Trend Factor in China*

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We propose a 4-factor model by adding an additional trend factor to Liu, Stambaugh and Yuan's (2018; LSY-3) 3-factor model: market, size and value. Since individual investors contribute about 80% of the trading volume in China, the trend factor captures well the resulting important price and volume trends, and has a monthly Sharpe ratio of 0.48, much greater than market (0.11), size (0.19) and value (0.28). The proposed 4-factor model explains all the reported Chinese anomalies, including turnover and illiquidity previously unexplained by LSY-3. Moreover, the model explains well mutual fund returns, an analogue of Carhart 4-factor model in China.

1. Introduction

Since China is the world's second largest stock market, it is important to see how well asset pricing theory previously developed in the US applies in China. The Fama-French 3-factor model (1993, FF-3, henceforth) is one of the most important models for pricing US stocks, but its replication does not work well for Chinese stocks. Accounting for unique features of the Chinese market, Liu, Stambaugh and Yuan (2018) propose two adjusted size and value factors, and show that these factors together with the market factor outperform substantially the replication of FF-3 in China. However, Liu, Stambaugh and Yuan' three-factor model (LSY-3, henceforth) still fails to explain certain important anomalies.

In this paper, we propose a 4-factor model: the market, size, value and trend, where the first three factors are those of the LSY-3. We construct the trend factor to capture short-, intermediate- and long-term price and volume trends in China. This is important because it is individual investors who contribute about 80% of the trading volume in China. Due to complex interactions of the various trends, momentum strategies do not work in Chinese stock market (see, e.g., Li, Qiu and Wu, 2010, Cheema and Nartea, 2014, and Cakici, Chan and Topyan, 2017). Unlike Han, Zhou and Zhu (2016) whose trend factor depends on only price signals, our trend factor exploits both price and volume information, which are important in China.[1] We also provide a theoretical model that sheds light on why trading volume has a unique role to play in the Chinese stock market.

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

The trend factor earns a significant monthly alpha of 1.47% and 1.17% with respect to the CAPM and LSY-3, respectively. The result indicates that the trend factor serves as a legitimate

[1] Our trend factor, accounting for the role of trading volume, outperforms substantially a replication of Han, Zhou and Zhu (2016).

extension of the LSY-3. Liu, Stambaugh and Yuan (2018) also propose a 4-factor model (LSY-4,henceforth) by adding a turnover factor. There are, however, three limitations of the turnover factor. First, the (value-weighted) 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 the LSY-4 model. Second, the portfolios sorted by exposures to the turnover factor exhibit non-monotonic return pattern. Third, the turnover factor captures investor sentiment in small stocks but not in large stocks. Most importantly, the our 4-factor model outperforms LSY-3 and LSY-4 in a number of ways.

First, our 4-factor model substantially dominates LSY-3 and LSY-4 in terms of explaining power. In comparison with LSY-3 and LSY-4, our model explains all the reported Chinese pricing anomalies, including those failed to be captured by LSY-3 or LSY-4, such as turnover, illiquidity and idiosyncratic volatility and so on. Moreover, our model also does a better job in explaining the mutual fund portfolios. It explains all the fund portfolios sorted by asset under management, and have smaller aggregate pricing errors than the LSY-3 and LSY-4 does. Since there is no momentum factor in China, our 4-factor model serves as an analogue of Carhart 4-factor model for Chinese mutual funds. Second, Fama-MacBeth regressions show that, after controlling factors in LSY-3 and LSY-4, our trend measure generates significant risk premia, while the measure of turnover factor in LSY-4 does not in presence of the trend measure. Third, the spanning test examines whether a portfolio of the benchmark factors, i.e., the LSY-3 and the LSY-4 factors, can mimic the trend factor. The result 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 so well in Chinese stock market? Our theoretical model and the associated numerical results show that the trend predictability increases with the market sentiment measured by noise trader demand volatility, and the fundamental economic volatility measured by dividend growth volatility. Empirically, we use three different measures to proxy for volatility, i.e., volatility of stock return, volatility of trading volume and volatility of earnings. We form trend factors with high, medium and low volatility, and find that the trend factor with high volatility earns significantly higher return, which is consistent with our model prediction.

The rest of the paper is organized as follows. In section 2, we discuss the construction of the trend factor and data. Section 3 investigates the trend factor in China and compare our 4-factor model with both LSY-3 and LSY-4 in various dimensions. Section 4 examines the cross-sectional return of our trend measure in comparison with the factor measures in LSY-3 and LSY-4. Section 5 proposes an explanation for the trend factor and examines the predictability of trend factor by volatilities. Section 6 examines the robustness of the trend factor and explores its performance in the US. Section 7 concludes.

2. Methodology and data

In this section we introduce the methodology and the 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, similar to Han, Zhou and Zhu (2016), signals, the MA of price of stock i with lag L in month t as

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

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. As in the case in the US, we normalize the MA signals by the closing price on the last trading day for stationarity:

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

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

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

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

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 can forecast returns by the following 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 $\widetilde{M}_{i,L_j}^{V,t-1}$ is the MA of volume of stock i with lag L_j at the end of month $t-1$, and $\beta_j^{V,t}$ is the coefficient of the MA signal of volume with lag L_j in month t. Then the expected return 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 moving average signals of price or volume with lag length L_j for month t+1, and is given by the exponential moving average of the betas in the past,

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

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 robustness.

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

2.2. Factor definition

We use the trend measure ER_{Trend}, along with stock's market capitalization (Size) and earnings-to-price ratio (EP), to construct the trend factor (*Trend*), the size factor (*SMB*), and the value factor (*VMG*) in our 4-factor model, applying a 2×3×3 sorting procedure similar to that used by Fama and French (2015).

