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The five-factor asset pricing model tests for the Chinese stock market

Bin Guo[a], Wei Zhang[b,c], Yongjie Zhang[b,d], Han Zhang[e,*]

[a] School of Finance, Nankai University, Tianjin, PR China
[b] College of Management and Economics, Tianjin University, Tianjin, PR China
[c] Key Laboratory of Computation and Analytics of Complex Management Systems, Tianjin, PR China
[d] China Center for Social Computing and Analytics, Tianjin University, Tianjin, PR China
[e] School of Business, Nankai University, Tianjin, PR China

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ABSTRACT

We provide out-of-sample tests of the five-factor model introduced by Fama and French (2015a) for the Chinese stock market. We find strong size, value and profitability patterns in average returns, but weak investment pattern. For portfolios we test, we find that the profitability factor significantly improves the description of average return, however, the investment factor makes marginal contributions. Factor spanning tests prove that the investment factor is redundant during 07/1995–06/2015 and 07/1997–12/2013 for the Chinese stock market. More importantly, the five-factor model passes the GRS tests of Gibbons et al. (1989) for most of portfolios we test.

1. Introduction

Inspired by the clean surplus relation of Miller and Modigliani (1961) that the total dividend equals total equity earnings minus the change in total book equity, Fama and French (2015a) introduce a five-factor asset pricing model that adds the profitability and investment factors to the three-factor model of Fama and French (1993). The five-factor time-series regression is

$$R_{it} - R_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}, \tag{1}$$

where $R_{it} - R_{Ft}$ is the portfolio i's return in excess of risk-free rate R_{Ft} for month t, Mkt_t is the value-weight (VW) market portfolio return in excess of risk-free rate, SMB_t, HML_t, RMW_t and CMA_t are respectively the size, value, profitability and investment factors. Before the establishment of the five-factor model, there is a large body of literature addressing the profitability and investment patterns in average returns for the U.S. stock market.[1]

* Corresponding author.
E-mail addresses: binguo.nk@gmail.com (B. Guo), weiz@tju.edu.cn (W. Zhang), yjz@tju.edu.cn (Y. Zhang), zhanghan@tju.edu.cn (H. Zhang).

[1] See, e.g., Fairfield et al. (2003), Titman et al. (2004), Fama and French (2006, 2008a), Aharoni et al. (2013) and Novy-Marx (2013).

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Fama and French (2015b) test the five-factor model for international developed stock markets including North America, Europe, Japan, and Asia Pacific, which is an out-of-sample test of the U.S. results of Fama and French (2015a). They find that the five-factor model significantly improves the performance of description for the anomaly patterns in average returns in global aspect.

However, different regions have different kinds of anomalies, which implies that the importance of a particular factor is diverse for different regions. For example, the value, profitability and investment effects are strong for North America, Europe, and Asia Pacific. But for Japan, there is little relation of average returns with profitability and investment. Fama and French (2012, 2015b) emphasize that the Global version of the factor asset pricing model performs poorly, and the Local version can give a clear explanation of the anomalies.

In this paper, we test the five-factor model of Fama and French (2015a) on the Chinese stock market. Although the Chinese stock market is still a developing market, by the end of July 2015, its capitalization had reached 50 trillion RMB yuan, and its number of listed firms had exceeded 2600, which leads the Chinese stock market to the second largest stock market following NYSE.[2] The cross-section regressions of Fama and MacBeth (1973) suggest that *Return on Equity* (*ROE*) is the best selected variable indicating profitability, and the growth rates of *Total Assets* and *Book Equity* (*InvA* and *InvB*) are similar to indicate investment. We find that average returns for the Chinese stock market typically increase with *Book-to-Market* ratio (*B/M*) and *ROE*, decrease with market cap (*Size*), and have little relation with *InvA* and *InvB*. Consequently, the profitability factor RMW improves the performance of the five-factor model, but the investment factor CMA does not. Factor spanning tests show that the investment factor CMA is redundant in the factor asset pricing model. We evaluate the empirical performance of the five-factor model by 5 factor variables (*Size*, *B/M*, *ROE*, *InvA* and *InvB*), and use other 9 well-documented anomaly variables to test the robustness of the five-factor model. All variables are tested by Fama (2016), Chen et al. (2015) and Chen et al. (2010). Following Fama and French (1996,2015a,b), the left-hand-side (LHS) portfolios tested in this paper are 25 (5 × 5) portfolios double sorted by factor variables and decile portfolios single sorted by anomaly variables. The return spreads of high and low anomaly variable portfolios in the Chinese stock market do not depend on *Size* typically, which is the reason why we use decile portfolios, rather than double sorted portfolios. The high-minus-low decile portfolios single formed by value variables (*Earning-to-Price ratio* (*E/P*) and *Market Leverage* (*A/P*)) and *Research & Development Expenses to Market* (*RD*) are significant, and others are not. Summary statistics prove that high *E/P* and *A/P* portfolios tend to have high *B/M*, and high *RD* portfolios tend to have small market cap. Our results are consistent with Chen et al. (2010), who show that many anomaly variables which are efficient in the U.S. market do not affect the average returns of the Chinese market, except the obvious value effect. More importantly, the four- (excluding CMA) and five-factor models pass the GRS test for most of portfolios we test, but the three-factor model does not. Hence, the profitability factor is critical for the Chinese stock market. Our study can be regarded as out-of-sample tests of Fama and French (2015a,b).

Hou et al. (2015) introduce a *q*-factor model, in which there are four factors without value factor. However, they do not illustrate the reason for dropping the value factor. Similarly, Fama and French (2015a) find that the factor HML is a redundant factor for the U.S. stock market, since it is totally spanned by other four factors. Different from them, we find that, in China, the strong and robust value effect in China can not be explained by profitability and investment factors, and the factor HML is not redundant, which is similar to the Japanese stock market. Our result is consistent with the international tests of Fama and French (2015b), which shows that the value factor HML spanning regressions give the intercepts that are more than 2.3 standard errors from zero, and the result is robust. Thus, the U.S. results are special among the global markets.

On the cross-section of expected returns in the Chinese stock market, Wang and Xu (2004) use a relatively short time sample (07/1996–06/2002) to find the strong size effect and weak value effect. Consequently, they define a new factor, free float, which is the ratio of public company shares to total company shares, to improve the performance of factor model. Hilliard and Zhang (2015) also find little evidence of value effect, because of using smaller number of stocks.[3] Chen et al. (2015) argue that the robust value effect in China is due to the extreme values in the early years from 1995 to 1996. However, they do not show the factor spanning tests for factors. Our time-series out-of-sample factor spanning tests omitting the period from 1995 to 1996 show that the value factor HML is still non-redundant, although it tends to be insignificant. Unlike them, Chen et al. (2010) only find the obvious value effect by the data from 07/1995 to 06/2007; Carpenter et al. (2015) and Cakici et al. (2015a) find strong size and value effects both in average returns using their own samples. Cakici et al. (2015b) show that the book-to-market decomposition described in Fama and French (2008b) improves the explanatory power of estimation for the Chinese shares. In addition, there exist some particular factors to the Chinese stock market, such as the price momentum emphasized by Kang et al. (2002) and Naughton et al. (2008), the volume factor considered by Wang and Cheng (2004), and the liquidity factor mentioned by Narayan and Zheng (2010). We find that different studies adopt different time-samples, different stock-samples, and different databases, which makes the results different. Furthermore, the studies mentioned above on the Chinese stock market use the full stock sample breakpoints for anomaly variables. However, Fama and French (1993) use NYSE breakpoints to avoid sorts dominated by tiny but plentiful stocks. Using the full stock sample breakpoints can not distinguish the average returns for portfolios with different level of anomaly variables. Hence, we use the spot China Securities Index 300 (CSI 300) underlying stocks breakpoints for variables, which consists of the biggest and highest liquidity 300 listed firms. As far as we

[2] Data is from monthly statistical report of China Securities Regulatory Commission.

[3] For example, in 2011, the number of listed firms is 1266 in their paper, and 2301 in our studies.

know, there is no studies concerning about the five-factor asset pricing model including profitability and investment factors for the Chinese stock market.

The rest of the paper is organized as follows. Section 2 briefly describes the data we use and the characteristics of the Chinese stock market. Section 3 provides the cross-section relations between expected returns and potential factor variables, and compares the different profitability and investment variables. Section 4 presents the summary statistics of LHS portfolio returns. Section 5 reports the summary statistics of right-hand-side (RHS) potential factor returns, and tests the redundancy of them. Section 6 examines the performance of three-, four-, and five-factor model for LHS portfolios mentioned in Section 4. Section 7 shows the regression details. Section 8 shows the robustness checks, using other 9 anomalies. Section 9 then gives the concluding remarks.

2. Data source and summary statistics for the Chinese stock market

2.1. Data source

The accounting data and returns of listed Chinese firms are obtained from the China Stock Market & Accounting Research (CSMAR) database, which follows the standards of CRSP and Compustat database. The Chinese stock market includes A-share stocks available for domestic investors using RMB denomination and B-share stocks available for foreign investors with U.S. dollar denomination, where B-share market is smaller and more illiquid than A-share market. Hence, we focus on the A-share stocks. The A-share stocks consist of all Shanghai and Shenzhen Main Broad, Shenzhen Small and Medium-sized Enterprise Board (SMEB) and Growth Enterprise Market (GEM) stocks. According to the approach of Fama and French (1993, 2015a), we use all A-share stocks listed on the Shanghai and Shenzhen exchanges except those with negative book value. The negative book value is caused by the changes in accounting procedures and regulations in China. Due to the extreme value in the early 1990s emphasized by Chen et al. (2015), our sample covers data from 07/1995 to 06/2014, 240 months.

2.2. Summary statistics for the Chinese stock market

The Chinese stock market consisting of Shanghai and Shenzhen stock exchanges is established in 1990. The Chinese stock market grows rapidly in the past three decades. Wang and Xu (2004) and Chen et al. (2015) comprehensively depict the Chinese stock market. We only show some relevant summary statistics in this paper.

Table 1 showing the summary statistics for A-share stocks provides an overall view. The number of traded stocks increasing from 311 at the end of 1995 to 2592 at the end of 2014 enlarged nearly eightfold, and the total market capitalization increasing from 333.78 billion to 37283 billion enlarged of more than 100 times in this period. By contrast, at the same time, the GDP in China only increased 11 times shown in column 8, although the increase is a miracle all over the world. The means of annual percent equal- and value-weighted market returns are 29% and 21%, respectively. Although the means of market returns are obviously bigger than the risk-free rate, the volatilities of market returns are high (the standard deviations of annual percent market returns are 64% and 52%). The t-statistics of annual equal- and value-weighted market returns are 2.04 and 1.79, respectively. The column 6 and 7 show the annual volatilities of market returns calculated by the standard deviations of daily percent returns multiplying by the square root of the average trading days ($\sqrt{243}$). As emphasized by Chen et al. (2015), the market was in drastic fluctuation before 1997. Besides this period, the A-share market drastically fluctuated between 2007 and 2009 in our sample.

More important, the Chinese stock market has little relation with the Chinese marcoeconomy. The correlation between equal-weighted market return and GDP growth is only 0.08, which almost equals the correlation between value-weighted market return and GDP growth (0.06). The total consumption growth rate performs a little bit better: The correlations are 0.09 and 0.07. The low correlation implies that the "equity premium puzzle" introduced by Mehra and Prescott (1985) also exists in China. However, the puzzle is different from the case in U.S. market: the high estimated risk aversion is caused by the low correlation between marcoeconomy and stock market in China, rather than the low volatility of market return in U.S..

3. Cross-section regressions

In this section, we test whether there exist size, value, profitability and investment patterns in average returns mentioned in Fama and French (2015a). Novy-Marx (2013) chooses three potential profitability variables (*Gross profitability*, *Earnings* and *Free cash flow*), and finds that after controlling size, value and momentum effects, *Gross profitability* has stronger predict power than other two profitability variables. Following him, we run the Fama and MacBeth (1973) cross-section regressions of returns on potential variables shown in Table 2. *Int* is the intercept term. For profitability variables, *Gross-prof-A* and *Gross-prof-B* are respectively gross profitabilities for year t scaled by total assets and by book equity at the end of year t; *ROE* is earnings for year t scaled by book equity at the end of year t; *Free cash flow* is net income plus amortization and depreciation minus changes in working capital expenditures for year t scaled by book equity at the end of year t. For investment variables, *InvA* is annual change in total assets for year t divided by total assets at the end of year $t-1$; similarly, *InvB* is annual growth rate in book equity. *B/M* is book equity at the end of year t divided by market cap at the end of year t. *Log(Size)* is natural logarithm market cap at the end of June of year $t+1$. The regressions are estimated monthly, using accounting variables that updated at the end of June of fiscal year $t+1$.

Table 1
Summary statistics for A-share market and Chinese macro-economy: 1995–2014. The table reports the summary statistics for A-share stocks. The *N* denotes the number of stocks effective to calculate their annual returns. The *TMC* denotes the total A-share market capitalization in billion RMB. The equal- and value-*Mkt* denote the annual percent equal- and value-weighted market returns respectively. The *Vol* denotes the annual volatility of market returns calculated by the standard deviation of daily percent returns multiplying by the square root of the average trading days ($\sqrt{243}$) in each year. The *GDP* denotes the percent growth rate of Chinese gross domestic product. The $\triangle\mathbf{C}$ denotes the percent growth rate of consumption.

