$) is defined as the ratio of the turnover in the past month to the average of monthly turnover in the last twelve months. R_{-1}, $R_{-6,-2}$ and $R_{-12,-2}$ are the prior month's return, the past six months' cumulative return skipping the last month, and the past twelve months' cumulative return skipping the last month, respectively. $IVOL$ is the idiosyncratic volatility relative to FF-3 estimated from daily returns in the past month. β 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 absolute daily return to RMB trading volume. Price-to-earnings ratio (PE), price-to-cash ratio (PC), and price-to-sales ratio (PS) are the ratio of total market capitalization at the end of the past month to earnings, to net cash flow from operating activities, and to sales in the most recently available four fiscal quarters, respectively.

Following Sloan (1996), we define accrual as $Accrual = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep$. ΔCA equals the most recent year-to-year change in current assets, $\Delta Cash$ is the change in cash or cash equivalents, ΔCL is the change in current liabilities, ΔSTD equals the change in debt included in current liabilities, ΔTP equals the change in income taxes payable, and Dep is 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 the Chinese stock market by first exploring the properties of our trend factor along with other factors. We then compare the performance of our trend factor to that of the turnover factor in sub-samples, controlling for other factor variables. Next, we carry out the spanning tests. Finally, we evaluate the performance of our 4-factor model with those of 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; hence, the effective sample period for our study is from January 2005 to July 2018. Again, we exclude the smallest 30% of stocks when constructing the factors.

3.1. Summary statistics

Panel A of table 1 presents the summary statistics for the trend factor (Trend) along with factors in LSY-3 and LSY-4 model: the market factor (MKT), the size factor (SMB), the value factor (VMG), and the turnover factor (PMO).[1] Of these factors, Trend produces the highest average return of 1.43% per month, while SMB generates only 0.97% per month and VMG earns 1.15%. Trend also earns the highest Sharpe ratio of 0.48, while the highest Sharpe ratio out of all the LSY-3 factors is only 0.28 (VMG). Furthermore, Trend produces the lowest maximum drawdown (MDD) of 13.17%, while those for SMB, VMG and PMO are 25.94%, 19.65% and 25.15%, respectively – indicating that Trend is resilient in recovery from downside risks 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 a fairly high correlation (0.52) with the

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

PMO factor in LSY-4. We will examine which factor performs better and captures more of the cross-sectional returns 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 $2\times3\times3$ triple sorting procedure to evaluate their performances 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. The *Size-EP-AbTurn* and *Size-Trend-AbTurn* sub-samples, and the associated Trend and PMO factors in these sub-samples, are produced in a similar way.

Table 2 shows the average monthly returns for our trend factor (Trend) and the turnover factor (PMO) in different sub-samples. In Panel A, controlling for size and EP, Trend generates persistent positive returns in all 6 $Size - EP$ sub-samples, producing an average return of 1.43% (t-statistic: 6.10). PMO, on the other hand, earns a monthly return of 0.82% (t-statistic: 2.82), with its performance mainly attributed to small stocks. Specifically, the average return of PMO in small stocks is 1.37% per month vs only 0.28% (t-statistic: 0.83) in large stocks, indicating that the turnover factor captures investor sentiment in small stocks, but not in large stocks. Likewise in Panel B, controlling for size and ER_{Trend}, PMO produces an average return of -0.28% (t-statistic: -0.79) in the big stock groups. Worse still, it fails to generate significant returns in all three trend groups by producing an average return of only 0.30% (t-statistic: 1.07), suggesting 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 the two size groups as well as three AbTurn groups, earning an average monthly return of 1.23% (t-statistic: 5.13). This result shows that our trend measure provides independent predictability beyond size and turnover, and is able to capture sentiment well in both small and large stocks.

In addition, the portfolios sorted by ER_{Trend} show a great monotonic return pattern with no exceptions 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.

In conclusion, the turnover factor in LSY-4 captures investor sentiment only in small stocks but not in big stocks, while our trend factor works well after controlling for size, EP and AbTurn. Moreover, our trend factor subsumes the predictability of turnover, and as a result, is able to 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 tests 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 the spanning tests. The hypothesis that the trend factor lies inside the mean-variance frontier of the LSY-3 and LSY-4 factors is strongly rejected. This illustrates that our trend measure is a unique factor that captures the cross-section 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's (2015) q-factor model (q-4) and Fama and French's (2015) 5-factor model (FF-5) as competitors to our 4-factor model in China.[2] We

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

first examine these models' performances in explaining factors in other models, and we compare their pricing abilities in explaining stock anomalies and mutual fund portfolios in the Chinese stock market. Then, we conduct Sharpe ratio tests.

To start off, we compute the alphas of factors, anomalies and mutual fund portfolios with respect to different benchmark models. The explaining power of a benchmark model is measured in three ways. 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, we measure the overall pricing errors following Shaken (1992) by providing a weighted summary of the alphas,

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

where Σ is the variance-covariance matrix of the residuals across the test portfolios. The smaller the aggregate pricing error Δ, the better the performance of a benchmark model. Third, we carry out the GRS test of Gibbons, Ross and Shanken (1989) to determine 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 order to compare existing factor models with our 4-factor model in their abilities to explain the factors in other models, we conduct a pairwise comparison of LSY-3, LSY-4, q-4 and FF-5 with our 4-factor model. We do this by calculating the alphas of factors (except the market factor) in a given factor model with respect to another benchmark model.