Following Liu, Stambaugh and Yuan (2018), we exclude the smallest 30% stocks to avoid the shell-value contamination caused by the IPO constraints in China, and we use the remaining stocks to construct factors. [2] At the end of each month, the remaining 70% stocks are independently sorted into two *Size* groups ($Size_{Small}$ and $Size_{Big}$) by the median of the market capitalization, three *EP* groups (EP_{Low}, EP_{Mid} and EP_{High}) and three *Trend* groups ($Trend_{Low}$, $Trend_{Mid}$ and $Trend_{High}$) by the 30th and 70th percentiles of the 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 $Size_{Small}$ (or $Size_{Big}$) group, 6 portfolios in the EP_{Low} (or EP_{Mid}, EP_{High}) group, and 6 portfolios in the $Trend_{Low}$ (or $Trend_{Mid}$, $Trend_{High}$) group. And we use the VW portfolios to construct our factors. Following Liu, Stambaugh and Yuan (2018), when forming VW portfolios, here and throughout the study, we weight each stock by the market capitalization of all its outstanding A shares, including non-tradable shares.

In our 4-factor model, the size factor (SMB) is defined as the average of the VW returns of 9 portfolios in the $Size_{small}$ group minus the average of the VW returns of 9 portfolios in the $Size_{Big}$ group. The value factor (VMG) is defined as the average of the VW returns of 6 portfolios in the EP_{High} group minus the average of the VW returns of 6 portfolios in the EP_{Low} group. The trend factor ($Trend$) is defined as the average of the VW returns of 6 portfolios in the $Trend_{High}$ group minus the average of the VW returns of 6 portfolios in the $Trend_{Low}$ group. Our sorting procedure controls jointly for the three factor variables, and the resulting factors are roughly neutral with respect to each other. The market factor (MKT) is the return on the VW portfolios of the top 70% stocks, in excess of the one-year deposit interest rate.

We follow Liu, Stambaugh and Yuan (2018) to construct the factors in LSY-3 and LSY-4 factor model. In LSY-3, the size factor and the value factor is based on the monthly independent sorting of stocks into two $Size$ groups and three EP groups using the same breakpoints as in our 4-factor model. The intersections of the groups produce six VW portfolios. The Size factor SMB is the average of the three small stock portfolio returns minus the average of the three big stock portfolio returns. The value factor VMG is the average of the two high EP portfolio returns minus the average of the two low EP portfolio returns. The market factor is the same as in our 4-factor model. In LSY-4, the additional turnover factor PMO (pessimistic minus optimistic) is based on abnormal turnover, which is the past month's share turnover divided by the past year's turnover. The turnover factor is constructed the in the same way as the value factor in LSY-3, except the

[2] We also use alternative size filters, i.e., exclude the smallest 10% stocks or exclude no small stocks, to construct the factors. The performance of our trend factor is robust and is provided in an online appendix.

factor 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 the firm financial data come from WIND database. The sample period is from January 4, 2000 through July 31, 2018.

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

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

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

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

3. Trend factor in China

In this section, we examine the empirical performance of the trend factor in Chinese stock market. We first examine the properties of our trend factor along with other factors. Then, we carry out the spanning tests and investigate the alphas of the trend factor. Finally, we compare the performance of our 4-factor model with the LSY-3 and LSY-4 in explaining pricing anomalies and mutual fund portfolios.

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

3.1. Summary statistics

Panel A of table 1 presents the summary statistics for the trend factor (Trend), in comparison with factors in LSY-3 and LSY-4 factor model, i.e., the market factor (MKT), the size factor (SMB) and the value factor (VMG), and the turnover factor (PMO). Among these factors, the trend factor produces the highest average return of 1.43% per month, while the average return generated by SMB factor is only 0.97% per month and the average monthly return of value factor is 1.15%. Besides, the trend factor earns the highest Sharpe ratio (0.48), while the highest Sharpe ratio of LSY-3 factors is only 0.28 (VMG). Further more, the trend factor earns the lower MDD at 13.17%, while those for the size, value and turnover factors are 25.94%, 19.65% and 25.15%, indicating that the trend factor is resilient in recovery from the downside risk and perform well in the extreme scenarios.

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

3.2. Mean-variance spanning tests

We carry out mean-variance spanning tests to check whether a portfolio of the benchmark factors, i.e., LSY-3 factors and LSY-4 factors, can mimic the performance of the trend factor. The null hypothesis of the spanning test is that N assets can be spanned in the mean-variance space by a set of K benchmark assets. Following Kan and Zhou (2012), we carry out six spanning tests: Wald test under conditional homoskedasticity, Wald test under independent and identically distributed (IID) 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 2 shows the results of the spanning tests. The hypothesis is strongly rejected that the trend factor lies inside the mean-variance frontier of the LSY-3 factors and the LSY-4 factors, indicating that our trend factor is clearly a unique factor that captures the cross-sectional of stock trends and performs far better than the factors in LSY-3 and LSY-4.

3.3. *Alpha*

In the previous subsection, we show that the trend factor and the turnover factor have fairly high correlation (0.52). In this subsection, we compare the performances of the two factors by examining their alphas with respect to different benchmark models.

Table 3 reports the time-series regression results of the trend factor and PMO factor with respect to CAPM, LSY-3, LSY-4 factor model and our 4-factor model. Panel A and Panel B shows that both the trend factor and the PMO factor have significant alpha values relative to CAPM and LSY-3 factor model as benchmark model. Panel C shows that our trend factor earns positive and significant alpha with respect to LSY-4 factor model, implying that the existing risk factors cannot explain the trend factor. However, the PMO factor fails to earn significant alpha with respect to our 4-factor model. In short, our trend factor outperforms PMO factor, and our 4-factor model dominates the LSY-3 and LSY-4 factor model.