Year	***N***	***TMC***	equal-***Mkt***	value-***Mkt***	equal-***Vol***	value-***Vol***	***GDP***	$\triangle\mathbf{C}$
1995	311	333.78	−11.22	−12.60	53.00	48.64	26.12	27.11
1996	514	952.87	100.57	97.02	47.86	41.78	17.07	19.70
1997	720	1731.75	31.82	26.10	39.13	36.16	11.00	7.64
1998	825	1934.49	12.04	−5.40	25.41	21.51	6.88	5.23
1999	923	2630.52	21.75	17.54	28.22	28.37	6.30	5.92
2000	1060	4780.02	69.58	54.68	22.14	21.82	10.73	11.22
2001	1139	4254.66	−22.22	−23.65	23.38	21.82	10.55	7.14
2002	1206	3768.46	−19.76	−17.12	28.06	25.25	9.79	7.89
2003	1266	4168.22	−12.09	3.98	18.39	17.61	12.90	7.08
2004	1362	3654.03	−15.10	−14.97	23.38	20.89	17.77	11.54
2005	1365	3184.68	−12.86	−7.02	26.66	22.60	15.74	12.32
2006	1417	8899.82	92.49	111.04	26.19	23.69	17.15	11.19
2007	1516	32,560.43	203.69	133.04	39.75	35.85	23.15	18.02
2008	1576	12,130.54	−57.60	−64.53	53.31	46.45	18.24	14.99
2009	1679	24,311.38	146.74	90.26	34.60	30.55	9.25	9.27
2010	2019	26,429.96	14.83	−7.55	27.44	23.38	18.32	14.76
2011	2301	21,473.68	−29.26	−23.10	24.01	19.49	18.47	20.29
2012	2456	22,902.53	4.94	5.20	25.25	19.02	10.44	11.92
2013	2470	23,857.40	21.31	0.79	22.92	19.17	10.16	10.15
2014	2592	37,283.94	47.45	52.27	20.73	17.30	8.19	9.81

The first column in Table 2 only considers *Log(Size)* as the independent variable. There is a strong negative relation between average return and *Log(Size)*. The Fama-MacBeth t-statistic for *Log(Size)* is nearly −3.5 standard errors from zero. Similarly, there is strong positive relation between average return and *B/M* (t = 2.51) in column (2). After controlling market cap, the value effect is reliable (t = 2.87), and vice versa for size effect (t = −3.64).

In the tests for profitability variables, we control *Log(Size)* and *B/M*. For four profitability variables, there are little relations between average return and *Gross-prof-A* (t = 0.06 after controlling *Log(Size)* in column (4) and t = 0.80 after controlling *Log(Size)* and *B/M* in column (5)), *Gross-prof-B* (t = 0.45 after controlling *Log(Size)* in column (6) and t = 1.09 after controlling *Log(Size)* and *B/M* in column (7)) and *Free cash flow* (t = −1.15 after controlling *Log(Size)* in column (10) and t = −0.62 after controlling *Log(Size)* and *B/M* in column (11)), except *ROE* (t = 1.29 after controlling *Log(Size)* in column (8) and t = 2.04 after controlling *Log(Size)* and *B/M* in column (9)). It is surprising that *Free cash flow* characterizing profitability has a negative relation with average return, although this relation is not reliable. In short, compared with other profitability variables, *ROE* has a stronger impact on average return.

For investment variables, *InvA* and *InvB* both perform poorly. There are no obvious relations between average return and *InvA* (t = −0.82 after controlling *Log(Size)* in column (12) and t = −0.11 after controlling *Log(Size)* and *B/M* in column (13)) and *InvB* (t = 0.11 after controlling *Log(Size)* in column (14) and t = −0.56 after controlling *Log(Size)* and *B/M* in column (15)).

Chen et al. (2010) find that many anomaly patterns significant in U.S. are not obvious in China. Likewise, the Fama-MacBeth t-statistics in our regressions tend to be small. Nevertheless, there is a relatively strong relation between average return and *ROE* after controlling *Log(Size)* and *B/M*. To supplement the results above, the columns (16)–(25) present multiple cross-section regressions contrasting *ROE* with other profitability variables, and multiple cross-section regressions contrasting *InvA* and *InvB*. When adding all profitability variables, none of variables has reliable relation with average return. In one-to-one contests, *ROE* outperforms *Gross-prof-A* and *Gross-prof-B*, no matter what the control variables are. However, in the contest of *ROE* and *Free cash flow*, the negative relations between average return and *Free cash flow* tend to be significant, even stronger than ROE after controlling *Log(Size)*. So far, we have not found a theory to support the negative relation between average return and profitability. Hence, we identify that *Free cash flow* is not an ideal variable characterizing profitability in China, and choose *ROE* as the profitability variable. On the investment variables, the results are mixed. When only control *Log(Size)*, *InvA* has a negative relation with average return, and *InvB* has a positive one. When control *Log(Size)* and *B/M* both, the result are opposite. More importantly, all the relations between average return and investment are insignificant. To double-check, we retain these two kinds of investment variables in the following work.

4. The playing field

Our goal in this section is to test that which model can explain average returns of portfolios formed on 5 factor variables we choose. Before testing the performance, we must present the anomaly patterns in average returns, and then construct the factor returns.

Table 3 reports average monthly percent returns in excess of the one-month risk-free rate for 25 VW portfolios double formed on *Size* and *B/M*, *Size* and *ROE*, *Size* and *InvA*, and *Size* and *InvB*. The method of forming portfolios follows the spirit of

Table 2
Fama-MacBeth cross-section regressions of returns: 07/1995–06/2015, 240 months. The table shows Fama and MacBeth (1973) regressions of returns on independent variables. The stock sample includes all Shanghai and Shenzhen main board stocks, Shenzhen Small and Medium-sized Enterprise Board and Growth Enterprise Market, where the maximum number of firms is 2592. *Int* is intercept term. *ROE* is earnings for fiscal year *t* scaled by book equity at the end of fiscal year *t*. *Gross-prof-A* and *Gross-prof-B* are respectively gross profitabilities for the fiscal year *t* scaled by total assets and by book equity at the end of fiscal year *t*. *Free cash flow* is net income plus amortization and depreciation minus changes in working capital expenditures for the fiscal year ending in calendar year *t* scaled by book equity at the end of fiscal year *t*. *InvA* are annual change in total assets for fiscal year *t* divided by total assets at the end of fiscal year $t-1$. *InvB* are annual change in book equity for fiscal year *t* divided by book equity at the end of fiscal year $t-1$. *B/M* is book equity at the end of fiscal year *t* divided by market capitalization at the end of fiscal year *t*. *Size* is market capitalization at the end of June of fiscal year $t+1$. The regressions are estimated monthly, using accounting variables that updated at the end of June of fiscal year $t+1$. Fama-MacBeth t-statistics are in parentheses.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
Int	10.56	11.68	10.32	11.17	10.93	10.53	10.53	10.89	10.61	11.23	10.84	10.37	9.98	10.54	9.89	11.37	10.90	11.17	11.58	10.42	11.45	11.03	10.96	11.32	9.88
	(3.89)	(2.61)	(3.90)	(4.24)	(4.28)	(4.12)	(4.30)	(4.13)	(4.16)	(4.03)	(4.04)	(3.81)	(3.78)	(3.83)	(3.74)	(4.41)	(4.30)	(4.25)	(4.30)	(3.84)	(4.66)	(4.53)	(4.31)	(4.37)	(3.77)
ROE				1.03	1.55											0.82	1.38	1.62	0.81		1.02	1.85	1.95	1.19	
				(1.29)	(2.04)											(0.95)	(1.98)	(1.87)	(1.04)		(1.14)	(2.53)	(2.15)	(1.59)	
Gross-prof-A						0.07	0.98									−0.83	−0.87				−0.09	−0.30			
						(0.06)	(0.80)									(−0.75)	(−0.86)				(−0.08)	(−0.27)			
Gross-prof-B								0.27	0.56							0.26		−0.53			0.33		−0.36		
								(0.45)	(1.09)							(0.47)		(−0.70)			(0.58)		(−0.53)		
Free cash flow										−0.19	−0.09					−0.13			−0.25		−0.09			−0.19	
										(−1.15)	(−0.62)					(−0.82)			(−1.85)		(−0.60)			(−1.51)	
InvA												−0.16	−0.02							−0.13					0.16
												(−0.82)	(−0.11)							(−0.74)					(1.16)
InvB														0.02	−0.11					0.05					−0.21
														(0.11)	(−0.56)					(0.35)					(−1.17)
B/M		1.12	1.22		1.25		1.20		1.25		1.11		1.22		1.21						1.11	1.18	1.22	1.14	1.22
		(2.51)	(2.87)		(2.83)		(2.97)		(2.99)		(2.43)		(2.86)		(2.84)						(2.50)	(2.78)	(2.78)	(2.51)	(2.85)
Log(Size)	−0.56		−0.59	−0.62	−0.64	−0.56	−0.60	−0.59	−0.61	−0.61	−0.62	−0.55	−0.56	−0.56	−0.55	−0.62	−0.60	−0.61	−0.64	−0.55	−0.67	−0.65	−0.64	−0.66	−0.56
	(−3.45)		(−3.64)	(−3.96)	(−4.22)	(−3.73)	(−4.18)	(−3.76)	(−4.00)	(−3.62)	(−3.79)	(−3.35)	(−3.51)	(−3.39)	(−3.46)	(−4.09)	(−4.00)	(−3.97)	(−3.97)	(−3.40)	(−4.62)	(−4.54)	(−4.25)	(−4.25)	(−3.50)

Table 3
Average monthly percent excess returns for 25 (5 × 5) VW portfolios formed on *Size* and *B/M*, *Size* and *ROE*, *Size* and *InvA*, *Size* and *InvB*: 07/1995–06/2015, 240 months. The stock sample includes all Shanghai and Shenzhen Main Broad, SMEB and GEM stocks. At the end of each June, stocks are allocated to five *Size* groups (Small to Big) using CSI300 stock sample market cap quintiles. Stocks are allocated independently to five *B/M* groups (Low to High) using CSI300 stock sample *B/M* quintiles. The intersections of this two sorts produce three 25 value-weight *Size-B/M* portfolios. In each June of fiscal year *t*, *Size* is the market cap at the end of June of fiscal year *t*, *B/M* is the book equity *B* at the end of December of year *t* − 1 divided by the market cap *M* at the end of December of year *t* − 1. The *Size-ROE*, *Size-InvA* and *Size-InvB* portfolios are constructed by the same way, except the *ROE*, *InvA* and *InvB* variables. The column of H–L shows the average returns of High variable portfolios minus average returns of Low variable portfolios for each row. Correspondingly, the rows S–B show the average returns of Small portfolio minus the average returns of Big portfolio for each column. The t-statistics are in parentheses.

	Low	2	3	4	High	H–L	Low	2	3	4	High	H–L
	Panel A: size-B/M portfolios						*Panel B: size-ROE portfolios*					
	Average excess returns						Average excess returns					
Small	0.70	1.19	1.44	1.70	1.64	0.94	1.03	1.36	1.50	1.64	1.33	0.31
						(2.62)						(1.07)
2	0.57	1.06	1.52	1.10	1.51	0.94	0.47	1.15	0.91	1.33	1.28	0.81
						(1.94)						(1.97)
3	0.29	0.41	0.85	1.68	1.18	0.90	0.58	0.23	1.01	1.09	1.63	1.06
						(1.75)						(2.28)
4	0.57	0.19	1.49	0.79	1.25	0.67	0.24	0.56	0.72	0.96	0.92	0.68
						(1.25)						(1.43)
Big	0.05	0.76	−0.01	1.45	1.24	1.20	0.23	1.14	0.88	0.54	1.04	0.81
						(2.43)						(1.18)
S-B	0.65	0.44	1.46	0.25	0.39		0.79	0.22	0.62	1.11	0.29	
	(1.41)	(0.79)	(2.62)	(0.31)	(0.79)		(1.33)	(0.32)	(1.16)	(2.19)	(0.47)	
	Panel C: size-InvA portfolios						*Panel D: size-InvB portfolios*					
	Average excess returns						Average excess returns					
Small	1.02	1.40	1.35	1.41	1.09	0.06	1.04	1.32	1.43	1.52	1.00	−0.04
						(0.25)						(−0.19)
2	0.75	0.71	1.12	1.05	1.22	0.47	0.61	0.85	1.18	1.39	1.01	0.40
						(1.56)						(1.16)
3	1.17	0.74	0.96	0.83	1.02	−0.14	0.73	0.46	1.01	1.23	0.96	0.23
						(−0.34)						(0.67)
4	0.40	0.85	1.18	0.54	0.53	0.13	0.61	0.51	1.26	1.12	0.39	−0.22
						(0.33)						(−0.47)
Big	−0.30	1.28	0.53	0.55	1.61	1.91	−0.05	0.70	0.60	0.73	1.03	1.09
						(2.64)						(1.64)
S-B	1.32	0.11	0.81	0.85	−0.52		1.10	0.62	0.84	0.79	−0.03	
	(2.08)	(0.18)	(1.68)	(1.57)	(−0.78)		(1.52)	(1.16)	(1.45)	(1.46)	(−0.06)	

Fama and French (1993): At the end of each June, all available stocks of Shanghai and Shenzhen Main Broad, SMEB and GEM are allocated independently to five *Size* groups using CSI 300 stock sample market cap quintiles. Similarly, stocks are allocated independently to five *B/M*, *ROE*, *InvA* and *InvB* groups respectively. The intersections of each two sorts produce 25 VW *Size-B/M*, *Size-ROE*, *Size-InvA* and *Size-InvB* portfolios. At the end of each June of year *t*, *Size* is the market cap at this time; *B/M* is the book equity *B* at the end of year *t* − 1 divided by the market cap *M* at the end of year *t* − 1; *ROE* is earnings for year *t* − 1 scaled by book equity at the end of year *t* − 1; *InvA* and *InvB* are respectively the growth rate of total assets and book equity for year *t* − 1.

Panel A of Table 3 is about 25 VW *Size-B/M* portfolios. The *B/M* columns show the size effect - average excess return typically falls from small stocks to big stocks. The last row "S-B" reports the differences between average returns of Small and Big portfolios in each column. The third column shows the largest size spread of 1.46% per month (t = 2.62). The size effects in other columns are smaller, and not significant. In each *Size* row, average return typically increases with *B/M* - value effect. The "H–L" column presents the difference between average return of High and Low *B/M* portfolios. The value effect produces larger spread in average return than size effect, where the average spread of H–L column is 0.93% per month, bigger than 0.64% per month produced by size effect. It is interesting that the value effect is stronger in microcap (0.94% per month with t-statistic of 2.62 in the Small row) and macrocap (1.20% per month with t-statistic of 2.43 in the Big row) portfolios, which is different from the *B/M* pattern in U.S. market reported by Fama and French (2015a).

Panel B of Table 3 depicts the average excess returns for 25 VW *Size-ROE* portfolios. The size effect is broadly consistent with the result of panel A. In each row, the average return typically increases with *ROE*, though there are some exceptions. The profitability effect produces the largest spread of 1.06% per month (t = 2.28) in the third row. The average spread of H–L column is 0.73% per month that is smaller than the average spread produced by value effect, which is proved in Fama-MacBeth cross-section regressions in Table 2.