The outcome shows that 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. This result strongly suggests that existing factor models cannot explain the performance of our trend factor. On the contrary, none of the factors in other models earns significant alphas with respect to our 4-factor model – for example, 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 an overall pricing error Δ of only 0.003, much smaller than LSY-3's Δ of 0.214. Moreover, the GRS p-value of our 4-factor model is 0.85 versus 10^{-4} for LSY-3, 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 is significantly low at 0.11% (0.54). Consistently, the overall pricing error Δ 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

Next, we compare the pricing ability of different factor models in explaining the stock anomalies in China. Based on existing literature, we compile 10 categories of anomalies, including all those examined by Liu, Stambaugh, and Yuan (2019). Within each category, one or more firm-level characteristics are identified to construct anomalies, producing a set consisting of 17 anomalies in total. The categories and their corresponding anomaly variables are: (1) size: market capitalization (Size); (2) value: earnings-to-price ratio (EP), book-to-market ratio (BM) and cash-flow-to-market ratio (CP); (3) turnover: turnover (Turn); (4) trend: TrendPV is based on our modified trend measure of price and volume MA (ER_{Trend}), while TrendP and TrendV are based on the trend measure of price MA (ER_{TrendP}) and trading volume MA (ER_{TrendV}), respectively. (5) illiquidity: Amihud (2002) illiquidity measure (ILLIQ); (6) past return: 1-month reversal (REV) and 2- to 12-month momentum (MOM); (7) profitability: return-on-equity (ROE); (8) volatility: volatility of daily returns (VOL), idiosyncratic volatility (IVOL) and the maximum daily return (MAX) in the past month; (9) accrual: accrual (Accrual); (10) investment: 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. For the reversal anomaly, we use the same procedure as Liu, Stambaugh, and Yuan (2019) to compute the returns. Since the one-month return reversal is a short-term anomaly, stocks are sorted into decile portfolios each day based on the returns over the most recent 20 days. We then hold the spread portfolios for five trading days, which means that there are five portfolios for reversal each day. The daily return of reversal is defined as the average return of the five portfolios and we use the result to calculate the monthly return for reversal. We exclude the smallest 30% of stocks to form the anomalies, and 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 anomalies all produce significant returns in the US, they fail to do so in China.[3] For our analysis from here onwards, we include only the remaining 14 anomalies that generate significant returns in China. The outcomes show that LSY factor models fail to explain certain important anomalies. For example, turnover, illiquidity, reversal, and idiosyncratic volatility earn alphas 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 fails to capture other three anomalies, leaving unexplained alphas 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 abilities of various competing factor models to explain stock anomalies. The 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 0.32%, while those of LSY-3 and LSY-4 are 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. Secondly, in terms of aggregate pricing error (Δ), our 4-factor model (0.140) also dominates all other factor models, including LSY-3 (0.296) and LSY-4 (0.256). Thirdly, 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.

To conclude, our 4-factor model substantially outperforms existing popular factor models in explaining stock anomalies in China.

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

3.4.3. *Explaining mutual funds*

Carhart's (1997) 4-factor model, which extends Fama and French's (1993) 3-factor model by adding a momentum factor to capture the momentum anomaly of Jegadeesh and Titman (1993), is commonly used to evaluate and explain mutual fund performances (see, e.g., Daniel, Grinblatt, Titman and Wermers, 1997, Wermers, 2000, and Fama, and French, 2010). However, because of compound interactions between 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). We argue that our 4-factor model is the prime candidate to fill this void by evaluating its explaining power in Chinese mutual funds returns against other existing models: namely, LSY-3, LSY-4, q-4, and FF-5.

In this comparison, we only include equity-oriented mutual funds and sort them at the end of each month by assets under management (AUM) into ten decile portfolios, from Fund1 (smallest) to Fund10 (biggest). The mutual fund data comes from the China Stock Market and Accounting Research (CSMAR) database.

Table 6 shows the results of this comparison between the various factor models' abilities to explain mutual fund returns in China. Our 4-factor model produces the smallest average absolute alpha, the lowest average absolute t-statistic, and the smallest aggregate pricing error, indicating that it outperforms other existing factor models in explaining mutual fund performances and is best suited to serve as an analogue of Carhart's (1997) 4-factor model in China.

3.4.4. *Sharpe ratio tests*

Previously, 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. Here, 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 μ 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 conclusion of Sharpe ratio tests is established regardless of the test assets (R) used to evaluate a model's pricing ability.

Table 7 reports the squared monthly Sharpe ratio for the factor models – LSY-3, LSY-4, q-4, FF-5, and our 4-factor models. Panel A shows the results for factor models in which we exclude the smallest 30% of stocks to form the factors. Among all five models, our 4-factor model earns the highest squared monthly Sharpe ratio of 0.598, compared with 0.387 for LSY-3 and 0.446 for LSY-4 0.446, indicating that our trend factor provides significant economic value beyond the LSY factor models. Our 4-factor model also strongly outperforms FF-5 ($Sh^2 = 0.404$), suggesting that it excels in both explanatory power and model parsimony. Interestingly, q-4 earns the smallest Sh^2 of only 0.240. This is partially because q-4 drops the value factor and replaces it with the investment factor, which 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, while our 4-factor model substantially outperforms all other factor models. Panel C and Panel D report similar results for the same tests repeated without excluding small stocks for the construction of factors. Specifically, our 4-factor model dominates all other factor models by earning the highest Sh^2 of 0.714, while there is no statistically significant difference in Sh^2 among other factor models

Overall, compared with other factor models, the increments in our 4-factor model's Sh^2 is highly economically and statistically significant, illustrating our model's superior performance against existing factor models in terms of explaining power. This result is consistent with the previously shown advantage of our 4-factor model in explaining other factors, stock anomalies and mutual funds, providing an even stronger evidence of its superiority.