3.4. *Explaining power*

In this subsection, we investigate the performance of our 4-factor model in explaining stock anomalies and the mutual fund portfolios in Chinese stock market, in comparison with that of LSY-3, and LSY-4 factor model.

We compute the alphas (α) of the anomalies and the mutual fund portfolios with respect to different benchmark models. The explaining power the model is measured in three perspectives. First, the significance of the alpha measures the performance of the benchmark model. The less the number of significant alpha's, the better performance of the benchmark model in explaining anomalies. We also calculate the average absolute alpha and the average absolute t-statistic. Second, to measure further the cross-sectional overall pricing errors, following Shaken (1992), we provide a weighted summary of the alphas,

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

where Σ is the variance-covariance matrix of the residuals. The smaller the Δ, the smaller the aggregate pricing error and the better performance of the benchmark model. Third, we carry out the GRS test of Gibbons, Ross and Shanken (1989) to test whether the benchmark model can fully explain the anomalies or the mutual fund portfolios in the sense that all the alphas are zero.

3.4.1. Explaining anomalies

We compile 17 anomalies in China that are reported in the literature. These anomalies falling into 10 categories cover all the anomaly categories examined in Liu, Stambaugh and Yuan (2018). The anomalies and the corresponding measures are: (1) size anomaly: market capitalization (Size); (2) value anomaly: earnings-to-price ratio (EP), book-to-market ratio (BM) and cash-flow-to-market ratio (CP); (3) turnover anomaly: turnover (Turn); (4) trend anomaly: trend measure of price and volume (TrendPV), trend measure of price (TrendP) and trend measure of volume (TrendV); (5) illiquidity anomaly: the Amihud (2002) illiquidity measure (Illiq); (6) past return anomaly: the 1-month reversal (Reversal), and the 12-month momentum (MOM); (7) profitability anomaly: return-on-equity (ROE); (8) volatility anomaly: the volatility of the daily return in the last month (Vol), the idiosyncratic volatility (IVol), and the maximum daily return in the last month (MAX); (9) accrual anomaly: accrual (Accrual); (10) investment anomaly: asset growth (Invest).

Following Liu, Stambaugh and Yuan (2018), we exclude the smallest 30% stocks to form the anomalies. For each anomaly except reversal, we compute a long-short return spread between the extreme decile portfolios sorted by the corresponding anomaly measures in the most recent month-end and rebalance the portfolios monthly. Since the one-month return reversal is a short-term anomaly, stocks are sorted into decile portfolios each day based on the return over the most recent 20 days, and we hold the spread portfolios for five trading days. As a result, there are five portfolios for reversal each day. The daily return of the reversal is defined as the average return of the five portfolios. Then, we use the resulting daily return to calculate the monthly return for reversal. Liu, Stambaugh and Yuan (2018) use the same procedure to compute the return for the reversal anomaly. All anomalies are based on the VW decile portfolios using the market capitalization in the most recent month-end as weight.

Although the momentum, accrual and investment produce significant returns in the US, they do not in China. For our later analysis of the pricing abilities of different factor models, we retain only the 14 anomalies that generate significant returns.

Table 4 reports the alphas of anomalies with respect to different models. Panel A reports the average monthly return of these anomalies. Panel B shows that LSY-3 explains only 5 of 14 anomalies, i.e., EP, CP, ROE, Vol and MAX. However, all three different trends, i.e., TrendPV, TrendP and TrendV, survives under LSY-3, earning a significant monthly alpha of 1.50%, 1.29% and 1.22%, with a t-statistic of 3.51, 2.46 and 3.81, respectively. Beside, book-to-market ratio, turnover, illiquidity and idiosyncratic volatility also earn significant alphas with respect to LSY-3. LSY-3 even fails to subsume the size effect that it is designed to capture. Panel C shows LSY-4 explains only 6 of 14 anomalies. The additional one that explained by LSY-4 but failed to be explained by LSY-3 is the turnover, which LSY-4 is designed to capture. In contrast, Panel D shows that our 4-factor model explains all these 14 anomalies, including those failed to be explained by LSY-3 and LSY-4.

Table 5 compares the pricing ability of the models to explain anomalies by reporting the average absolute alphas, the corresponding average absolute t-statistics, the aggregate pricing errors and the GRS tests. The competing models include the "unadjusted" return (i.e., for a model with no factors), LSY-3, LSY-4, and our 4-factor model. First, our 4-factor model produces the smallest average absolute alpha of only 0.32%, while that of LSY-3 and LSY-4 is 0.85% and 0.52%, respectively. The average absolute t-statistics of our 4-factor model (0.68) is also much lower than that of other models. Second, in terms of the aggregate pricing error (Δ), our 4-factor model also dominates LSY-3 and LSY-4. The aggregate pricing error of our 4-factor model is only 0.140, in comparison with LSY-3 (0.296) and LSY-4 (0.256). Third, in GRS tests, both LSY-3 and LSY-4 strongly rejects the 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 at conventional significance levels. Overall, our 4-factor model substantially dominates LSY-3 and LSY-4 factor model in explaining stock anomalies.

3.4.2. Explaining mutual funds

In this subsection, we compare the performance of our 4-factor model and LSY-3 and LSY-4 factor model in explaining the mutual fund portfolios. We include only equity-oriented mutual funds. At the end of each month, we sort the mutual funds by the asset under management (AUM) into ten decile portfolios, from Fund1 (small) to Fund10 (big).