Panels C and D of Table 3 provide the average excess returns for 25 VW *Size-InvA* and *Size-InvB* portfolios. It is surprising that there is no relation between average return and *Size* in the High investment column, no matter which variable represents investment. In addition, the spreads in S-B row are smaller than panels A and B. The average spreads produced by size effect in panels C and D are 0.51% per month and 0.66% per month. Based on the results above, we argue that the size effect is robust in the Chinese stock market. More importantly, we use panels C and D to double identify the investment pattern in average returns. Neither of the results is obvious. There are almost no relations between average return and investment, except the Big row in panel C. The H–L spread of 1.91% per month ($t = 2.64$) gives an opposite pattern on the U.S. market, which has a strong negative relation between average return and investment. In short, the investment pattern measured by the growth of total assets or the growth of book equity in average return does not exist in Chinese stock market, which is in line with the results of the Fama-MacBeth cross-section regressions in Section 3. A more detailed summary statistics table including average number of firms, average market cap, average *B/M* ratio, average *ROE*, and average investment for 25 VW portfolios is in Appendix A, which identifies the relations among the factor variables.

5. Factors

5.1. Factor construction and summary statistics

By the direction of Fama and French (1993), we construct the factor returns from an independent 6 (2 × 3) sorts on *Size* and other potential anomaly variables. For 6 VW *Size-B/M* portfolios, all stocks with available data are independently assigned to two *Size* groups (Small and Big), three *B/M* groups (Low, Neutral and High) using median market cap, and 30th and 70th percentiles of *B/M* provided by CSI 300 stocks. The intersection of the sorts produces the 6 (2 × 3) VW *Size-B/M* portfolios, SL, SN, SH, BL, BN, and BH, where S and B indicate Small and Big portfolios, and L, N and H indicate Low, Neutral and High *B/M* portfolios. The factor $SMB_{B/M}$ is the average return of three small stock portfolios minus the average return of three big stock portfolios, $SMB_{B/M} = (SL + SN + SH) / 3 - (BL + BN + BH) / 3$. The value factor HML is the average return of two high *B/M* portfolios minus the average return of two low *B/M* portfolios, $HML = (SH + BH) / 2 - (SL + BL) / 2$. The 6 VW *Size-ROE*, *Size-InvA* and *Size-InvB* portfolios are formed in the same way, and thereby producing another three size factors SMB_{ROE}, SMB_{InvA} and SMB_{InvB}. The comprehensive size factor $SMB = (SMB_{B/M} + SMB_{ROE} + SMB_{InvA} + SMB_{InvB}) / 4$. The profitability factor $RMW = (SH + BH) / 2 - (SL + BL) / 2$, where S, B, H and L are corresponding to 6 VW *Size-ROE* portfolios. The investment factor CMA (CMAB) = $(SL + BL) / 2 - (SH + BH) / 2$, where S, B, H and L are corresponding to 6 VW *Size-InvA* (*Size-InvB*) portfolios.

Table 4 gives summary statistics for the factors we constructed. Panel A of Table 4 presents the mean, standard deviation, t-statistic of mean and Sharpe ratio for each factor. During 07/1995 –06/2015, the VW market portfolio return is slightly higher than the risk-free rate. The mean of market portfolio excess return is 0.07% per month with 8.46% standard deviation per month, which leads to a low t-statistic of 1.35 and a low Sharpe ratio of 0.09. The low mean and high volatility of market portfolio excess return imply that the risk aversion is low in the Chinese stock market. For the five *Size* factors, the mean ranges from 0.38% to 0.56% per month with t-statistics all smaller than 1.69, where SMB_{ROE} achieves the highest mean of 0.56% per month and the lowest standard deviation of 5.14% per month. The value factor HML achieves the mean of 0.86% per month and the standard deviation of 4.93% per month. The t-statistic of mean for HML is 2.69 standard errors from zero, and the Sharpe ratio of HML (0.17) is the highest among all factors in this paper. The t-statistic of the mean for profitability factor RMW is 1.98 standard errors from zero, which is the second-high among these factors. The summary statistics of two investment factors are poor: The mean of CMA and CMAB are both negative and insignificant ($t = -0.93, -1.16$), though the standard deviations are smaller than others. To sum up, we find strong value and profitability effects, and unreliable investment effect in Chinese stock market again.

Panel B of Table 4 reports the correlation matrix of different size factors. Different size factors are strongly and positively correlated, where the smallest correlation coefficient is 0.95. Panel C shows the correlation matrix of different factors. Size factor SMB is negative correlated with Mkt, HML and RMW, and is positively correlated with CMA and CMAB. It makes sense that small stocks tend to have higher betas, lower value, lower profitability and lower investment. The negative correlation between HML and RMW and the positive correlation between HML and CMA imply that the high *B/M* firms tend to be low profitability and investment, which is in line with Fama and French (1995). It also makes sense that the profitability factor are strongly negatively correlated with the investment factors CMA and CMAB with correlations of −0.71 and −0.76. The profitable firms tend to invest more, which is shown in Appendix A. Almost all of the high absolute value of correlations, except the correlation between SMB and RMW (−0.47), are related to investment factors, which reminds us to test whether the investment factors are redundant. We will link the correlation analysis and factor spanning tests to show the explanatory power of factors in next section.

Fama and French (1993, 2012) and Loughran (1997) find that the value premium is larger for small stocks. However, we do not find this phenomenon in panel A of Table 3 on the Chinese stock market. Panel D of Table 4 proves the result again. The small end of HML is defined by SH − SL, and the big end of HML is defined by BH − BL. The column "S-B" represents the difference between the small and big ends factors. For HML, it is surprising that the average excess return of 0.73% per month for the small end is smaller than the average excess return of 0.98% per month for the big end. The t-statistic of the difference is only −0.87 standard error from zero. The last row shows the correlation between the small and big ends with the coefficient of 0.68. Hence, we can not distinguish the small end of HML from the big end. For RMW, there is a significant difference between the small and big ends of RMW ($t = -1.94$). However, in the following redundancy tests, we can not find obvious improvement of using the big end of RMW. For CMA and CMAB, the differences of small and big ends are mixed, but both insignificant. Therefor, we still use the traditional factors in the following tests.

Table 4

Summary statistics of factor returns: 07/1995–06/2015, 240 months. Mkt is the value-weight market portfolio return of Shanghai and Shenzhen Main Broad, SMEB and GEM stocks in China in excess of one-month risk free rate. At the end of each June, stocks are allocated independently to two *Size* groups (Small and Big) using CSI300 stock sample median market cap breakpoints, three *B/M*, *ROE*, *InvA* and *InvB* groups (Low, Neutral and High) using CSI300 stock sample 30th and 70th as breakpoints. The intersections of *Size* and other variable groups produce 6 (2 × 3) value-weight *Size-B/M*, *Size-ROE*, *Size-InvA* and *Size-InvB* portfolios, SL, SN, SH, BL, BN, and BH, where S and B indicate small and big portfolios, and L, N and H indicate low, neutral and high variable portfolios. $SMB_{B/M}$ is the average of the returns on the three small stock portfolios of 6 *Size-B/M* portfolios minus the average returns on the three big stock portfolios of 6 *Size-B/M* portfolios, $SMB_{B/M} = (SL + SN + SH) / 3 - (BL + BN + BH) / 3$. SMB_{ROE}, SMB_{InvA} and SMB_{InvB} are constructed by the same way, except the *ROE*, *InvA* and *InvB* variables. SMB is the average of $SMB_{B/M}$, SMB_{ROE}, SMB_{InvA} and SMB_{InvB}. HML is the average of the two high *B/M* stock portfolio returns of 6 *Size-B/M* portfolios minus the average of the two low *B/M* stock portfolio returns of 6 *Size-B/M* portfolios, $HML = (SH + BH) / 2 - (SL + SH) / 2$. RMW, CMA and CMAB are respectively constructed by 6 *Size-ROE*, *Size-InvA* and *Size-InvB* portfolios by the same way, except that $CMA\ (CMAB) = (SL + SL) / 2 - (SH + BH) / 2$. Panel A shows the average monthly percent factor return (Mean), the standard deviation, the t-statistic of mean (t(Mean)), and Sharpe Ratio. Panel B shows the correlations for five kinds of SMB factors. Panel C shows the correlations for factors. Panel D shows the summary statistics of small and big ends of HML, RMW, CMA and CMAB. Small end factor is constructed by SH - SL, and vice versa for big end factor. S-B indicates the percent return of small end factor minus the return of big end factor.

Panel A: average, standard deviations, t-statistics and Sharpe ratio for monthly factor returns

	Mkt	$SMB_{B/M}$	SMB_{ROE}	SMB_{InvA}	SMB_{InvB}	SMB	HML	RMW	CMA	CMAB
Mean	0.74	0.44	0.56	0.38	0.41	0.46	0.86	0.55	−0.21	−0.29
Std dev.	8.46	5.14	5.14	5.47	5.42	5.18	4.93	4.29	3.41	3.83
t(Mean)	1.35	1.32	1.69	1.08	1.17	1.38	2.69	1.98	−0.93	−1.16
Sharpe ratio	0.09	0.09	0.11	0.07	0.08	0.09	0.17	0.13	−0.06	−0.06

Panel B: correlations between different SMB factors

	$SMB_{B/M}$	SMB_{ROE}	SMB_{InvA}	SMB_{InvB}	SMB
$SMB_{B/M}$	1.00	0.95	0.97	0.95	0.99
SMB_{ROE}	0.95	1.00	0.96	0.96	0.98
SMB_{InvA}	0.97	0.96	1.00	0.99	0.99
SMB_{InvB}	0.95	0.96	0.99	1.00	0.98
SMB	0.99	0.98	0.99	0.98	1.00

Panel C: correlations between factors

	Mkt	SMB	HML	RMW	CMA	CMAB
Mkt	1.00	0.12	0.11	−0.08	0.03	0.07
SMB	0.12	1.00	−0.24	−0.47	0.31	0.33
HML	0.11	−0.24	1.00	−0.27	0.40	0.33
RMW	−0.08	−0.47	−0.27	1.00	−0.71	−0.76
CMA	0.03	0.31	0.40	−0.71	1.00	0.81
CMAB	0.07	0.33	0.33	−0.76	0.81	1.00

Panel D: summary statistics for the small and big ends of HML, RMW, CMA and CMAB

	HML			RMW			CMA			CMAB		
	Small	Big	S-B	Small	Big	S-B	Small	Big	S-B	Small	Big	S-B
Mean	0.73	0.98	−0.24	0.25	0.84	−0.59	−0.09	−0.32	0.23	−0.32	0.73	−1.05
Std dev.	4.92	5.83	4.41	3.76	5.82	4.75	3.02	5.21	5.09	4.17	7.63	10.11
t(Mean)	2.31	2.60	−0.87	1.03	2.25	−1.94	−0.46	−0.96	0.71	−1.20	1.48	−1.61
Correlation	0.68			0.58			0.33			−0.42		

5.2. Factor spanning tests

The factor spanning tests used in Fama and French (2015a,b) show that if the intercept in the regression of one factor on other factors is close to zero, then this LHS factor is redundant. Barillas and Shanken (2015) give a proof. Following them, we use four factors in regressions to explain the fifth factor. Because of the high correlation between CMA and CMAB, we do not choose CMAB as a RHS variable. Table 5 shows the results. It is surprising that the intercept of Mkt regression of 0.26% per month is insignificant ($t = 0.45$). However, the market monthly excess return has a high standard deviation of 8.46%, and R^2 is only around 4%, which indicates that a large part of volatility of market return is not explained by other factors, leaving a residual with high volatility, and thus leaving a high standard error. In addition, in the following performance test section, deleting Mkt sharply reduces the R^2 of time-series regressions. Hence, we can not identify the redundancy of Mkt.

For size factor SMB, the R^2 of 39% and the intercept of 1.16% ($t = 5.09$) mean that SMB can not be replicated by other factors in time-series and cross-section dimensions neither. The significant negative slopes of HML ($t = -4.30$) and RMW ($t = -4.11$) absorb the negative average SMB and leave the positive intercepts.

The value factor HML can improve the description of average return in this factor spanning tests. The intercept for the regression of HML on other factors is 1.24% per month, and 5.18 standard errors from zero. The R^2 of 35% is relatively small. The

Table 5
Factor spanning regressions. The table reports the results of regressions of a selected factor on other four factors. The construction of factors is in Table 4. The t-statistics are in parentheses. The sample time for panel A is 07/1995–06/2015. Panel B gives the out-of-sample results for 07/1997–12/2013.

	Int	Mkt	SMB	HML	RMW	CMA	R^2
Panel A: sample time: 07/1995–06/2015, 240months							
Mkt	0.26		0.31	0.35	−0.07	−0.33	0.04
	(0.45)		(1.72)	(2.29)	(−0.26)	(−0.93)	
SMB	1.16	0.07		−0.47	−0.58	0.22	0.39
	(5.09)	(1.71)		(−4.30)	(−4.11)	(1.25)	
HML	1.24	0.08	−0.45		−0.21	0.60	0.35
	(5.18)	(2.22)	(−5.29)		(−2.02)	(4.23)	
RMW	0.62	−0.01	−0.27	−0.10		−0.71	0.59
	(3.46)	(−0.25)	(−4.38)	(−1.77)		(−7.82)	
CMA	−0.12	−0.02	0.07	0.19	−0.47		0.56
	(−0.81)	(−0.90)	(1.21)	(4.48)	(−7.79)		
CMAB	−0.07	−0.00	0.03	0.12	−0.62		0.60
	(−0.48)	(−0.12)	(0.56)	(2.47)	(−9.35)		
Panel B: sample time: 07/1997–12/2013, 198months							
Mkt	0.09		0.21	0.11	−0.31	−0.48	0.03
	(0.14)		(1.11)	(0.51)	(−1.04)	(−1.23)	
SMB	1.01	0.04		−0.52	−0.63	0.28	0.40
	(4.11)	(1.14)		(−5.53)	(−4.54)	(1.44)	
HML	0.73	0.01	−0.37		−0.44	0.19	0.29
	(3.35)	(0.52)	(−5.34)		(−4.65)	(1.71)	
RMW	0.58	−0.03	−0.30	−0.30		−0.57	0.57
	(3.35)	(−1.00)	(−5.37)	(−5.01)		(−6.51)	
CMA	−0.07	−0.03	0.10	0.09	−0.42		0.46
	(−0.47)	(−1.14)	(1.47)	(1.59)	(−5.40)		
CMAB	−0.07	−0.03	0.16	0.13	−0.61	0.71	
	(−0.51)	(−1.47)	(3.37)	(2.50)	(−11.41)		

strongly negative slope of RMW proves that firms with high *B/M* tend to have low profit, which is supported by the distribution of average firm number in panel A of Table A1 in Appendix A.