4. Cross-sectional returns

In this section, we first examine 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 and turnover. These two methods are complementary.

4.1. Regression vs portfolio sorting

Assume a factor model with F factors. The factor exposures are given as X, an $N \times F$ matrix with each element X_{ij} representing the i-th security's exposure to the j-th factor. Factor exposures 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 β 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 (β) 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 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 – 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. Similar to factor portfolios produced by regressions, those produced by portfolio sorting methods are also self-financing portfolios.

So what does portfolio sorting really do, and how is it related to the Fama-MacBeth regression given above? Moreover, 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 and -1, according to their rankings. We know that 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 in this case, Equation (13) becomes $P = LX'$, indicating that the weights of factor portfolios produced by regressions are also proportional to the corresponding factor exposures. Therefore in the independent case, the above three methods produce the same results. Meanwhile, when the factor exposures are correlated, the independent sorting and the regression generate 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 exposures X_1 and X_2, corresponding to size and value.

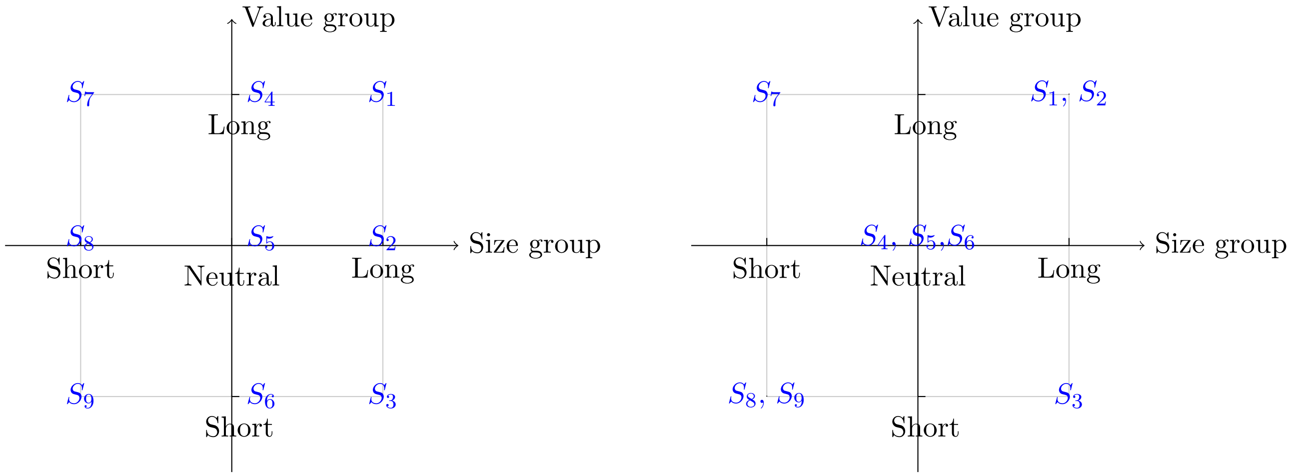
Case 1: Independent case

Suppose the exposures 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. Clearly, independent sorting and univariate sorting generate the same factor portfolios:

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



(A) Independent case

(B) Non-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.

By applying (13), it can be easily shown that the factor portfolios generated by OLS regressions are proportional to those generated by the sorting methods. Also, the factor portfolios have zero exposure on each other.

Case 2: Non-independent case

Suppose the exposures 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. We see that the factor portfolios generated by the independent sorting are

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

By applying (13), we can show that the factor portfolios generated by OLS regression are proportional to those generated by independent sorting. On the contrary, the factor portfolios generated by univariate sorting are

$$P_1 = [1, 1, 1, 0, 0, 0, -1, -1, -1]/3,$$
$$P_2 = [1, 1, -1, 0, 0, 0, 1, -1, -1]/3.$$

We can easily show that the factor portfolios generated by independent sorting and the regression approach have zero exposure on other factors, which is not true for univariate sorting. For example, the factor portfolio of size have an exposure of two-thirds on value in univariate sorting. Note that since independent sorting 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 the 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 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). 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 the factor exposures and assign three categories: 1, 0 and -1, according to their rankings. Since the WLS is equivalent to each factor exposure multiplied 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 the three factor measures in LSY-3, our trend measure (ER_{Trend}) generates a significant positive premium. In addition, controlling for the four factor measures in LSY-4 that includes an additional turnover factor, ER_{Trend} remains significant. AbTurn, on the other hand, is not significant in the presence of ER_{Trend}, which is consistent with failure of PMO in big stocks and ER_{Trend} portfolios as shown in Table 2. Again, our trend factor outperforms 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 answer an important and related question: what is the performance of the trend measure if we control for other firm characteristics that are known to predict cross-sectional 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 for both EW and VW portfolios. Size and book-to-market ratio, meanwhile, remain roughly flat across all five quintile portfolios. On the other hand, as ER_{Trend} goes up, 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. Furthermore, portfolios also show decreasing values measured by price-to-earnings, price-to-cash, and price-to-sales.

Table 10 shows the VW average monthly return of the double sorting portfolios after controlling for various firm characteristics: Size, EP, BM, R_{-1}, $R_{-6,-2}$, $R_{-12,-2}$, IVOL, illiquidity and turnover.[4] At the end of each month, we sort the stocks by one of the control variables into five quintile control groups, and within each control group, stocks are sorted into five trend groups by ER_{Trend}. We then 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 a monotonic pattern. Meanwhile, 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%, 1.17%, and 1.09% after controlling for Size, EP, BM, R_{-1}, $R_{-6,-2}$, $R_{-12,-2}$, IVOL, illiquidity, and turnover, respectively.