Table 6 reports the alphas of mutual fund portfolios with respect to different models. Panel B shows that there is two fund portfolios, i.e., Fund1 and Fund3, earning significant alphas with respect to LSY-3 factor model. Panel C shows that there is still one mutual fund portfolio (Fund3) earning significant alpha with respect to LSY-4 factor model. However, Panel D shows that no fund portfolio earns significant alpha with respect to our 4-factor model.

Table 7 compares the pricing ability of the models to explain anomalies. Our 4-factor model produces the smallest average absolute alpha, the smallest average absolute t-statistic, and the smallest aggregate pricing error. Again, our 4-factor model outperforms LSY-3 and LSY-4 factor model.

In conclusion, our 4-factor model explains all the pricing anomalies, including the those failed to be captured by LSY-3 and LSY-4. Besides, our 4-factor model explains the mutual fund portfolios well, an analogue of Carhart 4-factor model in China. Hence, our 4-factor model substantially dominates LSY-3 and LSY-4 in terms of explaining power.

4. Cross-sectional return

In this section, we examine the cross-sectional return of our trend measure using two different methods, the portfolio sorting method and the Fama-MacBeth regression method. We first discuss the complementariness of the two methods. Next, we conduct the Fama-MacBeth regressions. We then use triple sorting procedure to investigate the cross-sectional return of our trend measure in comparison with other factor variables in LSY-3 and LSY-4. Finally, we present the trend quintile portfolios after controlling for various firm characteristics such as size, EP, past returns, idiosyncratic volatility, turnover, etc.

4.1. Factor exposure vs portfolio sorting

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

Fama-MacBeth regression is given as

$$R = X * \beta + \epsilon, \tag{9}$$

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

$$\hat{\beta} = P * R, \tag{10}$$

where

$$P = (X'WX)^{-1}X'W, \tag{11}$$

an FxN matrix, whose row vectors are the portfolio weights of the N factor portfolios. W is the weighting matrix of the regression. $W = I$ corresponds to OLS. Note that $P * X = I$. This means that each factor portfolios has a exposure of one on itself and has a exposure of zero on all other factors. In particular, each factor portfolio, except for the intercept coefficient, is a self-financing portfolio.

So what does a portfolio sorting really do? How is it related to the FM regression given above? Consider the dual problem that, given F factor portfolios which can be formed by portfolio sorting, with row vectors representing the portfolio weights, the implied factor exposures can be given as

$$X = WF'(FWF')^{-1}. \tag{12}$$

Let's first assume $W = I$. Equation (12) says that if the portfolios are independent in the sense that $FF' = I$. This means that, if we use independent sorting, the resulting portfolio groups will have exactly the same number of securities. In this case, the factor exposure $X = F'$. However, suppose there exists two factors that are highly correlated, the "implied" factor exposure obtained by (12) may not be monotonic to the original factor exposure in the economic sense. To make it clear, let's consider a two factor model with factor exposure X_1 and X_2, corresponding to size and value.

Case 1: independent case

Suppose we use firm characteristics size and value sorting to obtain two portfolios

$$P_1 = [1, 1, 1, 0, 0, 0, -1, -1, -1],$$

and

$$P_2 = [1, 0, -1, 1, 0, -1, 1, 0, -1].$$

This corresponds to the case where the two portfolios are independent. By applying (12), we get the implied characteristics X_1 and X_2 as

$$\begin{aligned} X_1 &= [1, 1, 1, 0, 0, 0, -1, -1, -1]'/6 \\ X_2 &= [1, 0, -1, 1, 0, -1, 1, 0, -1]'/6 \end{aligned}$$

which is exactly what we expected.

Case 2: non-independent

Assume P_1 is the same as in case 1, while

$$P_2 = [1, 1, 0, -1, 0, 1, -1, 0, -1]. \tag{13}$$

The regression results are given as

$$\begin{aligned} X_1 &= [0.1, 0.1, 0.3, 0.2, 0, -0.2, -0.1, -0.3, -0.1]', \\ X_2 &= [0.1, 0.1, -0.2, -0.3, 0, 0.3, -0.1, 0.2, -0.1]', \end{aligned}$$

which is unexpected because the portfolio sorting shows that the securities with smallest size (X_1) are security 1,2 and 3, while the implied factor ranking says that the smallest are 3, 4, and 1(or 2). Same happens to the value (X_2) factor.

Hence, when using portfolio sorting method to construct factors in multi-factor models, it is important to make sure the portfolio factors are cross-sectionally independent, otherwise, unexpected factor rankings result. One way to check cross-sectional independence of portfolios is to examine the portfolio return monotonicity when using multiple sorting procedure.

4.2. Fama-MacBeth regressions

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

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

Table 8 reports the results of Fama-MacBeth regressions. The table shows that, controlling for three factors in LSY-3, our trend measure (ER_{Trend}) is positive and significant. In addition, controlling for four factors in LSY-4 with an additional turnover factor, the ER_{Trend} remains significant. However, AbTurn is not significant in presence of the trend measure. Again, our trend factor dominates the turnover factor in capturing cross-sectional returns.

4.3. Triple portfolios sorting

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 portfolios sorting.

At the end of each month, stocks are independently sorted into two *Size* group (Small and Big) by the median of the market capitalization, three *EP* groups (Low *EP*, Mid and High *EP*) and three *Trend* groups (Low ER_{Trend}, Mid and High ER_{Trend}), by the 30th and 70th percentiles of the EP and ER_{Trend}, respectively. As a result, there are 18 (2×3×3) *Size-EP-*ER_{Trend} portfolios. *Size-EP-AbTurn* portfolios and *Size-*ER_{Trend}*-AbTurn* portfolios are produced in the same way.