The profitability factor RMW is also important for describing average returns. The intercepts of RMW is 3.46 standard errors from zero. Since RMW is negatively correlated to other factors shown in Table 4, the slopes of other factors are all negative, especially the investment factor CMA with correlation of −0.71 (t = −7.82). Because of the high absolute value of correlation between RMW and CMA, the R^2 for regression of RMW increases to 59%.

The strongly negative correlation between RMW and CMA and the non-redundancy of RMW heralds the redundancy of CMA. The factor spanning tests suggest that the investment factors CMA and CMAB are not important for describing average return. The intercepts for these two factors are respectively −0.81 and −0.48 standard error from zero. The strongly negative slopes of RMW absorb large average CMA and CMAB returns. Compared with CMA, the intercept of CMAB regression is more close to zero. Considering the results above, we omit CMAB, and choose CMA as the unique investment factor, which is consistent with Fama and French (2015a) and Hou et al. (2015).

Chen et al. (2015) using the data from 07/1997–12/2013 find that value factor HML is not robust in the Chinese stock market. However, they do not give the redundancy test for factors. Panel B of Table 5 provides the out-of-sample test for factor spanning regressions with the sample time of 07/1997–12/2013. The results are not changed radically: the intercepts of SMB, HML and RMW are significant, whereas the intercepts of investment factors are not.

In the mean-variance framework, when a combination of factors is mean-variance efficient, i.e., it lies on the mean-variance frontier and does not equal to zero, the corresponding factor model can price any assets. In other words, we prefer the combination of factors achieving the Sharpe ratio as big as possible. MacKinlay (1995) shows that the maximum Sharpe ratio can be calculated by $\sqrt{\bar{f}'\sum^{-1}\bar{f}}$, where $\bar{f}$ is the vector of mean factor returns given in a model, and $\sum$ is the covariance matrix for the factor returns. To supplement the results of factor spanning tests, Table 6 reports the maximum monthly Sharpe ratios for different combinations of factors (or different factor models). The three-factor model produces a maximum Sharpe ratio of 0.23, and the four-factor model 0.39. However, there is no obvious differences between four- and five-factor models. The out-of-sample tests show the robustness of results. Table 6 strengthens the result of factor spanning tests that the investment factors CMA and CMAB are redundant.

Table 6
Maximum Sharpe ratio. The table reports the maximum monthly Sharpe ratio for CAPM (Mkt), Fama and French three-factor model (Mkt, SMB and HML), four-factor model (Mkt, SMB, HML and RMW), and five-factor model (Mkt, SMB, HML, RMW, and CMA or CMAB). The maximum Sharpe ratio is calculated as $\sqrt{\bar{f}'\sum^{-1}\bar{f}}$, where $\bar{f}$ is the vector of mean factor returns given in a model, and $\sum$ is the covariance matrix for the factor returns.

	CAPM	Three-factor	Four-factor	Five-factor (CMA)	Five-factor (CMAB)
07/1995–06/2015	0.09	0.23	0.39	0.39	0.39
07/1997–12/2013	0.02	0.16	0.33	0.34	0.34

6. Model performance

Fama and French (2015b) use four metrics including GRS statistics of Gibbons et al. (1989), average absolute value of intercepts $A|a_i|$ and so on. The whole spirit of these metrics is to identify whether the intercepts in time-series regressions of excess return for any portfolios on factors are jointly indistinguishable from zero, which is also the key point of asset pricing model. Using the metrics in Fama and French (2015b), we measure the performances of three models: the three-factor model of Fama and French (1993) including Mkt, SMB and HML, four-factor model including Mkt, SMB, HML and CMA, and five-factor model of Fama and French (2015a) in Eq. (1). The LHS portfolios are in the playing field, including four groups of 25 portfolios and five groups of 32 portfolios. Although we drop the investment factor CMAB, we also consider the portfolios sorted on InvB as the LHS variables.

Table 7 provides the summary test statistics of these three models. The p(GRS) is the p-value of GRS statistic, which tests whether the expected values of all intercepts are jointly zero. $A|a_i|$ is the average absolute value of intercepts. $A|a_i|/A|\bar{r}_i|$ is the average absolute value of intercepts scaled by the average absolute value of $\bar{r}_i$ that is the difference between the average return of portfolio i and the average return of VW market portfolio. $As^2(a_i)/A(a_i^2)$ is the average estimated squared standard error of intercepts scaled by the average absolute value of intercepts. The lower the $A|a_i|$, the better the model performs. Similarly, a low $A|a_i|/A|\bar{r}_i|$ means the intercept dispersion is low relative to the dispersion of LHS average returns, and a high $As^2(a_i)/A(a_i^2)$ means sampling error is high relative to the intercept dispersion, which are both good news for a model.

All four- and five-factor models pass the GRS test at 10% confidence level, except 25 *Size-ROE* portfolios and 32 *Size-ROE-InvB* portfolios. The three-factor model also passes the test for 25 *Size-B/M*, 32 *Size-B/M-InvA*, and 32 *Size-B/M-InvB* portfolios. However, we are more interested in the relative improvement among the models. There are obvious improvements from the three-factor model to four-factor model. The average increase of the p-value of GRS statistic is 29.1%. Since there are 6 groups of portfolios sorted on investment in 9 groups of LHS portfolios, the five-factor model should perform better than four-factor model for most of portfolios. However, for any LHS portfolios, the performance of four- and five-factor models is not easy to distinguish, which is in line with the factor spanning tests in Table 5 and maximum Sharpe ratio tests in Table 6. The differences between GRS statistics of four- and five-factor model are less than 0.05, which is not shown in tables. The five-factor model achieves slightly smaller GRS statistics for LHS portfolios, except 25 *Size-B/M* and 32 *Size-B/M-InvA* portfolios.

The GRS statistic only tests whether the model is true, but does not test which one is better. In GRS statistic, the covariance matrix of time-series regression residuals acts as the weight matrix for intercepts. Blowing up it easily reduces the statistic, and makes no progress on the intercepts a_i. We must fix the weight matrix for intercepts. The simplest way is using the average absolute value of intercepts $A|a_i|$. Relative to three-factor model, the improvements in average absolute intercepts produced by four-factor model are 4.0 –21.3 basis points per month, and the mean increase is 13.5 basis points per month. However, relative to four-factor model, the five-factor model produces a minor improvement (−1.4 –1.3 basis points).

The estimates of $A|a_i|/A|\bar{r}_i|$ indicate the dispersion of average returns the model fails to explain, and the estimates of $As^2(a_i)/A(a_i^2)$ indicate the proportion of sampling error in unexplained dispersion of average returns. For example, for the 25 *Size-B/M* portfolios, the estimate $A|a_i|/A|\bar{r}_i|$ ranges from 0.42 –0.50, which implies that these three models all fail to explain about half the dispersion of average returns. The improvements of this metric are slight. However, the estimate $As^2(a_i)/A(a_i^2)$ significantly increases by 0.34 from 0.73 of three-factor model to 1.07 of four-factor model, which means four-factor model

Table 7

Summary tests statistics of three-, four- and five-factor models for 25 (5 × 5) and 32 (2 × 4 × 4) VW portfolios: 07/1995–06/2015, 240 months. The table reports the summary tests of asset pricing models for the 25 (5 × 5) and 32 (2 × 4 × 4) VW portfolios. The asset pricing models are Fama and French (1993) three-factor model including Mkt, SMB and HML, four-factor model including Mkt, SMB, HML and RMW, and Fama and French (2015a) five-factor model including Mkt, SMB, HML, RMW and CMA. The probabilities p(GRS) are the p-values of GRS statistics that test whether the expected values of all intercepts are zero. $A|a_i|$ is the average absolute value of intercepts, $A|a_i|/A|\bar{r}_i|$ is the average absolute value of intercepts divided by the average absolute value of $\bar{r}_i$, which is the average return of portfolio *i* minus the average return of market portfolio. $As^2(a_i)/A\,(a_i^2)$ is the average estimated squared standard error of intercepts divided by the average absolute value of intercepts.

Market factors	p(GRS)	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{As^2(a_i)}{A(a_i^2)}$	p(GRS)	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{As^2(a_i)}{A(a_i^2)}$	p(GRS)	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|\bar{r}_i\|}$	$\frac{As^2(a_i)}{A(a_i^2)}$
	25 Size-B/M portfolios				*25 Size-ROE portfolios*				*25 Size-InvA portfolios*			
Three-factor	0.148	0.250	0.50	0.73	0.000	0.458	1.15	0.24	0.007	0.311	0.87	0.40
Four-factor	0.230	0.210	0.42	1.07	0.003	0.271	0.68	0.63	0.186	0.210	0.59	1.10
Five-factor	0.192	0.213	0.43	1.04	0.003	0.273	0.68	0.62	0.200	0.197	0.55	1.14
	25 Size-InvB portfolios				*32 Size-B/M-ROE portfolios*				*32 Size-B/M-InvA portfolios*			
Three-factor	0.059	0.318	0.95	0.51	0.039	0.388	0.78	0.50	0.160	0.292	0.61	0.75
Four-factor	0.575	0.172	0.51	1.64	0.466	0.237	0.48	1.10	0.717	0.201	0.42	1.45
Five-factor	0.612	0.168	0.50	1.66	0.469	0.244	0.49	1.03	0.695	0.198	0.42	1.40
	32 Size-B/M-InvB portfolios				*32 Size-ROE-InvA portfolios*				*32 Size-ROE-InvB portfolios*			
Three-factor	0.135	0.304	0.67	0.84	0.002	0.449	1.06	0.38	0.000	0.461	1.04	0.42
Four-factor	0.792	0.177	0.39	1.94	0.151	0.236	0.56	1.04	0.052	0.298	0.67	0.97
Five-factor	0.800	0.179	0.39	1.80	0.171	0.233	0.55	1.00	0.060	0.285	0.64	1.02

makes the dispersion of average return to be almost sampling error. Hence, the profitability factor improves the description of 25 *Size-B/M* portfolios that are not sorted on *ROE*. For other portfolios, the decline of $A|a_i|/A|\bar{r}_i|$ between three- and four-factor models ranges from 0.08 to 0.50, and the rise of $As^2(a_i)/A(a_i^2)$ between three- and four-factor models ranges from 0.34 to 1.13, which implies that four-model that adds RMW outperforms the traditional three-factor model for all portfolios we test except *MOM* decile portfolios. However, these two estimates are indistinguishable between four- and five-factor models. The biggest differences of $A|a_i|/A|\bar{r}_i|$ and $As^2(a_i)/A(a_i^2)$ are respectively 0.04 and 0.07. Thus, we can not identify that the five-factor model outperforms the four-factor model. For any tested portfolios, these three models have almost the same average adjusted R^2 not shown in tables. In short, dropping CMA does not produce big change for the four metrics, which is consistent with the factor spanning tests in Table 5.

7. Time-series regressions details

With the performance of models in hand, we report the estimate details of time-series regressions of factor models for the portfolios in the playing field of Section 4. Consider the limited effects of CMAB, we use CMA to act as the unique investment factor. Given an obvious anomaly pattern in average returns, if the slope of a particular factor return does not change markedly across portfolios, then the factor makes less contribution to improving the description of this anomaly difference of the average returns.

Table 8 reports the time-series intercepts of three- and four-factor models for 25 double sorted portfolios. Because of the similarity between four- and five-factor models, we omit the results of five-factor model. Panel A is about the 25 *Size-B/M* portfolios. The biggest absolute value of intercept of 0.84% per month ($t = 1.51$) for three-factor model (left side) is small. Recall that the three-factor model of Fama and French (1993) producing the p-value of GRS statistic of 0.148 passes the GRS test for

Table 8
Three- and four-factor intercepts for 25 (5×5) VW portfolios: 07/1995–06/2015, 240months. This table reports the intercepts of three- and four-factor model time-series regressions for 25 double sorted portfolios. The t-statistics are in parentheses.

	Low	2	3	4	High	Low	2	3	4	High
	Three – factor					*Four – factor*				
	Panel A: 25 Size-B/M portfolios									
Small	−0.10	0.26	0.16	0.12	−0.05	0.03	0.35	0.20	0.29	0.11
	(−0.72)	(1.93)	(1.20)	(0.74)	(−0.34)	(0.23)	(2.41)	(1.40)	(1.71)	(0.73)
2	−0.09	0.20	0.33	−0.18	−0.28	−0.14	0.06	−0.19	−0.14	−0.35
	(−0.53)	(1.01)	(0.96)	(−0.94)	(−1.19)	(−0.72)	(0.29)	(−0.61)	(−0.71)	(−1.33)
3	−0.08	−0.25	0.02	0.37	−0.22	−0.18	−0.19	−0.08	0.24	−0.05
	(−0.34)	(−0.99)	(0.07)	(1.50)	(−0.74)	(−0.80)	(−0.71)	(−0.27)	(0.87)	(−0.20)
4	0.35	−0.42	0.46	−0.18	−0.24	0.06	−0.27	0.68	−0.26	−0.23
	(1.66)	(−1.41)	(1.60)	(−0.63)	(−0.91)	(0.32)	(−0.85)	(2.29)	(−0.90)	(−0.80)
Big	−0.05	0.40	−0.49	0.84	0.09	−0.06	0.54	−0.34	0.08	0.13
	(−0.22)	(1.20)	(−1.59)	(1.51)	(0.39)	(−0.25)	(1.53)	(−1.23)	(0.13)	(0.54)
	Three – factor					*Four – factor*				
	Panel B: 25 Size-ROE portfolios									
Small	−0.50	0.33	0.50	0.75	0.09	−0.18	0.47	0.39	0.48	−0.28
	(−3.40)	(2.40)	(3.63)	(4.28)	(0.38)	(−1.28)	(3.56)	(3.07)	(3.07)	(−1.30)
2	−0.87	−0.01	−0.05	0.50	0.43	−0.48	−0.10	−0.25	0.21	−0.02
	(−3.73)	(−0.04)	(−0.25)	(2.22)	(1.69)	(−2.20)	(−0.46)	(−1.22)	(0.99)	(−0.09)
3	−0.63	−0.70	0.03	0.42	0.96	0.09	−0.57	−0.30	0.03	0.39
	(−1.90)	(−3.07)	(0.11)	(1.82)	(3.25)	(0.33)	(−2.40)	(−1.26)	(0.14)	(1.44)
4	−0.89	−0.72	0.02	0.22	0.50	−0.11	−0.44	0.12	−0.18	0.11
	(−2.50)	(−1.81)	(0.07)	(0.84)	(2.02)	(−0.36)	(−1.07)	(0.43)	(−0.68)	(0.47)
Big	−0.84	0.41	0.25	−0.11	0.74	0.33	0.55	0.49	0.06	−0.13
	(−1.89)	(1.08)	(0.85)	(−0.44)	(2.58)	(0.95)	(1.63)	(1.47)	(0.25)	(−0.54)
	Three – factor					*Four – factor*				
	Panel C: 25 Size-InvA portfolios									
Small	−0.41	0.11	0.09	0.30	0.11	−0.10	0.24	0.25	0.33	0.15
	(−2.46)	(0.92)	(0.71)	(1.86)	(0.67)	(−0.59)	(1.85)	(1.86)	(2.19)	(0.95)
2	−0.42	−0.43	−0.04	0.14	0.13	−0.33	−0.24	−0.20	0.03	−0.19
	(−2.13)	(−2.06)	(−0.20)	(0.56)	(0.62)	(−1.62)	(−1.15)	(−0.97)	(0.14)	(−0.84)
3	−0.04	−0.31	−0.09	0.30	0.25	0.12	−0.37	−0.06	0.12	−0.05
	(−0.12)	(−1.26)	(0.38)	(1.22)	(0.87)	(0.43)	(−1.41)	(−0.23)	(0.52)	(−0.16)
4	−0.56	0.02	0.40	0.08	−0.28	−0.23	−0.01	0.13	−0.12	−0.53
	(−1.86)	(0.05)	(1.28)	(0.31)	(−0.96)	(−0.76)	(−0.02)	(0.44)	(−0.49)	(−1.71)
Big	−1.17	0.50	−0.13	0.24	1.23	−0.52	0.47	−0.24	0.00	0.23
	(−2.37)	(1.49)	(−0.52)	(0.82)	(3.02)	(−1.03)	(1.60)	(−1.03)	(0.00)	(0.65)