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

5. Explanation

In the previous section, we illustrate the superior performance of our trend factor in various aspects. Why does it 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

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

where π_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 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, π_t, θ_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 θ_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, π_t, θ_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 for 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 σ_D, the other is the noise trader behavior, which can be measured by the volatility of noise trader demand σ_θ.

In Table 11, we present the impact of σ_θ and σ_D on γ_3 and γ_4, which are the predictive coefficients of volume trend and price trend. The table shows both predictive coefficients increase with σ_θ and σ_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 as proxies 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. In order to capture the volatility of noise trader demand, 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 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. The volatility of trading volume (Vol_{Volume}) is then 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 as the sum of the earnings in the most recent four fiscal quarters. The fiscal data is matched with the return data by 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 therefore 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 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} groups.

Table 12 shows the relationship between the trend effect and volatility in VW portfolios.[5] First, the trend factor earns significantly higher returns 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. 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] The results with EW portfolios are similar and are provided in an online appendix.

5.3. Trend effect and individual investor participation

In the previous subsections, we show that the predictability of our trend measure increases with volatilites. Intuitively, the higher the participation of individual investors, the greater the volatilies. This is especially true in China since the major market participants are retail investors. It is therefore important to examine whether the trend effect increases with individual investors' participation.

According to Shanghai Stock Exchange Statistics Annual 2018, over 194 million individuals had trading accounts at the end of 2017, making up more than 99% of the total number of trading accounts in A-Shares. Furthermore, individual investors contribute about 82% of the total trading volume, and hold about 77% of shareholdings average across stocks from 2005 to 2018. Hence, we use the shareholding ratio of individual investors, which is defined as one minus the shareholding ratio of institutional investors, as a proxy for individual participation. The data is from WIND database.

Table 13 reports the results for the trend effect with different retail participation in a sequential double sorting procedure. Consistent with our prediction, the trend effect rises with the increase of individual investor participation in both VW and EW portfolios. For example, the VW trend spread portfolio earns a significantly higher return in $Indiv_{High}$ group (1.95%) than in $Indiv_{Low}$ group (1.14%).

5.4. Trend effect and investor sentiment

Our trend factor is designed to capture the behavior of individual investors, who are more likely to be driven by sentiment. Hence, it is important to examine the trend effect with different investor sentiment.

Lee (2013) uses turnover to proxy sentiment at the individual-stock level. Here, we construct a sentiment index by taking the cross-sectional average of individual stocks' turnover on each month. A higher index implies a higher sentiment level. Table 14 shows the results of regressing the factor returns as long as their long and short legs on the previous month's sentiment index. Our trend factor earns significantly higher return following periods with high levels of sentiment, while the factors in LSY-3 and LSY-4, i.e., MKT, SMB, VMG, and PMO, produce no significant different with various sentiment levels, indicating that sentiment exhibit ability to predict our trend factor but not other factors. This result is consistent with a sentiment interpretation of our trend factor.[6]

5.5. The role of volume trend

In this subsection, we explore the role of volume trend by investigating whether it can predict future returns beyond price trend and by 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, and 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. Accordingly, 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-sectional 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 ($Vol_{Earnings}$) as defined in the previous subsection as proxy for the precision of the information about assets fundamentals. 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

[6] Consistent with this time-series result, we also show that the trend effect is strong in stock groups with higher turnover. The detailed results are provided in an online appendix.

of the institutional investors, defined as the shareholding ratio of the institutional investors, as proxy for the information quantity. Therefore, it follows that the greater the institutional investors' participation, the greater the information quantity.

Table 15 shows the average monthly return for the VW volume trend portfolios with different information settings.[7] The predictability of volume trend decreases with the rise of 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 that is 0.92% (0.47%) higher than that in the high information quality (quantity) group – an outcome 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 the volume trend provides predictability beyond the price trend. In addition, the return pattern of the orthogonal volume trend with different information quality (quantity) is similar to that of the volume trend. The detailed results are provided in an online appendix.

6. The US evidence

The original trend factor proposed for the US stock market by 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 developed for China 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 from price. The detailed results are provided in an online appendix.

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

6.2. Comparing volume trends 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 retail participation in China and in 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 are equally important, accounting for 42% and 58% of the overall trend, respectively. In the US, however, the performance of TrendPV is mainly attributed to TrendP, while TrendV contributes only 6% – consistent with the explanation that the Chinese stock market is dominated by the individual investors who make up about 80% of the total trading volume. Hence, this outcome emphasizes again the important and unique role that volume trend plays in China. The detailed results are provided in an online 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 of 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's (1993) 3-factor model (FF-3), Stambaugh and Yuan's (2016) 4-factor model (SY-4), and Fama and French's (2015) 5-factor model (FF-5). In addition, we evaluate the original trend factor against our modified trend factor by comparing their abilities 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 existing 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 ability of our 4-factor model to explain the 11 anomalies stated in Stambaugh and Yuan (2016) in the US market. While our 4-factor model explains all reported anomalies in China, its analogue fails to explain those in the US, reflecting the unique influence of the much higher retail 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. In the first method of exponential moving average (EMA), at the end of each month, we use the exponential average of all the 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 λ, the less the forecast relies on the latest coefficient. In the second method of simple moving average (SMA), we use the equal-weighted average of coefficients in the past 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 λ 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 models. 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 break-even transaction costs (BETCs). The first two are the transaction costs that would completely offset the returns or the CAPM risk-adjusted returns. The last 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 16 reports the transaction results for our trend factor (Trend) and the turnover factor (PMO). The turnover rate of our trend factor is 121.96% – slightly higher than that of PMO (105.43%). Since our trend factor exploits information over various investment horizons, it is not surprising to see that it yields a higher turnover rates than PMO. In terms of BETCs, however, our trend factor substantially outperforms PMO. On average, it takes 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 0.39% to do the same for PMO. Furthermore, we explore the level of transaction costs at which 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 dominates the turnover factor in terms of transaction costs.