Table 9 shows the VW average monthly returns for portfolios formed in the above 2×3×3 independent sorting procedure. In Panel A, after controlling for size and EP, the returns of portfolios increase with ER_{Trend} with no exception. Similarly, after controlling for size and AbTurn in Panel C, the portfolios sorted by ER_{Trend} still show a great monotonic return pattern with no exception. On the contrary, the portfolios sorted by the exposure to the PMO factor (AbTurn) shows a non-monotonic return pattern in large stocks. For example, in the $BigSize$-$MidEP$ group in Panel B, the return increases from 1.00% in the $LowAbTurn$ portfolio to 1.28% in the $MidAbTurn$ portfolio and then drops to 0.60% in the $HighAbTurn$ portfolio. Worse still, in the $BigSize$-$MidER_{Trend}$ group in Panel C, after controlling for size and ER_{Trend}, the returns of portfolios increase with AbTurn, which is contradict to the motivation of PMO factor in Liu, Stambaugh and Yuan (2018) that the low-turnover stocks, about which investors are relatively pessimistic, will have higher return. The mixed return pattern of the AbTurn portfolios in Table 9 is consistent with Fama-MacBeth result in Table 8 that the exposure to PMO (AbTurn) is not significant in presence of our trend measures. Overall, our trend measures works well in both small and large stocks, while the turnover factor captures investor sentiment only in small stocks but not in large stocks.

4.4. Trend quintile portfolios

Table 10 shows the average return and other firm characteristics of quintile portfolios sorted by the trend-expected return (ER_{Trend}). With increasing ER_{Trend}, the quintile portfolio returns increase monotonically, with both EW and VW portfolios. This table reports other characteristics of the five quintile portfolios. First, they show roughly flat pattern with size and book-to-market ratio. Second, from bottom to top trend quintile portfolios, the portfolios show a decreasing pattern with past returns, e.g., from 8.49% in the Low group to -1.19% in the High group for R_{-1}, indicating that it captures the reversal effect. Third, they also show decreasing value measured by price-to-earnings, price-to-cash, and price-to-sales.

Table 11 show the sequentially double sorting result of the VW portfolios sorted by trend-expected return (ER_{Trend}) after controlling for various firm characteristics, including Size, EP, BM, R_{-1}, $R_{-6,-2}$, $R_{-12,-2}$, IVol , illiquidity and turnover. [3] At the end of each month, we first sort stocks by one of the control variables into five quintile control groups, and then in each control group, stocks are sorted into five trend groups by ER_{Trend}. As a result, there are 25 (5×5) portfolios. Finally, we average the portfolios across the five quintile portfolios of the control variable to get a new trend quintile portfolio. After controlling for these variables, the returns of the quintile portfolios sorted by ER_{Trend} preserve the monotonic pattern, and the high minus low trend factors in all controlled groups still earn significant monthly returns of 1.76%, 1.31%, 1.18%, 1.20%, 1.51%, 1.62%, 1.38%, 1.07%, 1.09% after controlling for Size, EP, BM, R_{-1}, $R_{-6,-2}$, $R_{-12,-2}$, IVol , illiquidity and turnover respectively.

5. Explanation

In the previous section, we have shown the superior performance of our trend factor in various aspects. Why does the trend factor performs so well in Chinese stock market? In this section, we present an explanation for our trend factor. First, we provide a theoretical model that sheds light on the driving factors behind the trend effect. Then, we empirically examine the implication of the model.

[3] The result of the sequentially double sorting for the EW portfolios is similar and is provided in an online appendix.

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

In this subsection, we provide an explanation for the trend factor in China proposed in the paper based on a model in Han, Zhou, and Zhu (2016).

In their model, they propose a risky asset trading 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 on the supply of the stock, which is given by an exogenous process $1 + \theta_t$ with

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

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

There exists an equilibrium price given in the following Proposition.

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

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

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

The proposition says that the equilibrium price is a linear function of the state variables D_t, 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 to the Chinese stock market since it is populated mainly by retail investors, whose trading volume consists of 80% of the whole market volume. Hence, trading volume can be a strong indicator for noise trader behavior. In our empirical study, since trading volume can be clustered and persistent, we use the trend of volume or a sum of moving averages of trading volume as defined in (4) to predict future returns. Indeed, we find that the 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, another is the noise trader behavior, which can be measured by the volatility of noise trader demand σ_θ.

In Table 12, 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 to proxy for volatility: volatility of stock return (Vol_{Rt}) , volatility of RMB trading volume (Vol_{Volume}), and volatility of earnings ($Vol_{Earnings}$).

Vol_{Rt} is defined as the volatility of monthly return in the past 12 months. For the volatility of RMB trading volume , since we want to capture noise trader demand, instead of simply calculating the volatility of trading volume, we first use AR(1) to model the monthly RMB trading volume in the past 12 months and use the resulting trading volume residual to measure the noise trader demand. The magnitude of the trading volume affects the volatility of the trading volume. 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 get the normalized trading volume residual by dividing the trading volume residual by the average of the trading volume residual in the past 12 months. Then, the volatility of trading volume (Vol_{Volume}) is defined as the volatility of the normalized trading volume residual in the past 12 months.

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

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

After constructing the proxies for volatility, we use the sequentially double sorting procedure to examine the relationship between the trend effect and the volatility. At the end of each month, stocks are first sorted by the volatility proxy into three tertiles: VolLow, VolMid and VolHigh. Then, in each volatility group, stocks are sorted by ER_{Trend} into five trend quintile portfolios, from Low to High. As a result, there are 15 (3×5) stock portfolios. In each volatility group, we define the return for the trend factor as the return spread between the High and Low portfolio. $\Delta(Trend)$ is defined as the difference of the trend factor between the VolHigh and VolLow group. Again, it is important to note that only information in month t or prior is used to construct the volatility proxies and to calculate the ER_{Trend}, so our study is an out-of-sample analysis.