25 VW *Size-B/M* portfolios in Table 7. The good performance of three-factor model leaves little room to reduce the absolute value of intercepts. Nevertheless, the factor RMW amplifies the average sampling error of intercepts relative to the unexplained dispersion of average returns, which is shown in panel A of Table 7. Intuitively, we can not identify that the right side for four-factor model is better than the left side.

It is a tautology that the factors produced by the anomaly portfolios are used to explain average returns for corresponding anomaly portfolios. The three-factor model fails to explain the average returns for portfolios sorted on other variables (Table 7). Panel B of Table 8 presents the intercepts for each portfolio of 25 *Size-ROE* portfolios, where the average returns in Small row, Low and High column are deadly for the three-factor model. The intercepts of three-factor model for extremely low profitability stocks are −0.89% per month to −0.50% per month with t-statistics ranging from −3.73 to −1.89. The three-factor intercepts are significant for small stocks, except the Small-High portfolio (0.09% per month). Although the four-factor intercepts decrease relative to three-factor model, small stocks are also a problem for the four-factor model. In the right side of panel B, the four-factor intercepts of Small-2 *ROE*, Small-3 *ROE* and Small-4 *ROE* portfolios are respectively 0.47% (t = 3.56), 0.39% (t = 3.07) and 0.48% (t = 3.07), which makes the four-factor model fail to pass the GRS test. The intercept problem in the four-factor model remains in the five-factor model, which is not shown in the table.

The next is about 25 *Size-InvA* portfolios shown in panel C of Table 8. On the left side, the three-factor intercepts for big stocks in the lowest and highest *InvA* columns are −1.17% per month (t = −2.37) and 1.23% per month (t = 3.02) respectively, which is a shortage for three-factor model. The profitability factor RMW absorbs the low average return of Big-Low *InvA* portfolio and the high average return of Big-High *InvA* portfolio. For the four-factor model on the right side, the low average return increases to −0.52% per month and the high average return decreases to 0.23% per month.

We now turn to the portfolios triple sorted in the playing field. Table A2 in the Appendix A shows that the patterns in average return are clearer for portfolios triple sorted. Table 9 reports the regression intercepts for 32 *Size-B/M-ROE* portfolios. The three-factor intercept for small stocks on the left side of panel A is a disaster. There are 9 absolute values of intercepts in 16 small stock portfolios that are more than 2.0 standard errors from zero. The intercepts for big stocks tend to be insignificant. After

Table 9
Three- and four-factor intercepts for 32 (2×4×4) VW portfolios: 07/1995–06/2015, 240months. This table reports the intercepts of three- and four-factor model time-series regressions for 32 triply sorted portfolios. The t-statistics are in parentheses.

	Small				Big				Small				Big			
	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
	Three – factor								*Four – factor*							
	Panel A: 32 Size-B/M-ROE portfolios															
Low *ROE*	−0.52	−0.39	−0.14	−0.53	−0.90	−0.13	−0.47	−0.40	−0.13	−0.08	0.20	−0.29	−0.30	1.07	0.37	0.37
	(−2.21)	(−2.31)	(−0.79)	(−3.13)	(−1.70)	(−0.18)	(−1.32)	(−1.25)	(−0.54)	(−0.52)	(1.16)	(−1.63)	(−0.62)	(1.38)	(1.16)	(1.22)
2	−0.04	0.38	0.30	0.17	0.24	0.55	−0.38	0.04	0.08	0.21	0.23	0.01	0.49	0.34	−0.07	−0.10
	(−0.22)	(2.16)	(1.90)	(0.76)	(0.54)	(1.16)	(−0.83)	(0.12)	(0.41)	(1.14)	(1.42)	(0.05)	(0.98)	(0.76)	(−0.15)	(−0.34)
3	0.45	0.65	0.40	0.26	0.02	−0.09	0.47	0.05	0.33	0.47	0.10	−0.21	0.02	0.03	0.22	−0.17
	(2.58)	(3.42)	(2.07)	(0.95)	(0.09)	(−0.29)	(1.46)	(0.15)	(1.80)	(2.61)	(0.59)	(−0.77)	(0.08)	(0.10)	(0.70)	(−0.46)
High *ROE*	0.43	0.45	1.02	0.05	0.31	0.34	0.69	1.14	0.11	−0.01	0.64	0.03	0.04	−0.31	−0.13	0.41
	(2.22)	(1.68)	(2.61)	(0.11)	(1.40)	(0.83)	(1.99)	(2.79)	(0.54)	(−0.03)	(1.62)	(0.07)	(0.19)	(−0.76)	(−0.46)	(0.92)
	Three – factor								*Four – factor*							
	Panel B: 32 Size-B/M-InvA portfolios															
Low *InvA*	−0.54	−0.21	0.03	−0.13	−0.77	−0.46	−0.85	0.13	−0.25	−0.04	0.22	−0.04	−0.31	−0.03	−0.56	0.39
	(−2.30)	(−1.16)	(0.14)	(−0.61)	(−1.88)	(−1.03)	(−2.00)	(0.46)	(−1.08)	(−0.20)	(1.12)	(−0.18)	(−0.74)	(−0.07)	(−1.39)	(1.37)
2	0.37	0.20	−0.07	−0.37	−0.01	−0.25	0.47	0.13	0.26	0.25	0.10	−0.31	0.00	−0.14	0.24	0.04
	(1.20)	(1.22)	(−0.36)	(−2.18)	(−0.03)	(−0.58)	(1.35)	(0.39)	(0.95)	(1.40)	(0.52)	(−1.72)	(0.00)	(−0.33)	(0.71)	(0.10)
3	−0.11	0.45	0.30	0.11	0.22	0.08	0.59	−0.45	−0.12	0.39	0.30	−0.07	0.06	0.10	0.05	−0.65
	(−0.53)	(2.40)	(1.67)	(0.48)	(0.80)	(0.19)	(1.40)	(−1.30)	(−0.60)	(2.18)	(1.59)	(−0.31)	(0.22)	(0.24)	(0.15)	(−2.01)
High *InvA*	0.27	0.19	0.27	−0.25	0.45	0.14	0.12	0.37	0.09	0.17	0.08	−0.24	0.20	−0.19	−0.32	0.22
	(1.22)	(0.98)	(1.13)	(−1.00)	(1.65)	(0.35)	(0.29)	(0.90)	(0.40)	(0.76)	(0.30)	(−0.96)	(0.81)	(−0.50)	(−0.85)	(0.55)
	Three – factor								*four – factor*							
	Panel C: 32 Size-ROE-InvA portfolios															
Low *InvA*	−0.50	0.19	0.50	−0.80	−1.01	−0.08	0.23	−0.61	−0.14	0.25	0.38	−0.78	−0.12	−0.04	0.61	−0.56
	(−3.38)	(0.99)	(1.64)	(−1.84)	(−3.29)	(−0.16)	(0.43)	(−1.43)	(−1.02)	(1.28)	(1.34)	(−1.68)	(−0.45)	(−0.09)	(0.99)	(−1.26)
2	−0.49	0.41	0.50	0.13	−0.41	−0.12	−0.40	−0.09	−0.15	0.34	0.25	−0.24	0.44	−0.12	−0.43	−0.66
	(−3.16)	(2.67)	(2.45)	(0.32)	(−0.82)	(−0.41)	(−1.17)	(−0.16)	(−0.92)	(2.01)	(1.25)	(−0.57)	(0.92)	(−0.39)	(−1.16)	(−1.12)
3	−0.28	−0.13	0.56	0.30	−1.53	−0.59	−0.21	0.46	−0.08	−0.22	0.41	−0.25	−0.77	−0.13	−0.32	0.04
	(−0.97)	(−0.58)	(3.12)	(1.26)	(−2.45)	(−1.34)	(−0.71)	(1.64)	(−0.30)	(−1.03)	(2.26)	(−1.08)	(−1.37)	(−0.30)	(−1.02)	(0.14)
High *InvA*	−0.64	−0.06	0.25	0.67	−0.81	−0.24	0.56	0.98	−0.37	0.03	−0.17	0.16	0.22	−0.09	0.47	0.30
	(−2.22)	(−0.22)	(0.93)	(2.21)	(−1.44)	(−0.48)	(1.83)	(2.99)	(−1.30)	(0.13)	(−0.66)	(0.62)	(0.49)	(−0.18)	(1.46)	(0.99)

adding RMW, the biggest intercept for small stocks reduces to 0.47% per month (t = 2.61), which is the only one more than 2.0 standard errors from zero on the right side of panel A.

There are some big absolute values of three-factor intercepts for 32 *Size-B/M-InvA* portfolios on the left side of panel B of Table 9, such as the small portfolio lying in the intersection of the lowest *B/M* row and the lowest *InvA* column (−0.54% per month with t-statistic of −2.30). The average absolute values of three-factor intercepts are respectively 0.24% per month for small stocks and 0.34% per month for big stocks, where the situation for big stocks is better than the small stocks. Although there are some exceptions, the factor RMW eases most of the absolute values of four-factor intercepts that are less than 2.0 standard errors from zero on the right side of panel B. The average absolute values of four-factor intercepts are respectively 0.18% per month for small stocks and 0.22% per month for big stocks.

Panel C of Table 9 reports the regression intercepts for 32 *Size-ROE-InvA* portfolios. The three-factor model has a flaw in the low *ROE* and *InvA* respects. The intercepts in the upper-left corner are −0.50% per month (t = −3.38) for small stocks and −1.01% per month (t = −3.29) for big stocks. The four-factor model narrowing the intercepts achieves the p-value of GRS statistic of 15.1% (Table 7).

Table B1 and B2 in Appendix B show the slopes of HML, RMW and CMA for 25 and 32 VW portfolios, respectively.

8. Robustness tests

In this section, we use 9 well-documented anomaly variables to test the robustness of factor model mentioned above.

Table 10 shows the average returns for the high and low deciles formed on these anomaly variables we study. Since the excess returns of high-minus-low anomaly portfolios are not depend on market cap, we use the single sorted portfolios independent on *Size*. Panel A of Table 10 reports the average excess returns for anomaly extreme deciles. The result is same with Chen et al. (2010) typically: The t-statistics of the high-minus-low decile sorted by anomalies variables including *E/P*, *A/P* and RD are 2.15, 1.96 and 1.93, which are relatively significant. Many anomalies significant in the U.S. market do not affect the average returns in the Chinese market. Panel B reports the correlations between high-minus-low deciles returns and factor returns. Although the excess return of *E/P* high-minus-low deciles has strongly negative correlation of −0.76 with SMB, it has a high positive correlation of 0.72 with RMW making this excess return significant. For the significant *A/P* decile, HML has the high correlation of 0.81, dominating the excess return of high-minus-low *A/P* deciles. As mentioned before, the significant excess return of high-minus-low *RD* deciles is driven by the factor SMB, where the correlation is 0.44. In these significant groups, CMA does not play an important role in the correlation analysis. Appendix C gives a detailed summary statistics of these 9 groups of anomaly deciles.

Like Table 7, Table 11 summarizes the model performance for anomaly deciles. The four- and five-factor models pass all of GRS tests at 10% confidence level. The average increase of p-value of GRS statistic between three- and four-factor model is 29.1%, almost the same as before. The average absolute value of intercepts $A|a_i|$ decreases 5.7 basis points per month from three-factor model to four-factor model. The average decline of $A|a_i|/A|\bar{r}_i|$ and the average rise of $As^2(a_i)/A\left(a_i^2\right)$ between three- and four-factor models are 0.26 and 0.6, respectively. As before, the five-factor model can not obviously outperform the four-factor model.

It is worth noting that the *MOM* deciles are an exception. The three-factor model performs better than four- and five-factor models, where the absolute values of average intercepts are increased by 6.5 and 6.2 basis points per month respectively. However, all models pass the GRS tests.