8. Conclusion

In this paper, we propose a 4-factor model for the Chinese stock market by adding the trend factor to Liu, Stambaugh, and Yuan's (2019) 3-factor model. While Liu, Stambaugh, and Yuan's model is a substantial improvement over the replication of Fama and French's (1993) 3-factor model in China, ours further enhances performance by exploiting both price and volume information across various investment horizons. This approach allows us to capture the unique characteristic in China, where over 80% of total trading volume comes from individual investors.

Empirical results show that our 4-factor model substantially outperforms existing factor models in terms of explaining power. Our model not only can explain the factors in other models, including LSY-3, LSY-4, q-4, and FF-5, it can also explain all reported stock anomalies in China including those that LSY-3 and LSY-4 fail to capture, such as turnover, reversal, illiquidity, and idiosyncratic volatility. Furthermore, our model is able to explain mutual fund portfolios, making it a prime candidate to serve as an analogue of Carhart's (1997) 4-factor model in China.

The superior performance of the trend factor is robust in different constructions and against various firm and market characteristics, including size, market beta, book-to-market ratio, 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 much higher in China than in the US, highlighting the importance of volume in China and showing consistency with the heterogeneous retail investor trading intensities in these two markets. We also provide a theoretical explanation for the trend factor and illustrate that volume trend provides predictability beyond price trend. Our model shows that the high trading volume driven by noise traders in China is the key to why the volume trend excels in capturing the essence of the Chinese stock market.

Table 1

Summary statistics

This table reports the summary statistics for the trend factor (*Trend*) and the factors that make up LSY-3 and LSY-4: the market factor (*MKT*), the size factor (*SMB*), 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 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 results 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 performances in explaining factors in other models

This table reports the pairwise comparison of model performances 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 report 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 $\|\alpha\|$	0.49	0.05	0.40	0.11
Average $\|t\|$	2.63	0.50	2.65	0.54
Δ	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 $\|\alpha\|$	0.80	0.11	0.58	0.12
Average $\|t\|$	3.86	0.67	3.03	0.30
Δ	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 performances in explaining anomalies

This table compares the pricing ability of different factor models, including Liu, Stambaugh, and Yuan's (2019) 3-factor (LSY-3) and 4-factor (LSY-4), Hou, Xue, and Zhang's (2015) q-factor (q-4), Fama and French's (2015) 5-factor (FF-5), and our 4-factor model, in explaining anomalies. Also reported are results for "unadjusted" return spread (i.e., a model with no factors). For each model, the table shows 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
Δ	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 performances in explaining mutual funds

This table compares the pricing ability of different factor models, including Liu, Stambaugh, and Yuan's (2019) 3-factor (LSY-3) and 4-factor (LSY-4), Hou, Xue, and Zhang's (2015) q-factor (q-4), Fama and French's (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., a model with no factors). For each model, the table shows 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
Δ	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 existing factor models in China, including Liu, Stambaugh, and Yuan's (2019) 3-factor (LSY-3) and 4-factor (LSY-4), Hou, Xue, and Zhang's (2015) q-factor (q-4), Fama and French's (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% of stocks to form the factors, while Panel C and Panel D report the results for all stocks. The sample period is from January 2005 through 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 characteristics. For stocks in the bottom group, the label of the related characteristics is -1; for stocks in the medium group, it is 0; and for stocks in the top group, the label 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 (β), the market capitalization (Size), the earnings-to-price ratio (EP) and the abnormal turnover (AbTurn). In this first step of the Fama-MacBeth regression, we conduct modified cross-sectional regressions with market-value-weighted least squares (VWLS). 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]
β	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 returns and other characteristics of the quintile portfolios, sorted by the trend measure (ER_{Trend}). R_{EW} (%) is the EW average monthly return, and R_{VW} (%) is the VW average monthly return. Size is the market capitalization and is expressed in ten-thousands 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 expressed in thousands of RMB and ILLIQ is rescaled by multiplying by 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	0.85	61.08	22.62	53.75	5.98
2	1.41	1.14	1727557	0.39	3.4	16.04	36.76	1.97	0.85	49.05	20.43	49.87	5.34
3	1.75	1.38	1732769	0.42	1.21	13.16	33.6	1.76	0.91	43.76	19.19	45.97	4.99
4	2.15	1.65	1636636	0.44	-0.10	10.78	30.63	1.62	0.94	40.01	18.46	44.49	4.84
High	2.30	1.86	1733243	0.44	-1.19	8.19	28.85	1.50	1.00	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 within 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 each 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	0.83	1.66*	1.88**	2.01**	2.00**	1.17***
	(0.99)	(1.88)	(2.12)	(2.46)	(2.50)	(4.11)
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 σ_θ and σ_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 γ_3 and γ_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: γ_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: γ_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} groups. 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 $Indiv_{Low}$ groups. 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

Factors and investor sentiment

This table reports the estimates of the coefficients (b) in the regression

$$R_t = a + bS_{t-1} + \epsilon_t,$$

where R_t is the return in month t on either the long leg, the short leg, or the long-short spread for factors (Trend, MKT, SMB, VMG and PMO), and S_{t-1} is the previous month's sentiment index defined as the cross-sectional average of individual stocks' turnover in month $t-1$. The t-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