Table 13 shows the result of the relationship between the trend factor and volatility in VW portfolios.[4] First, the trend factor earns significantly higher return in the VolHigh group than in the VolLow group. For example, for Vol_{Rt}, the return of the trend factor increases from 0.79% in the VolLow group to 1.54% in the VolHigh group. And the difference ($\Delta(Trend)$) is 0.75% with a t-statistic of 2.35. The results are similar for Vol_{Volume} and $Vol_{Earnings}$, indicating that the trend factor predictability increases with both the noise trader demand volatility and the fundamental variable volatility, which is consistent with the model prediction in Table 12. 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 much higher than that of Vol_{Rt} (0.75%), Vol_{Volume} (0.90%) and $Vol_{Earings}$ (0.58%). In conclusion, Table 13 confirms our model prediction that the trend predictability increases with the volatility of noise trader demand and the fundamental economic uncertainty.

6. Robustness

In this section, we show that the superior performance of the trend forecasts is robust. We first use alternative methods to forecast the coefficients of MA signals. We then explore the issue of turnover and transaction costs. Finally, we investigate the performance of our trend factor in the US stock market.

[4] The result of the relationship between trend factor and volatility in EW portfolios is similar and is provided in an online appendix.

6.1. *Alternative constructions*

In this subsection, we use two different methods to forecast the coefficient of MA signals to construct the trend factor as robustness check.

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

Table 14 reports the performance of the trend factor under these two alternative methods for the coefficient forecast with various parameters. In the method of EMA, we set λ to 0.01, 0.03 and 0.05. In the method of SMA, we set M to 12, 24, and 36. Panel A shows that the trend factor in all these cases earns significant return and the results are comparable among different construction methods. Panel B, C and D shows that the trend factor in all these cases earns significant alpha with respect to CAPM, LSY-3 and LSY-4 factor model, respectively. In conclusion, the performance of the trend factor is robust to different constructions for coefficient forecast.

6.2. *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), Barroso and Santa-Clara(2015), and Han, Zhou and Zhu (2016), we compute four different types of the break-even transaction costs (BETCs). The first two are the transaction costs that that would completely offset the return or the CAPM risk-adjusted returns. The second two are the costs that make the returns or the risk-adjusted returns insignificant at 5% level. We also calculate the results for the turnover factor for comparison.

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

6.3. Evidence in the US

The original trend factor proposed in the US stock market in Han, Zhou and Zhu (2016) captures only price trend, while our modified trend factor captures both price and volume trends. An interesting question is whether our modified trend factor also brings any economic gains compared with the original one in the US? In this subsection, we analyze our modified trend factor (TrendPV) in comparison with the original trend factor (TrendP) in the US.

Since there are more stocks and longer sample period in the US, following Han, Zhou and Zhu (2016), we use MAs of lag lengths 3-, 5-, 10-, 20-, 50-, 100-, 200-, 400-, 600-, 800-, and 1000-days to construct the trend measures. The trend factor is the return spread between the extreme VW quintile portfolios sorted by the trend measures. Also, we neutralize the trend factor to size. Specifically, we sort the stocks by the size median in NYSE into two size groups. And the trend factor is defined as the average of the trend factors in the two size groups. [5]

Table 16 reports the summary statistics of the original trend factor (TrendP) and our modified trend factor (TrendPV) in the US. First, our modified trend factor earns an average monthly return of 1.76%, while the original trend factor only earns 1.23%. Our modified trend factor also produces a higher Sharpe ratio (0.47) than the original one does (0.34). Second, the increment is 0.52% per monthly with a t-statistic of 4.70, indicating that the volume trend can provide incremental information independent to the price trend.

[5] If the trend factors are equal-weighted, or value-weighted without size-neutralization, our conclusion still holds.

In the previous section, Table 3 shows that the existing factor models can not explain our trend factor in China. Here, we ask a similar question, whether the trend factors can be explained by the factor models in the US. We explore several well-known factor models, including CAPM, Fama-French 3-factor model (FF-3) of Fama and French (1993), and Stambaugh-Yuan 4-factor model (SY-4) with two mispricing factors, i.e., MGMT and PERF, in addition to the market and size factor of Stambaugh and Yuan (2016). [6] In addition, we also compares the two trend factors by regressing one on the market factor with the other one.

As shown in Table 17, both TrendP and TrendPV earn significant alphas with respect to CAPM, FF-3 and SY-4. However, TrendP is almost totally explained by TrendPV, producing a monthly alpha of only 0.01% with a t-statistic of 0.11. In contrast, TrendPV earns a significant monthly alpha of 0.81% with respect to CAPM with TrendP. Overall, exiting factor models cannot explain the return on the trend factors, and our modified trend factor substantially outperforms the original one in the US.

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

7. Conclusion

In this paper, we propose a 4-factor model for the Chinese stock market, which adds one additional trend factor to Liu, Stambaugh and Yuan's (2018) 3-factor model. While Liu, Stambaugh and Yuan's model improves substantially over the replication of Fama-French (1993) 3-factor model in China, ours improves further the performance. Our trend factor exploits both price and volume information of various investment horizons to account for the about 80% participation of individual investors in trading in China.

Our empirical results show that the trend factor outperforms substantially the LSY-3 factors. First, the trend factor produces the highest average return of 1.43% per month, in comparison

[6] The factor data of FF-3 is from the Kenneth R. French Data Library. The factor data of SY-4 is from the personal website of Robert F. Stambaugh.

with 0.97% for size factor and 1.15% for value factor. The trend factor also generates the highest monthly Sharpe ratio of 0.48, almost doubling that of value factor (0.28), and much higher than that of market factor (0.11) and size factor (0.19). Second, the trend factor earns a significant monthly alpha of 1.47%, 1.17% and 0.82% with respect to CAPM, LSY-3 and LSY-4 factor models.