Table 10
Average returns of high and low deciles formed on anomaly variables: 07/1995–06/2015, 240 months. The table reports average percent returns for low, high and high-minus-low deciles formed on anomaly variables, and correlations between returns of high-minus-low deciles and factor returns. *E/P* is earning-to-price ratio (Basu, 1983), net income for year $t-1$ divided by market cap at the end of year $t-1$. *D/P* is dividend-to-price ratio (Litzenberger and Ramaswamy, 1979), total dividends paid from July of year $t-1$ to June of year t per RMB of equity in June of year t. *A/P* is market leverage (Bhandari, 1988), total assets for year $t-1$ divided by market cap at the end of year $t-1$. *A/B* is asset-to-book ratio (Chen et al., 2015), total assets for year $t-1$ divided by book equity for year $t-1$. β (Black et al., 1972; Fama and MacBeth, 1973) is estimated by the preceding two years of past monthly returns. *ACC* is accruals (Sloan, 1996), the change in operating working capital per share from the fiscal year ending $t-2$ to $t-1$ divided by book equity per share at year $t-1$. *MOM* is momentum (Jagadeesh and Titman, 1993), cumulative return for preceding 2–12 months. *RD* is research & development expenses to market (Chan et al., 2001), selling, general and administrative expenses for $t-1$ divided by market cap at the end of year $t-1$. *FLO* is floating ratio (Wang and Xu, 2004), the fraction of floating share out of total outstanding share at the end of year t.

	E/P	D/P	A/P	A/B	β	ACC	MOM	RD	FLO
Panel A: average excess returns									
Low	0.29	0.75	0.43	0.78	1.00	0.54	0.84	0.63	0.72
High	1.37	1.36	1.40	1.10	0.49	0.76	0.68	1.22	1.07
High–Low	1.08	0.61	0.97	0.32	−0.51	0.21	−0.16	0.59	0.36
	(2.15)	(1.29)	(1.96)	(0.80)	(−1.25)	(0.78)	(−0.35)	(1.93)	(0.93)
Panel B: correlations with factor returns									
Mkt	0.02	−0.18	−0.01	0.01	0.06	−0.03	−0.14	0.08	0.27
SMB	−0.76	−0.41	−0.46	−0.54	−0.03	−0.25	−0.11	0.44	0.34
HML	0.25	0.66	0.81	0.32	−0.15	−0.30	−0.20	−0.35	0.18
RMW	0.72	0.03	−0.03	0.30	−0.09	0.48	0.41	0.13	−0.11
CMA	−0.48	0.21	0.17	−0.24	0.06	−0.55	−0.25	−0.14	0.00

Table 11
Summary tests statistics of three-, four- and five-factor models for 9 groups of anomaly deciles: 07/1995–06/2015, 240 months. The table is same with Table 7, except the tested portfolios are anomaly deciles formed on variables in Table 10.

Market factors	p(GRS)	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|r_i\|}$	$\frac{As^2(a_i)}{A(a_i^2)}$	p(GRS)	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|r_i\|}$	$\frac{As^2(a_i)}{A(a_i^2)}$	p(GRS)	$A\|a_i\|$	$\frac{A\|a_i\|}{A\|r_i\|}$	$\frac{As^2(a_i)}{A(a_i^2)}$
	10 E/P portfolios				*10 D/P portfolios*				*10 A/P portfolios*			
Three-factor	0.000	0.329	1.06	0.21	0.481	0.180	0.66	0.99	0.784	0.112	0.34	1.80
Four-factor	0.199	0.185	0.59	0.82	0.784	0.138	0.51	1.39	0.958	0.086	0.26	2.93
Five-factor	0.162	0.197	0.63	0.75	0.820	0.133	0.49	1.50	0.971	0.084	0.25	2.98
	10 A/B portfolios				*10 β portfolios*				*10 ACC portfolios*			
Three-factor	0.072	0.207	1.33	0.56	0.634	0.224	0.76	0.87	0.145	0.194	1.35	0.82
Four-factor	0.541	0.147	0.95	1.24	0.979	0.120	0.40	2.82	0.792	0.099	0.69	2.24
Five-factor	0.536	0.146	0.93	1.24	0.982	0.122	0.41	2.78	0.764	0.102	0.71	2.06
	10 MOM portfolios				*10 RD portfolios*				*10 FLO portfolios*			
Three-factor	0.840	0.125	0.56	2.39	0.014	0.244	1.29	0.44	0.156	0.206	0.98	0.64
Four-factor	0.750	0.190	0.86	0.97	0.193	0.190	1.00	0.69	0.505	0.154	0.73	1.02
Five-factor	0.710	0.187	0.84	0.99	0.172	0.192	1.01	0.67	0.442	0.157	0.75	0.93

Table 12 shows the time-series regression details for high-minus-low decile portfolios single sorted. The number after the estimated coefficient indicates the number of factor for factor models. For example, $a3$ is the intercept in three-factor model, and $s4$ is the loading of SMB in four-factor model. To save space, we omit the slopes b_i of Mkt, which is not helpful for explaining other types of difference in average returns. Compared with three-factor model, the four- and five-factor model respectively reduce the absolute values of intercepts for 0.22% and 0.24% per month on average, where these two factor models can not improve the description on average returns of high-minus-low *MOM* and *FLO* portfolios. Across the 9 high-minus-low deciles, the SMB loadings s significant for most of high-minus-low deciles vary from −1.14% to 0.42% for three-factor model, −0.62% to 0.59% for four-factor model, and −0.60% to 0.62% for five-factor model. There are small differences between $s4$ and $s5$. The HML loadings $h4$ and $h5$ are significant for all of portfolios except *MOM* and *RD*. However, $h3$ is significant for these two high-minus-low deciles with t-statistics of −2.27 and −3.15. That is because the probability factor RMW helps to explain the return

Table 12
Regressions for high-minus-low decile VW portfolios: 07/1995–06/2015, 240 months. The five-factor model is

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

The three-factor model includes Mkt, SMB and HML, and the four-factor model includes Mkt, SMB, HML and RMW. The left-hand-side portfolios are 9 groups of high-minus-low decile VW portfolios. The number after the estimate coefficient represents the number of factor, for example, a3 are the intercepts in three-factor model, s4 are the loadings of SMB in four-factor model. The t-statistics are in the parentheses.

	E/P	D/P	A/P	A/B	β	ACC	MOM	RD	FLO
*a*3	1.45	0.10	0.19	0.37	−0.32	0.62	0.28	0.64	−0.19
	(4.35)	(0.33)	(0.71)	(1.11)	(−0.84)	(2.55)	(0.63)	(2.33)	(−0.56)
*a*4	0.29	−0.09	0.09	0.09	0.11	0.25	−0.48	0.20	−0.55
	(1.31)	(−0.30)	(0.33)	(0.29)	(0.31)	(1.03)	(−1.13)	(0.82)	(−1.78)
*a*5	0.26	−0.04	0.07	0.05	0.14	0.20	−0.45	0.20	−0.62
	(1.19)	(−0.15)	(0.26)	(0.14)	(0.37)	(0.86)	(−1.08)	(0.81)	(−1.97)
*s*3	−1.14	−0.33	−0.39	−0.61	−0.10	−0.29	−0.22	0.32	0.42
	(−14.79)	(−3.84)	(−4.67)	(−5.64)	(−0.80)	(−5.29)	(−1.66)	(4.29)	(3.24)
*s*4	−0.62	−0.24	−0.35	−0.48	−0.30	−0.12	0.12	0.52	0.59
	(−7.87)	(−2.02)	(−3.64)	(−3.14)	(−1.48)	(−1.75)	(0.77)	(5.59)	(4.21)
*s*5	−0.60	−0.27	−0.34	−0.46	−0.31	−0.09	0.11	0.52	0.62
	(−7.59)	(−2.13)	(−3.40)	(−2.85)	(−1.53)	(−1.38)	(0.67)	(5.49)	(4.29)
*h*3	0.08	0.94	1.16	0.24	−0.23	−0.34	−0.33	−0.26	0.30
	(0.83)	(8.76)	(14.65)	(2.30)	(−2.09)	(−6.04)	(−2.27)	(−3.15)	(2.73)
*h*4	0.48	1.00	1.20	0.33	−0.38	−0.22	−0.07	−0.11	0.42
	(6.96)	(8.66)	(14.41)	(2.82)	(−2.60)	(−3.75)	(−0.52)	(−1.58)	(3.67)
*h*5	0.52	0.93	1.23	0.40	−0.41	−0.14	−0.11	−0.11	0.52
	(6.61)	(6.96)	(13.07)	(3.08)	(−2.63)	(−2.19)	(−0.82)	(−1.46)	(4.30)
*r*4	1.10	0.18	0.10	0.26	−0.41	0.35	0.72	0.41	0.34
	(12.19)	(1.19)	(0.90)	(1.23)	(−1.65)	(3.99)	(3.81)	(3.17)	(2.23)
*r*5	0.99	0.35	0.03	0.08	−0.31	0.14	0.82	0.40	0.10
	(9,41)	(2.63)	(0.20)	(0.38)	(−1.20)	(1.44)	(4.04)	(2.66)	(0.58)
*c*5	−0.23	0.37	−0.15	−0.38	0.21	−0.44	0.22	−0.02	−0.51
	(−2.05)	(1.89)	(−0.94)	(−1.86)	(0.64)	(−3.90)	(0.89)	(−0.13)	(−2.32)

anomalies: The t-statistics of $r4$ and $r5$ are 3.17 and 2.66 for high-minus-low *RD* decile. For the 9 high-minus-low deciles, the investment loadings $c5$ are significant for *E/P*, *ACC* and *FLO* portfolios.

9. Concluding remarks

In this paper, we find strong size, value and probability patterns in average returns of the Chinese stock market. Chen et al. (2015) strengthen that the significant value effect is due to the extreme values in the early years of the Chinese stock market. Although the significance of HML is weaken by omitting the data of early years, our time-series out-of-sample factor spanning tests show that the value factor HML is still non-redundant. Time-series out-of-sample tests of maximum Sharpe ratio also support this result.

Fama and French (2015b) find that the investment factor CMA is redundant for Europe, Japan and Asia Pacific confirmed by the factor spanning tests and time-series regression details. We find the same result for the Chinese stock market. Different from CMA, the profitability factor RWM strongly improves the description of average returns for all portfolios we examine. There is a surprising result that the four-factor model adding RMW passes the GRS tests at 10% confidence level, except the 25 *Size-ROE* portfolios (p-value = 0.003) and 32 *Size-ROE-InvB* portfolios (p-value = 0.052).

We find that investment pattern in average returns is weak in the Chinese stock market, and Fama and French (2015b) find that it is not obvious in the Japanese stock market. By the clean surplus relation that dividend equals profitability minus investment, the low dividend of the Chinese stock market means that profitability is closed to investment. However, the strong profitability pattern and weak investment pattern imply that the clean surplus relation fails for the Chinese stock market. Although the four-factor model passes GRS test in most cases, a more realistic dividend determining equation for the Chinese stock market is still required.

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Appendix A. Summary statistics for 25 and 32 VW portfolios

To identify the clear relations among the factor variables, Table A1 reports the summary statistics for the 25 VW portfolios. Panel A of Table A1 provides the average number of firms for each portfolio. Since we use the breakpoints of CSI 300 stocks to avoid the impact of plentiful small stocks, the number of firms decreases with the size. Panel B shows the average market cap for each portfolio. Although the average numbers of firms for small portfolios are large, the market cap is also small, which implies that the tiny stocks are plentiful. Fixing *Size* in each row, there are no consistent or obvious trends for market cap in each portfolios, except for *Size-ROE* portfolios. The market cap is typically increasing with probability in each row, which implies that big companies tend to make more profit than small one in China. This result is intuitive, because the big firms tend to be state-owned enterprises protected by the government. Since we find that small stock portfolios and high probability portfolios tend to have high average return from Table 3, the profitability effect weakens the *Size* effect, and vice versa.

Panel C of Table A1 reports the average *B/M* ratio. No matter what the portfolios are, the *B/M* ratio has no significant trend with *Size* and investment variables. However, the higher the *ROE*, the lower the *B/M* ratio. In the following section, we will find that the probability factor has relative high absolute values of correlation with SMB and HML, but it can not be spanned by these two factors. The average *ROE* is shown in panel D. The *ROE* is typically increasing with *Size* and decreasing with *B/M*, which is consistent with panel B and C. In addition, *ROE* is generally increasing with investment variables *InvA* and *InvB* for 25 *Size-InvA* and *Size-InvB* portfolios. However, in panel E and F, no relations between investment variable *InvA* or *InvB* and other variable. Following Fama and French(2015a, 2015b), we construct the 32 ($2 \times 4 \times 4$) VW portfolios triple sorted by *Size*, *B/M*, *ROE*, *InvA* and *InvB* in the Appendix. The results are same with the 25 portfolios.

Table A2 presents the summary statistics including the average excess returns and other characteristics in Table A1 for 32 ($2 \times 4 \times 4$) VW portfolios, providing more clear patterns in average returns to reinforce the results of 5×5 portfolios. Panel A of Table A2 shows the results of 32 VW *Size-B/M-ROE* portfolios. In each *ROE* row, regardless of Small or Big portfolios, the average return typically increases with *B/M*. Similarly, in each *B/M* column, the average return typically increases with *ROE*. For small stocks, the average spread of High and Low *B/M* portfolios is 0.45% per month, and the average spread of High and Low *ROE* portfolios is 0.48% per month; for big stocks counterparts, the average spreads are respectively 1.12% per month and 0.70% per month. The comparatively small spreads for small stocks is caused by the abnormally small average return of 0.80% per month for Small-High *B/M*-High *ROE* portfolio. Because small firms tend to have low profitabilities, and profitability and B/M are negatively correlated for small stocks, there are only three firms for this portfolio in average. The few numbers of firms make the average return abnormal. For big stocks, the problem disappears. In brief, the value and profitability effects are relatively obvious in 32 ($2 \times 4 \times 4$) VW *Size-B/M-ROE* portfolios. Other characteristics show the same patterns with 25 portfolios typically.

Table A1

Summary statistics for 25 (5 × 5) VW portfolios formed on *Size* and *B/M*, *Size* and *ROE*, *Size* and *InvA*, *Size* and *InvB*: 07/1995–06/2015, 240 months. The table shows average characteristics of the 25 portfolios in Table 3. The characteristics include the average number of firms, average equally weighted market cap (in billion, RMB), average *B/M* ratio, average ROE, and two average investment variables (*InvA* and *InvB*) defined in Table 2.

