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# **Trend Factor in China: The Role of Large Individual Trading** Yang Liu<sup>1</sup>, Guofu Zhou<sup>2</sup>, Yingzi Zhu<sup>1</sup> Tsinghua University<sup>1</sup>, Washington University in St. Louis<sup>2</sup>



Abstract

We propose a 4-factor model for the Chinese stock market by adding a trend factor into the market, size, and value of Liu, Stambaugh, and Yuan's (2019) 3-factor model. Because of up to 80% of individual trading, the trend factor captures salient relevant price and volume trends, and earns a monthly Sharpe ratio of 0.48, much greater than that of the market (0.11), size (0.20), and value (0.28). The 4-factor model explains well a number of stylized facts and anomalies of the Chinese stock market. It also explains well mutual fund returns, serving as an analogue of Carhart's (1997) model in China.

Then, the expected return for stock *i* in month t+1 at month *t* is:

$$ER_{Trend}^{i,t} = \sum_{j} E_t(\beta_j^{P,t+1}) \widetilde{M}_{i,L}^{P,t} + \sum_{j} E_t(\beta_j^{V,t+1}) \widetilde{M}_{i,L}^{V,t}$$

where  $E_t(\beta_i^{x,t+1})$  (x=P,V) is the forecasting coefficient and given by an exponential moving average of the past coefficients. **Factor construction** 

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

**Economic explanation** 

#### **Trend effect and noise trader risk**

- Trend effect increases with retail trader participation measured by share-holing ratio of retail investors.
- Trend effect increases with noise trader risk measured by the volatility of residual trading volume.

	Low		3	3 4		Trend	$\Delta T$ rend
Panel A: T	rend and	the parti	cipation o	of retail inv	estors		
<i>Retail<sub>Low</sub></i>	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)
Retail <sub>Mid</sub>	0.44	0.93	1.22	1.73**	1.85*	1.42***	
	(0.52)	(1.04)	(1.56)	(1.98)	(1.96)	(3.19)	
Retail <sub>High</sub>	-0.78	0.35	0.98	0.94	1.17	1.95***	
Ū	(-0.86)	(0.38)	(1.07)	(0.95)	(1.24)	(4.13)	
Panel B: T	rend and	the volat	tility of no	oise trader	demand		
VolLow	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 <sub>Mid</sub>	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 <sub>High</sub>	0.30	1.01	1.38	1.77*	2.01**	1.71***	
0	(0.34)	(1.11)	(1.57)	(1.92)	(2.22)	(4.04)	

Keywords: Chinese Stock Market, Individual Trading, Factor Model, Anomalies

### Motivation

China's stock market is the world's second largest stock market after the US, and hence it is important to examine how well asset pricing models perform in China. Fama and French's 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 factors, and show that these adjusted factors together with the market factor outperform substantially the replication of FF-3 in China. However, Liu, Stambaugh, and Yuan's 3-factor model (LSY-3, henceforth) still cannot explain certain important anomalies.

The reason we argue is that, for models to work well in China, they

#### Data

We use all Chinese A share stocks listed in the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Following LSY, we exclude the smallest 30% stocks each month. All the stock trading data and firm financial data come from WIND database. The effective sample period is from January, 2005 to July, 2018.

### Main Results

#### **Summary statistics**

- Trend factor produces the greatest mean return of 1.43% per month, and it generates the highest Sharpe ratio of 0.48.
- Trend factor is resilient in recovery from downside risk, and has a maximum drawdown (MDD) of only 13.17%.
- The LSY's size (value) factor has a strong correlation with ours, and the performances are largely the same.

	MKT	SMB	VMG	PMO	$SMB^*$	$VMG^*$	Trend						
Panel A: Summary statistics													
Mean (%)	0.91	1.00**	1.09***	0.89***	0.90**	1.29***	1.43***						
	(1.20)	(2.42)	(4.06)	(3.26)	(2.46)	(5.11)	(6.10)						
Std. dev. (%)	8.30	4.96	3.97	3.92	4.32	3.35	3.00						

#### **International study – the role of volume**

- We use the Sharpe (1988) style analysis to identify the contribution of volume and price in our trend factor. TrendPV<sub>t</sub> =  $\alpha + \beta_V$  TrendV<sub>t</sub> +  $\beta_P$  TrendP<sub>t</sub> +  $\epsilon_t$ , s.t.  $\beta_V \geq 0, \beta_P \geq 0, \beta_V + \beta_P = 1.$
- Cross-market comparison:
  - Volume contributes the highest of 0.48 in China, and the lowest of 0.05 in the US.
  - Volume is more important in emerging markets.
- Time-series comparison:
  - Volume is more important in the earlier period.

40\*\*\* 0.00\*\*\* 0.02\*\*\* 0.02\*\*\* 0.05\*\*\* 0.05\*\*\* 0.12\*\*\* 0.12\*\*\* 0.00\*\*\*

• Volume is persistently important in China, consistent with the fact that retail investors is more persistent over time.

	Emerging markets						Developed markets							
	China	India	Malaysia	S.Korea	Taiwan	US	Canada	UK	Germany	France	Italy	Japan		
anel A: Coefficients of TrendV ( $\beta_V$ ) in the Sharpe style regressions														

need to take another important feature of China's stock market into consideration: individual investors contribute about 80% of the total trading volume.