In terms of cross-sectional pricing ability, our 4-factor model also substantially dominates the LSY-3 and LSY-4. The results show that our 4-factor model explains all the anomalies including those failed to be captured by LSY-3 or LSY-4, such as turnover, illiquidity and idiosyncratic volatility and so on. It also explains the mutual fund portfolios sorted by asset under management, serving as Carhart model in China.

The superior performance of trend factor is robust to different constructions and to various firm and market characteristics, including size, market beta, book-to-market equity, earnings-to-price ratio, past returns, IVol, illiquidity and turnover.

We provide also a theoretical explanation for the trend factor. The volume trend provides predictability beyond the price trend. Our model shows that the usefulness of trading volume is due to the fact that the trading volume is driven by noise traders demand which determine the profitability of investors.

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Table 1

Summary statistics

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

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

Table 2

Mean-variance spanning tests

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

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

Table 3

Comparison of alphas of the trend and the turnover factor

This table reports the alphas of the trend factor (*Trend*) and the turnover factor (*PMO*) with respect to different benchmark models. Panel A reports the result for CAPM, Panel B reports the result for LSY-3 factor model, Panel C reports the result for LSY-4 factor model, and Panel D reports the result for our 4-factor model. Newey-West (1987) adjusted t-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

	Trend	PMO	Trend	PMO
	Panel A: CAPM		*Panel B: LSY-3 factor model*	
$\alpha(\%)$	1.47***	0.90***	1.17***	0.91***
	(6.30)	(4.70)	(3.91)	(2.96)
β_{MKT}	-0.04	-0.13***	-0.04	-0.14**
	(-1.31)	(-2.61)	(-0.92)	(-2.48)
β_{SMB}			0.15	0.07
			(1.48)	(0.64)
β_{VMG}			0.13	-0.06
			(1.15)	(-0.39)
	Panel C: LSY-4 factor model		*Panel D: Our 4-factor model*	
$\alpha(\%)$	0.82***			0.26
	(3.35)			(0.95)
β_{MKT}	0.03			-0.12***
	(1.05)			(-2.99)
β_{SMB}	0.10			-0.03
	(1.41)			(-0.36)
β_{VMG}	0.15**			-0.17
	(2.07)			(-1.41)
β_{PMO}	0.43***			
	(5.44)			
β_{Trend}				0.61***
				(4.31)

Table 4

Alphas of anomalies

This table reports the mean return and the alphas of the anomalies under three different factor models: LSY-3, LSY-4, and our 4-factor model. For each anomalies, we compute a monthly long-short VW return spread based on the decile portfolios sorted by the corresponding characteristics in the most recent month-end. The anomalies and the corresponding characteristics are: *Size*: market capitalization, *EP*: earnings-to-price ratio, *BM*: book-to-market ratio, *CP*: cashflow-to-market ratio, *Turnover*: turnover, *TrendPV*: trend of price and volume, *TrendP*: trend of price, *TrendV*: trend of volume, *Illiq*: the Amihud (2002) illiquidity measure, *Reversal*: 1-month reversal, *ROE*: return-on-equity, *Vol*: the volatility of the daily return in the last month, *IVol*: idiosyncratic volatility, *MAX*: the maximum daily return in the last month. Newey-West(1987) adjusted t-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

	Size	EP	BM	CP	Turnover	TrendPV	TrendP	TrendV	Illiq	Reversal	ROE	Vol	IVol	MAX
Panel A: Mean return (%)														
Mean	1.03*	1.37**	1.62***	0.80*	1.56**	1.83***	1.60***	1.42***	1.39**	1.62***	0.84*	1.07*	1.43***	1.05*
	(1.68)	(2.47)	(2.98)	(1.71)	(2.55)	(5.11)	(3.88)	(4.78)	(2.16)	(2.72)	(1.74)	(1.88)	(2.67)	(1.80)
Panel B: Alpha w.r.t. LSY-3 factor model (%)														
α	0.31**	0.22	1.05*	0.19	1.23**	1.50***	1.29**	1.22***	0.71***	1.59**	0.05	0.60	1.21**	0.77
	(2.44)	(0.71)	(1.83)	(0.57)	(2.31)	(3.51)	(2.46)	(3.81)	(3.44)	(2.51)	(0.17)	(0.85)	(2.28)	(1.21)
Panel C: Alpha w.r.t. LSY-4 factor model (%)														
α	0.33*	0.20	1.02*	-0.04	0.22	0.99***	0.95*	0.59**	0.47*	1.23**	-0.01	-0.06	1.06*	-0.13
	(1.91)	(0.65)	(1.70)	(-0.11)	(0.45)	(2.62)	(1.93)	(2.04)	(1.97)	(2.00)	(-0.04)	(-0.09)	(1.69)	(-0.24)
Panel D: Alpha w.r.t. our 4-factor model (%)														
α	0.13	0.23	0.47	0.00	0.45	0.11	-0.22	0.36	0.44	0.67	0.17	-0.06	0.92	-0.18
	(0.51)	(0.63)	(0.79)	(0.01)	(0.81)	(0.33)	(-0.55)	(1.20)	(1.39)	(1.00)	(0.45)	(-0.09)	(1.48)	(-0.32)

Table 5

Comparison of the model performance in explaining anomalies

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

Measure	Unadjusted	LSY-3	LSY-4	Our-4
Average $\lvert\alpha\rvert$	1.33	0.85	0.52	0.32
Average $\lvert t\rvert$	2.72	2.01	1.25	0.68
Δ	0.527	0.296	0.256	0.140
GRS	5.60***	2.24***	1.84**	0.91
	[0.00]	[0.00]	[0.03]	[0.55]

Table 6

Alphas of mutual funds

This table reports the mean return and the alphas of the mutual fund portfolios under three different factor models: LSY-3, LSY-4, and our 4-factor model. We construct the mutual fund decile portfolios sorted by asset under management (AUM) in the most recent month-end and rebalance the portfolios monthly. Newey-West(1987) adjusted t-statistics are reported in parentheses. The sample period is from January 2005 through July 2018.