	Low	2	3	4	High	Low	2	3	4	High
Panel A: average number of firms										
	Size-B/M portfolios					*Size-ROE portfolios*				
Small	278	219	180	124	88	347	231	170	95	72
2	58	35	26	24	17	33	36	37	30	25
3	34	19	17	14	12	17	19	20	19	21
4	24	14	10	11	10	11	11	12	15	20
Big	16	9	11	11	11	7	7	9	13	21
	Size-InvA portfolios					*Size-InvB portfolios*				
Small	304	209	155	124	124	304	232	169	98	111
2	29	31	31	31	37	31	32	33	29	34
3	16	18	17	20	24	16	17	19	20	23
4	13	11	12	15	17	11	13	13	14	17
Big	8	11	12	12	14	8	9	10	15	16
Panel B: average market cap (in billion, RMB)										
	Size-B/M portfolios					*Size-ROE portfolios*				
Small	2.75	2.81	2.68	2.60	2.69	2.32	2.77	2.90	3.38	3.16
2	6.02	5.82	5.59	4.98	5.42	5.08	5.33	5.92	6.03	6.63
3	10.02	9.59	9.69	8.08	8.43	8.62	9.57	9.29	10.13	10.17
4	16.29	16.14	15.43	15.41	15.40	15.10	15.67	16.05	16.67	16.38
Big	40.38	67.37	89.19	111.34	111.471	36.27	52.60	70.62	117.18	93.27
	Size-InvA portfolios					*Size-InvB portfolios*				
Small	2.46	2.78	2.87	2.94	3.06	2.43	2.70	2.86	3.24	3.11
2	5.63	6.00	5.76	5.79	6.31	5.62	5.70	5.88	5.93	6.41
3	9.33	9.60	10.49	9.66	9.98	9.96	9.14	9.56	10.53	9.86
4	15.62	15.18	16.19	16.76	18.29	15.36	14.78	16.76	16.69	18.45
Big	40.03	68.56	151.46	82.08	52.39	46.68	61.90	117.92	104.93	61.57
Panel C: average B/M ratio										
	Size-B/M portfolios					*Size-ROE portfolios*				
Small	0.17	0.29	0.38	0.51	0.76	0.40	0.36	0.31	0.27	0.18
2	0.18	0.29	0.38	0.51	0.82	0.43	0.40	0.36	0.30	0.24
3	0.18	0.29	0.38	0.50	0.77	0.43	0.41	0.36	0.33	0.26
4	0.16	0.28	0.39	0.51	0.90	0.47	0.43	0.37	0.36	0.29
Big	0.16	0.28	0.39	0.51	1.00	0.52	0.41	0.40	0.41	0.44
	Size-InvA portfolios					*Size-InvB portfolios*				
Small	0.34	0.40	0.39	0.38	0.34	0.35	0.39	0.35	0.34	0.36
2	0.41	0.41	0.40	0.35	0.34	0.41	0.41	0.36	0.38	0.34
3	0.43	0.42	0.37	0.38	0.35	0.41	0.43	0.39	0.37	0.35
4	0.46	0.46	0.46	0.34	0.33	0.44	0.47	0.39	0.35	0.35
Big	0.43	0.47	0.58	0.41	0.37	0.40	0.47	0.49	0.54	0.38
Panel D: average ROE										
	Size-B/M portfolios					*Size-ROE portfolios*				
Small	−0.05	0.06	0.05	0.03	0.03	−0.16	0.07	0.09	0.12	1.06
2	0.09	0.09	0.08	0.07	0.05	−0.03	0.07	0.10	0.12	0.23
3	0.12	0.10	0.09	0.07	0.06	0.00	0.07	0.10	0.12	0.21
4	0.16	0.10	0.10	0.09	0.06	−0.01	0.07	0.09	0.13	0.21
Big	0.17	0.12	0.11	0.12	0.09	−0.01	0.06	0.09	0.13	0.22
	Size-InvA portfolios					*Size-InvB portfolios*				
Small	0.09	0.03	0.05	0.06	0.09	0.04	0.05	0.08	0.11	0.11
2	0.01	0.08	0.09	0.11	0.11	0.00	0.08	0.10	0.12	0.11
3	0.06	0.08	0.11	0.12	0.12	0.03	0.08	0.11	0.13	0.13
4	0.07	0.09	0.12	0.14	0.16	0.05	0.08	0.12	0.17	0.16
Big	0.08	0.11	0.13	0.17	0.16	0.06	0.09	0.13	0.16	0.16

Table A1 (*continued*)

	Low	2	3	4	High	Low	2	3	4	High
Panel E: average InvA										
	Size-BM portfolios					*Size-ROE portfolios*				
Small	0.47	0.16	0.52	0.17	0.24	0.60	0.53	0.16	0.26	0.27
2	0.37	0.44	1.18	0.20	0.21	0.25	0.19	0.23	0.23	1.61
3	0.40	0.31	3.64	0.23	0.34	0.30	0.31	2.39	0.27	0.36
4	0.41	0.44	0.26	0.21	0.23	0.28	0.17	0.21	0.34	0.48
Big	1.19	0.20	0.36	0.33	0.31	0.40	0.32	0.21	0.50	0.74
	Size-InvA portfolios					*Size-InvB portfolios*				
Small	−0.08	0.11	0.23	0.45	0.66	0.30	0.12	0.17	0.38	1.64
2	−0.07	0.09	0.18	0.27	1.72	0.76	0.14	0.22	0.35	1.42
3	−0.04	0.08	0.19	0.32	3.07	2.73	0.17	0.22	0.35	0.99
4	−0.07	0.08	0.20	0.32	1.26	0.12	0.12	0.22	0.29	1.07
Big	−0.07	0.06	0.14	0.31	1.99	0.03	0.10	0.19	0.28	1.65
Panel F: average InvB										
	Size-BM portfolios					*Size-ROE portfolios*				
Small	0.34	0.65	0.18	0.10	0.22	1.05	0.11	0.15	0.26	0.05
2	0.24	−1.29	1.54	0.21	0.15	0.25	0.20	0.20	0.20	0.18
3	0.32	0.31	−1.84	0.24	0.95	0.64	0.22	0.22	0.18	−1.06
4	0.08	0.30	0.19	0.22	0.18	0.22	0.20	0.15	0.29	0.11
Big	0.64	0.19	0.28	0.28	0.20	0.24	0.31	0.18	0.36	0.52
	Size-InvA portfolios					*Size-InvB portfolios*				
Small	−0.08	0.22	0.34	0.36	2.69	−0.33	0.08	0.11	0.39	3.59
2	0.00	0.09	0.19	0.25	0.57	−2.31	0.07	0.17	0.32	1.97
3	0.05	0.14	0.16	0.30	−0.45	−2.72	0.09	0.17	0.30	1.37
4	−0.41	0.09	0.15	0.25	0.99	−0.61	0.07	0.12	0.21	1.14
Big	0.01	0.08	0.13	0.32	1.16	−0.09	0.09	0.16	0.20	1.24

Panel B shows the average excess returns for 32 VW *Size-B/M-InvA* portfolios. Consistent with the findings above, there is no reliable relation between average return and investment, neither Small nor Big portfolios. The average number of firms and other average characteristics prove that the unreliable relation between average return and investment is not caused by the small number of firms for portfolios.

Table A2

Summary statistics for 32 (2 × 4 × 4) VW portfolios formed on (1) *Size*, *B/M* and *ROE*, (2) *Size*, *B/M* and *InvA*, and (3) *Size*, *ROE* and *InvA*: 07/1995–06/2015, 240 months. The stock sample includes all Shanghai and Shenzhen Main Broad, SMEB and GEM stocks. At the end of each June, stocks are allocated to two *Size* groups (Small to Big) using CSI300 stock sample median market cap breakpoints. Stocks are allocated independently to four *B/M* groups (Low to High) using CSI300 stock sample *B/M* quartiles and four *ROE* groups (Low to High) using CSI300 stock sample *ROE* quartiles. The intersections of this three sorts produce 32 value-weight *Size-B/M-ROE* portfolios. The *Size-B/M-InvA* and *Size-ROE-InvA* portfolios are constructed by the same way. The summary statistics include average percent excess returns, average number of firms, average equally weighted market cap (in billion, RMB), average *B/M* ratio, average *ROE*, and two average investment variables (*InvA* and *InvB*) defined in Table 2.

	Small				Big				Small				Big			
Panel A: Size-B/M-ROE portfolios																
	Average percent excess returns								Average number of firms							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *ROE*	0.32	0.79	1.35	1.27	−0.47	0.48	0.61	0.94	152	113	113	102	7	7	8	10
2	0.74	1.34	1.47	1.51	0.57	1.08	0.68	1.16	109	116	74	33	10	9	8	9
3	1.09	1.37	1.56	1.59	0.32	0.55	1.48	1.34	99	64	33	14	15	10	9	8
High *ROE*	1.24	1.41	2.21	0.80	0.41	0.84	1.22	1.87	83	28	10	3	34	12	10	8
	Average market cap (in billion)								Average B/M							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *ROE*	2.89	2.81	2.77	2.84	16.09	21.17	22.54	21.07	0.17	0.32	0.44	0.72	0.17	0.30	0.44	0.78
2	3.24	3.20	3.32	3.91	15.24	36.44	26.30	27.91	0.19	0.32	0.45	0.68	0.18	0.30	0.45	0.73
3	4.21	3.95	4.26	5.09	20.33	35.70	77.90	55.17	0.19	0.31	0.43	0.66	0.18	0.32	0.45	0.69
High *ROE*	4.79	5.11	5.63	4.85	25.26	40.12	76.83	119.05	0.16	0.31	0.43	0.57	0.16	0.33	0.44	1.05

Table A2 (*continued*)

	Small				Big				Small				Big			
Panel A: Size-B/M-ROE portfolios																
	Average ROE								Average InvA							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *ROE*	−0.42	−0.01	0.00	0.01	−0.01	0.01	0.01	0.01	0.66	0.53	0.14	0.34	0.35	0.18	0.32	0.44
2	0.07	0.08	0.08	0.07	0.07	0.07	0.08	0.08	0.15	0.41	0.17	0.23	0.28	0.17	0.19	0.25
3	0.11	0.11	0.10	0.10	0.11	0.12	0.12	0.11	0.22	0.20	0.19	0.25	0.24	0.33	0.51	0.32
High *ROE*	0.57	0.18	0.16	0.18	0.21	0.21	0.17	0.16	0.40	0.44	2.44	0.29	0.80	0.28	0.28	0.25
Panel B: Size-B/M-InvA portfolios																
	Average percent excess returns								Average number of firms							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *InvA*	0.29	0.90	1.47	1.57	−0.43	0.22	0.34	1.38	150	94	79	58	10	9	8	8
2	1.09	1.11	1.39	1.34	0.16	0.49	1.12	1.58	94	74	59	42	11	8	8	9
3	0.67	1.32	1.52	1.50	0.42	0.34	1.28	0.88	81	58	42	27	16	9	8	9
High *InvA*	0.93	1.12	1.48	1.16	0.57	0.79	1.14	1.09	86	59	36	21	24	9	9	7
	Average market cap (in billion)								Average B/M							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *InvA*	2.97	2.97	2.96	2.99	17.06	23.58	31.05	32.17	0.18	0.33	0.47	0.76	0.19	0.33	0.48	0.87
2	3.92	3.46	3.30	3.32	21.71	29.02	85.90	53.02	0.20	0.33	0.47	0.76	0.17	0.32	0.46	0.89
3	3.95	3.67	3.42	3.67	22.82	48.74	73.31	80.97	0.19	0.33	0.47	0.75	0.18	0.33	0.47	0.89
High *InvA*	4.42	4.03	4.24	4.02	24.38	22.83	31.29	37.90	0.19	0.33	0.47	0.74	0.17	0.31	0.45	0.71
	Average ROE								Average InvA							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *InvA*	−0.10	0.01	0.01	0.01	0.11	0.08	0.06	0.05	−0.08	−0.01	−0.03	−0.02	−0.04	−0.05	−0.05	−0.04
2	0.06	0.06	0.05	0.04	0.14	0.09	0.10	0.09	0.12	0.12	0.12	0.16	0.08	0.11	0.09	0.09
3	0.06	0.08	0.08	0.06	0.17	0.12	0.12	0.10	0.25	0.28	0.26	0.30	0.27	0.26	0.22	0.21
High *InvA*	0.12	0.09	0.07	0.07	0.19	0.12	0.12	0.10	1.95	2.66	1.70	1.03	1.48	0.87	1.03	1.17
Panel C: Size-ROE-InvA portfolios																
	Average percent excess returns								Average number of firms							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *InvB*	0.90	1.01	1.46	0.24	0.11	0.36	1.58	0.62	238	82	42	33	12	9	6	8
2	0.91	1.38	1.41	1.34	0.61	0.96	0.62	1.10	110	84	51	25	7	8	9	11
3	0.88	1.38	1.41	1.13	−0.06	0.52	0.60	0.91	64	63	49	31	5	8	11	17
High *InvB*	0.45	1.04	1.57	1.24	−0.42	0.74	1.17	1.10	57	62	47	39	6	8	12	24
	Average market cap (in billion)								Average B/M							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *InvB*	2.57	3.28	3.84	3.51	18.40	20.67	35.00	36.85	0.36	0.35	0.32	0.17	0.49	0.41	0.39	0.38
2	2.87	3.41	4.34	5.43	19.20	28.50	66.77	59.34	0.42	0.39	0.34	0.27	0.47	0.45	0.40	0.44
3	2.99	3.28	4.41	5.04	21.75	19.75	54.34	68.22	0.41	0.39	0.31	0.26	0.46	0.41	0.38	0.43
High *InvB*	3.77	3.66	4.63	5.30	25.98	23.99	25.31	29.97	0.41	0.36	0.32	0.24	0.41	0.44	0.35	0.28
	Average ROE								Average InvA							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Low *InvB*	−0.24	0.07	0.11	2.17	−0.02	0.07	0.12	0.19	−0.07	−0.05	−0.05	−0.15	−0.07	−0.05	−0.05	−0.07
2	−0.01	0.07	0.11	0.21	0.02	0.08	0.11	0.18	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09
3	−0.04	0.08	0.11	0.19	0.01	0.08	0.11	0.21	0.21	0.26	0.22	0.22	0.19	0.21	0.21	0.27
High *InvB*	0.00	0.07	0.11	0.23	0.02	0.07	0.11	0.22	3.59	1.44	0.94	1.65	1.41	0.86	1.20	1.37

In panel C, the second anomaly variable is replaced by *ROE*. Small stocks tend to be less profitable, and tend to invest little. The unbalanced distribution of firms' numbers for each small portfolio weakens the profitability effect. For big stocks, the average numbers of firms in upper left corner and lower right corner are both larger, implying a strongly positive relation between profitability and investment. This strong relation also weakens the profitability pattern. The results above are consistent with 25 portfolios.