## Methodology

### **Trend signal**

Our trend factor extends the original price trend factor of Han, Zhou, and Zhu (2016) by adding volume signals to reflect noise trader behavior in China. Define  $\widetilde{M}_{i,L}^{P,t}$  and  $\widetilde{M}_{i,L}^{V,t}$  is the moving average of price and volume of stock *i* with lag *L* in month t. Following Brock et al. (1992), we use the various lag lengths to detect price trends over different time horizons.

At the end of each month *t*, we run the following predictive cross-section regression:

 $\mathbf{r}_{i}^{t} = \beta_{0} + \sum_{j} \beta_{j}^{P,t} \widetilde{M}_{i,L}^{P,t-1} + \sum_{j} \beta_{j}^{V,t} \widetilde{M}_{i,L}^{V,t-1} + \epsilon_{i}^{t}$ 

Sharpe ratio	0.11	0.20	0.28	0.23	0.21	0.38	0.48
Skewness	-0.38	-0.05	0.21	-0.73	0.08	0.14	0.33
MDD (%)	69.33	26.06	19.69	25.69	23.09	13.06	13.1

### **Explanatory power**

- We compare the explanatory power of different factor models in explaining 10 categories of anomalies in China.
- Our-4 produces the smallest average alpha of 0.35% with the  $\bullet$ lowest t-stat of 0.77. It also generates the smallest aggregate pricing error of 0.18. GRS test indicates that Our-4 fully explain these anomalies.
- Our-4 also substantially outperforms other models in explaining factors in other models, and mutual fund returns.

Measure	Unadjusted	LSY-3	LSY-4	q-4	FF-5	Our-4
Average $ \alpha $	1.29	0.88	0.53	1.25	0.94	0.35
Average $ t $	2.66	2.05	1.33	2.92	2.36	0.77
$\Delta$	0.55	0.35	0.30	0.47	0.38	0.18
GRS	$5.41^{***}$	$2.50^{***}$	$2.04^{**}$	$3.75^{***}$	$2.91^{***}$	1.08
	$[<10^{-8}]$	[0.00]	[0.02]	$[<10^{-4}]$	$[<10^{-3}]$	[0.38]

$eta_V$	$0.48^{***}$	$0.22^{***}$	$0.33^{***}$	$0.27^{***}$	$0.38^{***}$	$0.05^{***}$	$0.13^{***}$	$0.17^{***}$	$0.08^{***}$	$0.15^{***}$	$0.20^{***}$	$0.09^{***}$
	(14.56)	(8.74)	(9.61)	(5.73)	(6.74)	(5.57)	(3.82)	(8.43)	(2.93)	(6.99)	(7.18)	(6.21)
$\Delta_{China}$	_	-0.26***	-0.15***	-0.21***	-0.10	-0.43***	-0.35***	-0.31***	-0.40***	-0.33***	-0.28***	-0.39***
	_	$[<10^{-3}]$	[0.03]	[0.00]	[0.48]	$[<10^{-5}]$	$[<10^{-4}]$	$[<10^{-4}]$	$[<10^{-4}]$	$[<10^{-4}]$	$[<10^{-4}]$	$[<10^{-3}]$
$\Delta_{US}$	0.43***	0.17***	0.28***	0.22***	0.33***	_	$0.07^{*}$	$0.12^{***}$	0.03	0.10***	0.15***	0.04
	$[<10^{-5}]$	$[<10^{-3}]$	$[<10^{-4}]$	$[<10^{-3}]$	[0.00]	_	[0.09]	[0.00]	[0.41]	[0.00]	[0.00]	[0.33]

#### Panel B: Coefficients of TrendV ( $\beta_V$ ) in different periods

Earlier	0.47***	0.29***	0.46***	0.37***	0.44***	0.05***	0.14***	0.19***	0.09*	0.24***	0.29***	0.08***
	(8.81)	(7.38)	(8.27)	(4.55)	(4.70)	(4.33)	(2.65)	(6.35)	(1.89)	(7.23)	(5.98)	(3.49)
Recent	0.49***	0.08***	0.13***	$0.17^{***}$	0.22***	0.06***	0.12***	0.11***	$0.06^{**}$	0.03	0.10***	0.10***
	(11.59)	(2.99)	(4.54)	(3.45)	(4.49)	(3.46)	(2.81)	(3.76)	(1.99)	(1.17)	(3.80)	(7.09)
$\Delta_{Recent}^{Earlier}$	-0.02	0.21***	0.33***	0.20**	0.22	-0.01	0.02	0.08	0.03	0.21***	$0.19^{***}$	-0.02
	[0.82]	$[<10^{-2}]$	$[<10^{-3}]$	[0.03]	[0.24]	[0.68]	[0.73]	[0.25]	[0.74]	[0.00]	[0.00]	[0.67]

### Conclusion

- We extend LSY model into a 4-factor model by adding a Trend factor to account for large individual participation in China.
- Our model dominates all existing models in China, serving as Carhart model there.
- Noise trader risk is the key driving force behind the trend factor.
- International comparison highlights the particular importance of volume in China.

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