Factor	Long Leg	Short Leg	Long-Short
Trend	0.51	0.30	0.22**
	(1.63)	(0.92)	(2.18)
MKT			0.25
			(0.91)
SMB	0.50	0.25	0.25
	(1.40)	(0.87)	(1.46)
VMG	0.41	0.37	0.04
	(1.45)	(1.07)	(0.29)
PMO	0.41	0.37	0.05
	(1.37)	(1.10)	(0.37)

Table 15

Volume trend, information quality and information quantity

This table reports the VW average monthly returns 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}. Information quality is measured by the volatility of the normalized earnings, while 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) groups. 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 16

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 report 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

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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's (2015) q-factor model (q-4) and Fama and French's (2015) 5-factor model (FF-5) in China. Section A.3 provides detailed results for portfolios constructed in triple sorting procedures. Section A.4 examines the trend effects in stock groups with different sentiment. Section A.5 constructs orthogonal volume trend independent of price trend. Section A.6 presents the result for EW trend portfolios. Section A.7 examines the trend factor under alternative constructions. Section A.8 explores the trend factor in the US. Section A.9 compares moving average signals and return signals.

A.1. Factors using all stocks

In this section, we use all stocks (including the smallest 30%) to construct our trend factors. We do the same for the LSY factors. Table A1 shows the summary statistics for our trend factor (Trend) along with factors in LSY-3 and LSY-4 model: the market factor (MKT), the size factor (SMB), the value factor (VMG), and the turnover factor (PMO).

Trend generates an average monthly return of 1.64%, while that for VMG is 1.05% and for PMO is 0.89%. Trend also produces the highest Sharpe ratio of 0.54, while the highest Sharpe ratio out of all the LSY-3 factors is only 0.31 (SMB). Moreover, Trend earns the lowest maximum drawdown (MDD) of 9.41%, versus 22.47% for SMB, 23.04% for VMG, and 32.63% for PMO.

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

We replicate q-4 and FF-5 in China using two stock universes. The first universe excludes the smallest 30% of stocks, while the second universe contains all stock (including the smallest 30% of stocks). The market factor (MKT) in q-4 and FF-5 is the same, and 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 size factor (SMB), the profitability factor (ROE), and the investment factor (I/A) in q-4, 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 shareholder 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. Note that 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 profitability 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 size factor (SMB), the value factor (HML), the profitability factor (RMW), and the investment factor(CMA) in FF-5, from independent 2×3 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 shareholder equity from the most recently reported quarterly statement to the market capitalization at the end of the past 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, denoted as SMB_{ROE} and SMB_{Inv}. The size factor (SMB) in FF-5 is then 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 market, it fails to do so in China. Specifically, I/A produces an average monthly return of 0.13% (t-statistic: 1.06) in the largest 70% of stocks, and 0.12% (t-statistic: 1.13) in all stocks. On the contrary, 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 investment factor (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% of stocks, and -0.08% in all stocks.

A.3. Triple sorting portfolios

Here, we report the detailed results for the triple sorting portfolios. 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* portfolios. The *Size-EP-AbTurn* portfolios and *Size-Trend-AbTurn* portfolios are constructed in the same way.

Table A4 shows the VW average monthly returns for the triple sorting portfolios. In Panel A, controlling for size and EP, the returns of portfolios increase with the rise of ER_{Trend} with no exceptions. Similarly, in Panel C, controlling for size and AbTurn, the portfolios sorted by ER_{Trend} preserve a great monotonic return pattern. On the contrary, the portfolios sorted by AbTurn show 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.

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. Trend effect and investor sentiment

In this section, we explore the trend effect in stock groups with different sentiment. Following Lee (2013), we use turnover as a sentiment measure at the individual-stock level. We then examine the trend effect with different sentiment by conducting a sequential double sorting of turnover and ER_{Trend}.

Table A5 shows that the trend effect increases with the sentiment measured by turnover. For example, in Panel A, the VW trend spread return increases from 1.02% in $Senti_{Low}$ group to 1.82% in $Senti_{High}$ group. Similar results are reported in Panel B for EW portfolios. These findings are consistent with the time-series result that the trend effect is stronger following periods with higher levels of sentiment.

A.5. Orthogonal volume trend

In this section, we investigate whether volume trend can provide additional predictability independent of price trend. 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 A6 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 the institutional investors to measure information quality and information quantity, respectively. The results show that within each information quality (quantity) group, the portfolios sorted by $ER^{\perp}_{TrendV}$ show a increasing return pattern and produce a positive return spread, indicating that volume trend can provide independent predictability beyond price trend. Besides, the return on the spread portfolio deceases with the rise of 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 as information quality and information quantity increases.

A.6. *Results for EW portfolios*

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

Table A7 shows the performance of EW trend portfolios after controlling various firm characteristics in a sequentially double sorting procedure. After controlling for the control variables, the returns of the quintile portfolios sorted by ER_{Trend} preserve monotonic patterns. The associated spread portfolios yield significant monthly returns of 1.73%, 1.63%, 1.53%, 1.55%, 1.75%, 1.73%, 1.56%, 1.29%, and 1.17% after controlling for Size, EP, BM, R_{-1}, $R_{-6,-2}$, $R_{-12,-2}$, IVOL, illiquidity, and turnover, respectively.

Table A8 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 differences of the trend factor between the low volatility and high volatility group are 0.67%, 0.87%, 0.66%, and 1.15% for Vol_{Rt}, Vol_{Volume}, $Vol_{Earnings}$, and Vol_{Index}, respectively.

Table A9 reports the performance of EW volume trend portfolios with different information quality and information quantity. We can see that volume trend decreases with the rise of information quality and information quantity. The difference of the volume trend factor between the low and high information quality (quantity) group is 0.51% (0.58%).