	Fund1	Fund2	Fund3	Fund4	Fund5	Fund6	Fund7	Fund8	Fund9	Fund10
Panel A: Mean return (%)										
Mean	1.55**	1.20*	1.42*	1.52**	1.64**	1.54*	1.58*	1.58*	1.50*	1.12
	(2.05)	(1.69)	(1.84)	(2.02)	(2.05)	(1.82)	(1.77)	(1.87)	(1.67)	(1.31)
Panel B: Alpha w.r.t. LSY-3 factor model (%)										
α	0.43*	0.28	0.48*	0.36	0.31	0.39	0.55	0.43	0.19	0.12
	(1.93)	(1.18)	(1.90)	(1.53)	(1.56)	(1.36)	(1.55)	(1.58)	(0.64)	(0.53)
Panel C: Alpha w.r.t. LSY-4 factor model (%)										
α	0.24	0.28	0.45*	0.37	0.21	0.31	0.50	0.35	0.20	0.13
	(0.97)	(1.07)	(1.73)	(1.42)	(0.96)	(0.93)	(1.24)	(1.11)	(0.58)	(0.45)
Panel D: Alpha w.r.t. our 4-factor model (%)										
α	0.18	0.30	0.26	0.29	0.20	0.24	0.49	0.28	0.20	0.20
	(0.68)	(1.07)	(0.95)	(1.14)	(0.84)	(0.69)	(1.21)	(0.87)	(0.57)	(0.74)

Table 7

Comparison of the model performance in explaining mutual funds

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

Measure	Unadjusted	LSY-3	LSY-4	Our-4
Average $\|\alpha\|$	1.47	0.35	0.30	0.26
Average $\|t\|$	1.81	1.38	1.05	0.88
Δ	0.109	0.045	0.034	0.025
GRS	1.670*	0.49	0.35	0.24
	[0.09]	[0.89]	[0.96]	[0.99]

Table 8

Fama-MacBeth regressions

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

		(1)	(2)	(3)	(4)
Intercept	Coeff	0.015*	0.015*	0.015*	0.015*
	t-stat	(1.721)	(1.712)	(1.723)	(1.715)
	p-value	[0.087]	[0.089]	[0.087]	[0.088]
ER_{Trend}	Coeff		0.005***		0.005***
	t-stat		(3.301)		(3.350)
	p-value		[0.001]		[0.001]
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 returns of triple sorting portfolios

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

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

Table 10

Average return and other characteristics of the trend quintile portfolios

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

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

Table 11

Performance after controlling firm characteristics

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

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

Table 12

Price Trend Predictability vs 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 the 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 13

Trend and volatility

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

	Low	2	3	4	High	Trend	$\Delta Trend$
Panel A: Vol_{Rt}							
Vol Low	1.26	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 14

Performance of the trend factor under alternative coefficient forecasts

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

	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 15

Transaction costs

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

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

Table 16

Summary statistics of trend factors in US

This table reports the summary statistics of two trend factors in US. *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. *Increment* is the difference between the two trend factors. Newey-West(1987) adjusted t-statistics are reported in parentheses. The sample period is from January 1963 through December 2014.

	Mean(%)	Std dev(%)	Sharpe ratio
TrendP	1.23***	3.66	0.34
	(9.11)		
TrendPV	1.76***	3.76	0.47
	(11.81)		
Increment	0.52***	2.78	0.19
	(4.70)		

Table 17

Alphas of trend factors in the US

This table reports the alphas of two trend factors under different factor models. $TrendP$ is the original trend factor of Han, Zhou and Zhu (2016) which only captures price trend. $TrendPV$ is our modified trend factor which captures both price and volume trend. FF-3 is the Fama-French 3 factor model of Fama and French (1993). SY-4 is the 4-factor model with two mispricing factors, i.e., MGMT and PERF, in addition to market and size factor of Stambaugh and Yuan (2016). We also compares the two trend factors by regressing one on the market factor with the other one. Newey-West(1987) adjusted t-statistics are reported in parentheses. The sample period is from January 1963 through December 2014.

	TrendP				TrendPV			
	CAPM	FF-3	SY-4	TrendPV	CAPM	FF-3	SY-4	TrendP
$\alpha(\%)$	1.22***	1.23***	0.86***	0.01	1.71***	1.66***	1.49***	0.81***
	(8.98)	(8.21)	(5.33)	(0.11)	(11.65)	(10.77)	(7.55)	(6.25)
β_{MKT}	0.02	-0.04	0.06	-0.03	0.08*	0.07	0.12**	0.06*
	(0.44)	(-0.60)	(1.26)	(-0.91)	(1.78)	(1.18)	(2.32)	(1.89)
β_{SMB}		0.23	0.22			0.14	0.15	
		(1.45)	(1.63)			(1.04)	(1.36)	
β_{HML}		-0.08				0.08		
		(-0.67)				(0.99)		
β_{MGMT}			0.05				0.14	
			(0.51)				(1.47)	
β_{PERF}			0.30***				0.08	
			(3.56)				(0.97)	
β_{TrendP}								0.74***
								(12.50)
$\beta_{TrendPV}$				0.71***				
				(11.46)				