Table A10 reports the performance of EW orthogonal volume trend portfolios with different information quality and information quantity. The results are similar to those in Table A6 for 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. Secondly, the trend effect decreases with information quality and quantity.

A.7. *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 past 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 A11 shows that our trend factor generates persistent and comparable performance under alternative coefficient forecasts. Specifically, in EMA with λ 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, the trend factor yields an average return of 0.91%, 1.10%, and 1.16% per month, respectively. Moreover, our trend factor also earns significant alphas with respect to CAPM, LSY-3, and LSY-4 factor model under these alternative constructions.

A.8. 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 for the trend factors. Then, we explore the role of trend volume in China vs 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.8.1. Summary statistics in the US

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). 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. The trend factor is defined as the VW return spread between the extreme quintile portfolios sorted by the associated trend measures.

Table A12 reports the summary statistics for the three trend factors in the US. 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 month with a t-statistic of 2.37, indicating that volume can provide incremental predictive information independent to price. TrendV also produces a significant return, but its magnitude (0.35%) is smaller compared with those of TrendPV and TrendP.

A.8.2. Sharpe style regressions

In the previous section, we show that volume trend can provide predictability beyond price trend in both China and the US. In this section, we compare the relative contribution of volume trend to the overall trend in the two markets.

The stock markets in China and the US have essentially different information environment. First, the US stock market is mainly populated by institutional investors who have advantage in acquiring and analyzing information, which improves information precision, while the Chinese stock market is dominated by retail investors who are more likely to be driven by sentiment. Moreover, the stock market in the US is more open than that in China. Consequently, global investors can easily access the US stock market, which flourishes the information set. Hence, we argue that information quality and information quantity in the US stock market is higher than that in China. Note that in the previous section, we show the predictability of volume trend decreases with information quality and information quantity. Hence, 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 regressions to examine the contribution of volume trend to the overall trend in the two markets. The 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 return of our modified trend factor (TrendPV) on the returns of the trend factor of price (TrendP) and trend factor of volume (TrendV). The coefficients are constrained to be non-negative and their sum is constrained to be one. Hence, the style regression examines the contribution of volume trend and price trend on the overall trend.

Table A13 shows the results of style regressions in China and the US.[8] In China, volume trend and price trend are equally important, accounting for 42% and 58% of the overall trend, respectively. In the US, however, price trend contributes 94% to the overall trend, while volume trend makes up 6%. This result is consistent with the explanation that the Chinese stock market is dominated by individual investors and it emphasizes again the importance of volume trend in China.

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

A.8.3. *Alphas in the US*

The previous section shows that the existing factor models can not explain our trend factor in China. Here, we investigate that whether the trend factors can be explained by factor models in the US. We examine various well-known factor models, including CAPM, Fama and French's (1993) 3-factor model (FF-3), Stambaugh and Yuan's (2016) 4-factor model (SY-4), and Fama and French's (2015) 5-factor model (FF-5).[9]

As shown in Table A14, 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. This result suggests that the factor models cannot explain neither TrendPV nor TrendP in the US. In addition, we evaluate the two trend factors by comparing their abilities to explain each other. The results show TrendP is explained by TrendPV, producing a monthly alpha of only 0.01% (t-statistic: 0.10). TrendPV, on the other hand, earns a monthly alpha of 0.21% (t-statistic: 3.20) with respect to CAPM with TrendP. Overall, existing factor models cannot explain the return on the trend factors, and our modified trend factor outperforms the original one in the US.

We investigate the explaining power of our 4-four factor model to explain the 11 anomalies examined in Stambaugh and Yuan (2016) in the US. While our 4-factor model explains all the anomalies in China, Table A15 shows its analogue fails to explains the anomalies in the US, which reflects the unique influence of the great individual investors participation in China.

A.9. *MA signals vs return signals*

In this section, we compare moving average (MA) signals with return signals. To do so, we form an return-based aggregated momentum factor (MOM_{All}) 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 formed on the return signals over the same time horizons as those of MA signals in TrendP. Furthermore, we form two associated 4-factor models for TrendP and MOM_{All}, denoted as TrendP-4 and MOM_{All}-4, respectively, using the same construction method as our 4-factor model.

[9] 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.

Table A16 shows the performances of two MA-based factors (TrendPV and TrendP) along 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 compares the abilities of the factor models to explain other factors. 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 MA-based factors substantially outperform the return-based factor in terms of both Sharpe ratio and explaining power.

Table A1

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

This table reports the summary statistics for the trend factor (*Trend*) and the factors that make up LSY-3 and LSY-4: the market factor (*MKT*), the size factor (*SMB*), the value factor (*VMG*) and the turnover factor (*PMO*). We use all stocks (including the smallest 30%) to construct factors. We report the sample mean, Newey-West (1987) adjusted t-statistics, sample standard deviation, Sharpe ratio, skewness and maximum drawdown (MDD) for each factor. 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 the q-4 factors

This table reports the summary statistics for Hou, Xue, and Zhang's (2015) q-4 factors: the market factor (*MKT*), the size factor (*SMB*), the profitability factor (*ROE*), and the investment factor (*I/A*). Panel A reports the results in which we exclude the smallest 30% of stocks to construct factors. Panel B reports the results in which we use all stocks (including the smallest 30%) to construct factors. 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 the FF-5 factors

This table reports the summary statistics for Fama and French's (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 results in which we exclude the smallest 30% of stocks to construct factors. Panel B reports the results in which we use all stocks (including the smallest 30%) to construct factors. 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 average monthly VW return for the portfolios formed 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. *Size-EP-AbTurn* portfolios and *Size-Trend-AbTurn* portfolios are produced in similar way. The Newey-West (1987) adjusted t-statistics are reported in parentheses. 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
Trend-Low	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
Trend-High	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
EP-Low	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
EP-High	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
Trend-Low	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
Trend-High	3.03	2.40	1.74	1.73	1.66	1.98

Table A5

Trend and investor sentiment

This table reports the VW and EW average monthly returns of the trend quintile portfolios in stock groups with different investor sentiment, which is measured by the turnover. Stocks are first sorted by the turnover into three groups: $Senti_{Low}$, $Senti_{Mid}$ and $Senti_{High}$. Then, in each group, stocks are sorted by ER_{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 $Senti_{Low}$ and $Senti_{High}$ groups. 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							
$Senti_{Low}$	1.19	1.60*	1.87**	2.12**	2.22**	1.02***	0.80***
	(1.36)	(1.77)	(2.20)	(2.41)	(2.49)	(2.70)	(2.84)
$Senti_{Mid}$	0.92	1.40	1.79*	2.04**	2.05**	1.12***	
	(1.04)	(1.51)	(1.96)	(2.21)	(2.34)	(2.97)	
$Senti_{High}$	0.23	1.07	1.52	1.79*	2.06**	1.82***	
	(0.26)	(1.11)	(1.59)	(1.87)	(2.19)	(4.59)	
Panel B: Equal-weighted							
$Senti_{Low}$	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)
$Senti_{Mid}$	0.89	1.43	1.76*	2.05**	2.26**	1.37***	
	(0.99)	(1.58)	(1.92)	(2.13)	(2.48)	(4.49)	
$Senti_{High}$	0.39	1.02	1.58	1.96**	2.28**	1.89***	
	(0.42)	(1.08)	(1.64)	(2.01)	(2.40)	(5.81)	

Table A6

Orthogonal volume trend, information quality and information quantity

This table reports the EW 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 residuals of the cross-sectional regression in which the volume trend measure (ER_{TrendV}) is regressed on the price trend measure (ER_{TrendP}). Information quality is measured by the volatility of the normalized earnings, while 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 $ER^{\perp}_{TrendV}$ 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) groups. 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 A7

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 within 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 each 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.

	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	0.84	1.65*	1.94**	2.11**	2.13**	1.29***
	(0.93)	(1.80)	(2.11)	(2.34)	(2.43)	(5.06)
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 A8

Trend and volatility: EW portfolios

This table reports the EW 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} groups. 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 A9

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 A10

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

This table reports the EW 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 residuals of the cross-sectional regression in which the volume trend measure (ER_{TrendV}) is regressed on the price trend measure (ER_{TrendP}). Information quality is measured by the volatility of the normalized earnings, while 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 $ER^{\perp}_{TrendV}$ 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) groups. 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 A11

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. In the first method of exponential moving average (EMA), we set the parameter λ to 0.01, 0.03, and 0.05. In the second method of simple moving average (SMA), we set the parameter M to 12, 24, and 36. Panel A reports the average monthly 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.

	λ 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						
α	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						
α	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						
α	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 A12

Summary statistics of the trend factors in the US

This table reports the summary statistics for the trend factors in US. $TrendPV$ is our modified trend factor that captures both price and volume trend. $TrendP$ is the original trend factor of Han, Zhou, and Zhu (2016) that 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 A13

Sharpe style regressions in China and the US

This table reports the Sharpe style regression results regressing the return of our modified trend factor ($TrendPV$) 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 the US. The t-statistics are shown in parentheses. The sample period is from January 2005 through December 2016.

	China	US
TrendV	0.42***	0.06***
	(10.94)	(2.82)
TrendP	0.58***	0.94***
	(15.08)	(40.83)

Table A14

Alphas of trend factors in the US

This table reports the alphas of the 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's (1993) 3-factor model. SY-4 is the Stambaugh and Yuan's (2016) 4-factor model. FF-5 is the Fama and French's (2015) 5-factor model. 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)
β_{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)
β_{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)	
β_{HML}		0.03		-0.08			-0.02		-0.18	
		(0.31)		(-0.54)			(-0.18)		(-1.29)	
β_{MGMT}			0.11					0.08		
			(1.06)					(0.87)		
β_{PERF}			0.08					0.04		
			(0.96)					(0.45)		
β_{RMW}				-0.14					-0.18	
				(-0.74)					(-1.00)	
β_{CMA}				0.22					0.31	
				(1.02)					(1.53)	
$\beta_{TrendPV}$										0.90***
										(29.86)
β_{TrendP}					0.95***					
					(42.51)					

Table A15

Alphas of anomalies in the US

This table reports the alphas and the associated Newey-West(1987) adjusted t-statistics for the 11 anomalies stated in Stambaugh and Yuan (2016) with respect to our 4-factor model in the US market. 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 A16

Moving-average signals vs return signals

This table compares the performance of factors based on return signals 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 formed on price MAs. MOM_{All} is constructed in the similar way as $TrendP$, except that it is based on return signals over the same time horizons as those of price MA signals used in $TrendP$. $TrendPV$ and the associated 4-factor model is constructed in the $2 \times 3 \times 3$ sorting procedure introduced in subsection 2.2. Similarly, $TrendP$, MOM_{All}, and two resulting 4-factor models are constructed in the same way. We exclude the smallest 30% of stocks to construct the factors. Panel A reports the summary statistics for these factors: $TrendPV$, $TrendP$ and MOM_{All}. Panel B reports the alphas for the three factors under different factor models. 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 2005 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			
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)	

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