Appendix B. Factor slopes of five-factor model

Table B1 shows the slopes of HML, RMW and CMA in five-factor model. To save space, we omit the slopes b_i of Mkt and s_i of SMB, since all b_i are around one and s_i decrease with the market cap.

The regression details for 25 *Size-B/M* portfolios are shown in panel A of Table B1, where the slope *h* increases with *B/M* in each row. For example, *h* increases from −0.34 to 0.58 in Small row. The same slope pattern exists in other rows. On the contrary, there are no obvious patterns for the slopes *r* of RMW and *c* of CMA, whether in rows or columns. For the 25 *Size-ROE* portfolios shown in panel B, the slopes *h* and *c* show unclear patterns in horizontal or vertical directions, but the slope *r* gives a strong increase in each row. Panel C shows the results of 25 *Size-InvA* portfolios. There is a strong positive relation between the slope *r* and *InvA*. Because of the strong negative relation between CMA and RMW (−0.71 in Table 4), RMW can explain the investment pattern in average returns. The pattern of slope *r* is adverse to the pattern of slope *c* in five-factor regressions. For middle size stocks in the third row, for example, *r* typically increases from -0.09 in low *InvA* column to 0.13 in high *InvA* column, whereas *c* decreases from 0.15 to −0.32. The increased pattern of *r* disappears for the Small portfolios. Due to the negative mean of CMA shown in panel A of Table 6, the opposite pattern of *c* actually improves the description of average return in *InvA*. However, the improvement is mixed, and not obvious. Table B2 reports the regression details for 32 portfolios, which are same with 25 portfolios basically. The main results do not depend on the type of sorts.

Table B1
Five-factor HML, RMW and CMA slopes and t-statistics for 25 (5 × 5) VW portfolios: 07/1995–06/2015, 240 months. The five-factor model is

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

B/M →	Low	2	3	4	High	Low	2	3	4	High
Panel A: Size-B/M portfolios										
	h					*t*(*h*)				
Small	−0.34	−0.19	0.15	0.40	0.58	−4.66	−2.91	2.92	7.66	10.39
2	−0.34	−0.12	0.28	0.36	0.84	−4.37	−1.42	1.19	5.22	8.97
3	−0.50	−0.29	0.03	0.50	0.62	−6.60	−3.29	0.40	6.03	7.08
4	−0.51	−0.22	0.15	0.37	0.72	−8.45	−2.56	1.71	3.65	8.48
Big	−0.52	−0.26	−0.05	0.45	0.62	−6.91	−2.18	−0.41	3.08	5.22
	r					*t*(*r*)				
Small	−0.11	−0.05	0.00	−0.10	−0.11	−1.29	−0.56	0.01	−1.35	−1.44
2	0.12	0.16	0.41	−0.04	0.11	1.38	1.68	1.76	−0.48	1.17
3	0.16	0.06	−0.11	0.13	−0.16	1.89	0.50	−1.14	1.19	−0.81
4	0.25	−0.13	−0.10	0.10	0.13	2.40	−0.97	−0.88	0.80	1.13
Big	−0.01	−0.03	−0.07	0.60	0.16	−0.06	−0.18	−0.39	1.81	1.21
	c					*t*(*c*)				
Small	0.04	0.07	0.08	0.13	0.10	0.44	0.73	0.78	1.25	0.98
2	0.16	0.07	−0.16	−0.01	0.09	1.49	0.54	−0.44	−0.05	0.72
3	0.13	0.25	−0.44	0.00	0.00	0.90	1.64	−2.62	−0.01	−0.02
4	−0.04	0.03	0.23	0.04	0.29	−0.29	0.13	1.75	0.25	1.81
Big	−0.03	0.22	0.15	−0.25	0.40	−0.21	1.12	0.80	−0.62	2.65
ROE →	Low	2	3	4	High	Low	2	3	4	High
Panel B: Size-ROE portfolios										
	h					*t*(*h*)				
Small	0.22	−0.09	−0.07	−0.04	0.21	5.01	−1.91	−1.97	−0.82	2.50
2	0.14	0.12	0.03	−0.03	0.07	1.55	1.14	0.41	−0.45	1.09
3	0.07	0.03	0.12	−0.05	0.03	0.65	0.28	1.52	−0.66	0.35
4	0.00	0.40	−0.16	0.22	−0.22	0.00	2.22	−1.23	2.43	−2.48
Big	−0.04	0.19	0.06	0.06	0.11	−0.31	2.03	0.51	0.49	1.58
	r					c *t*(*r*)				
Small	−0.23	−0.15	0.15	0.26	0.42	−3.30	−2.31	1.85	3.34	3.61
2	−0.27	0.08	0.17	0.37	0.46	−3.14	0.63	2.03	3.66	5.81
3	−0.71	−0.16	0.38	0.36	0.49	−3.27	−1.47	3.12	4.31	4.57
4	−0.83	−0.05	0.03	0.29	0.31	−5.00	−0.22	0.23	2.36	2.32
Big	−1.04	−0.03	−0.19	−0.04	0.79	−3.76	−0.10	−1.26	−0.29	5.70

Table B1 (*continued*)

B/M →	Low	2	3	4	High	Low	2	3	4	High
Panel B: Size-ROE portfolios										
	c					*t*(*c*)				
Small	0.15	−0.02	0.11	0.02	0.16	1.72	−0.21	1.08	0.22	1.38
2	0.21	−0.01	−0.03	0.20	0.08	1.65	−0.08	−0.22	1.43	0.71
3	−0.06	−0.07	0.16	0.00	−0.10	−0.41	−0.45	1.19	0.02	−0.59
4	−0.21	0.46	0.27	−0.18	−0.12	−1.06	1.88	1.50	−1.19	−0.74
Big	0.14	0.20	0.07	0.27	−0.07	0.58	0.50	0.36	1.47	−0.45
Panel C: Size-InvA portfolios										
	h					*t*(*h*)				
Small	0.11	0.09	0.08	0.04	−0.06	2.56	2.46	1.94	0.92	−0.99
2	0.12	0.05	0.22	−0.05	0.13	1.88	0.91	3.74	−0.67	1.32
3	0.22	0.11	0.02	−0.15	0.07	2.09	1.22	0.22	−1.92	0.72
4	0.02	0.06	0.17	−0.19	0.12	0.16	0.43	1.53	−1.96	1.21
Big	−0.12	0.09	0.16	−0.11	0.39	−0.88	1.22	1.81	−1.17	1.77
	r					*t*(*r*)				
Small	−0.16	−0.08	−0.14	−0.06	−0.14	−1.99	−0.99	−2.17	−0.86	−1.48
2	−0.02	−0.08	0.15	0.08	0.26	−0.20	−0.98	1.69	0.78	2.00
3	−0.09	0.22	0.17	0.02	0.13	−0.31	2.11	1.73	0.20	0.97
4	−0.12	0.17	0.16	0.08	0.14	−0.82	1.07	1.50	0.66	1.07
Big	0.00	0.44	0.16	0.19	0.38	0.02	1.68	1.07	1.48	1.55
	c					*t*(*c*)				
Small	0.29	0.08	0.02	−0.07	−0.23	2.92	0.88	0.24	−0.57	−1.94
2	0.14	0.22	0.01	−0.04	−0.09	1.29	2.01	0.07	−0.28	−0.53
3	0.15	0.33	0.06	−0.30	−0.32	0.70	2.07	0.45	−2.00	−1.58
4	0.40	0.30	−0.20	−0.22	−0.19	2.08	1.22	−1.05	−1.44	−1.13
Big	1.29	0.88	0.12	−0.06	−1.17	5.09	2.77	0.78	−0.34	−4.24

Appendix C. Summary statistics of anomaly deciles

Table C1 reports the summary statistics of the 9 groups of anomaly deciles. Panel A shows the average *B/M* ratios, where there are obvious *B/M* increases for the *E/P* and *A/P* deciles. The *D/P* decile without significant average return spread ($t = 1.29$ in Table 12) also shows the *B/M* increase. Other anomaly deciles do not show *B/M* trend. To save space, the average number of firms and market cap are not shown. However, the significant return of high-minus-low *RD* portfolio is due to the *Size* decrease from low to high *RD* portfolios. There is a positive relation between *E/P* and *ROE* shown in Panel B, where the *ROE* increases from −0.07 for low *E/P* decile to 0.19 for high *E/P* decile. Because of the positive relation between *Size* and *ROE*, *ROE* decreases 0.12 (0.10 – (−0.02)) from low *RD* decile to high *RD* decile. All anomaly variables show no relations with investment variable *InvA* in Panel C.

Table B2
Five-factor HML, RMW and CMA slopes and t-statistics for 32 (2 × 4 × 4) VW portfolios: 07/1995–06/2015, 240 months. The five-factor model is

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

	Small								Big							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Panel A: Size-B/M-ROE portfolios																
	h				*t*(*h*)				*h*				*t*(*h*)			
Low *ROE*	−0.36	−0.06	0.24	0.65	−4.04	−1.16	4.77	10.00	−0.51	−0.67	0.13	0.51	−3.31	−2.14	1.03	5.83
2	−0.32	−0.08	0.21	0.50	−4.71	−0.62	3.72	9.74	−0.52	−0.01	0.41	0.64	−2.66	−0.06	2.17	5.62
3	−0.40	−0.21	0.34	0.68	−6.14	−2.87	7.39	5.76	−0.43	−0.02	0.51	0.68	−5.45	−0.19	4.53	5.73
High *ROE*	−0.13	0.23	0.37	0.16	−1.11	2.74	2.78	1.04	−0.46	0.20	0.33	0.50	−6.91	1.13	3.57	2.81

(*continued on next page*)

Table B2 (*continued*)

	Small								Big							
B/M →	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
Panel A: Size-B/M-ROE portfolios																
	r				*t*(*r*)				*r*				*t*(*r*)			
Low *ROE*	−0.37	−0.23	−0.27	−0.16	−3.40	−3.34	−3.67	−2.04	−0.77	−0.94	−0.76	−0.70	−2.78	−5.33	−4.73	−3.99
2	−0.08	0.11	0.06	0.16	−0.77	0.85	0.72	1.95	−0.14	0.35	−0.36	0.13	−0.86	1.05	−1.19	0.86
3	0.20	0.18	0.26	0.47	2.89	1.71	3.57	3.82	−0.05	−0.03	0.22	0.45	−0.49	−0.18	1.54	3.07
High *ROE*	0.32	0.43	0.44	−0.10	3.48	4.18	2.85	−0.49	0.25	0.48	0.66	0.85	1.86	2.46	3.82	4.61
	c				*t*(*c*)				*c*				*t*(*c*)			
Low *ROE*	0.00	0.12	0.10	0.16	0.03	1.31	1.02	1.69	−0.44	0.40	0.07	0.05	−1.55	1.07	0.36	0.28
2	0.08	−0.11	−0.02	0.02	0.59	−0.61	−0.15	0.14	0.20	0.34	−0.15	−0.01	0.74	0.79	−0.49	−0.03
3	0.17	0.04	−0.04	0.05	1.84	0.31	−0.38	0.28	−0.10	0.19	−0.03	0.50	−0.63	0.98	−0.16	2.65
High *ROE*	0.04	−0.02	0.18	−0.24	0.39	−0.13	0.82	−1.01	0.00	−0.26	−0.25	0.34	−0.03	−1.17	−1.10	1.56
Panel B: Size-B/M-InvA portfolios																
	h				*t*(*h*)				*h*				*t*(*h*)			
Low *InvA*	−0.40	−0.04	0.31	0.66	−4.95	−0.46	5.66	8.41	−0.60	−0.44	0.38	0.52	−5.13	−3.70	2.75	4.71
2	−0.28	−0.17	0.31	0.66	−3.15	−3.16	3.68	9.04	−0.52	0.08	0.30	0.73	−3.47	0.58	2.74	6.67
3	−0.26	−0.09	0.22	0.57	−3.81	−1.43	2.69	5.72	−0.45	−0.29	0.26	0.83	−5.74	−2.87	2.10	3.93
High *InvA*	−0.27	−0.05	0.33	0.53	−2.83	−0.50	2.31	5.51	−0.39	0.32	0.72	0.43	−4.96	1.50	5.44	3.08
	r				*t*(*r*)				c *r*				*t*(*r*)			
Low *InvA*	−0.16	−0.08	−0.08	0.00	−1.31	−0.95	−0.98	0.04	−0.28	0.08	−0.13	0.08	−1.62	0.43	−0.64	0.58
2	0.01	−0.01	−0.12	0.03	0.10	−0.08	−1.18	0.38	−0.01	−0.03	0.07	0.27	−0.07	−0.11	0.40	1.72
3	0.06	0.05	−0.06	0.08	0.53	0.49	−0.66	0.72	0.13	−0.14	0.43	0.21	1.08	−0.84	2.19	0.85
High *InvA*	0.04	−0.04	0.14	−0.12	0.35	−0.40	1.26	−0.99	0.09	−0.03	0.05	−0.28	0.39	−0.11	0.24	−1.30
	c				*t*(*c*)				*c*				*t*(*c*)			
Low *InvA*	0.24	0.18	0.20	0.18	1.75	1.54	1.68	1.95	0.33	1.03	0.30	0.68	1.37	3.33	1.31	4.94
2	−0.19	0.09	0.08	0.17	−1.26	0.90	0.59	1.75	−0.01	0.16	−0.31	0.38	−0.02	0.40	−1.42	2.02
3	0.09	−0.02	−0.14	−0.19	0.69	−0.11	−1.05	−1.18	−0.05	−0.25	−0.16	0.04	−0.30	−1.01	−0.54	0.17
High *InvA*	−0.27	−0.14	−0.08	−0.24	−2.04	−1.14	−0.60	−1.57	−0.31	−0.72	−0.76	−0.89	−1.28	−2.46	−2.82	−3.11
Panel C: Size-ROE-InvA portfolios																
	h				*t*(*h*)				*h*				*t*(*h*)			
Low *InvA*	0.14	−0.00	−0.03	0.05	3.41	−0.03	−0.32	0.47	0.04	−0.16	0.01	0.04	0.42	−1.14	0.03	0.20
2	0.25	−0.02	0.07	0.30	3.58	−0.40	0.59	4.46	−0.03	0.20	0.28	0.20	−0.24	1.30	2.70	1.75
3	−0.02	0.05	−0.09	0.10	−0.24	0.84	−1.28	1.39	−0.17	0.21	0.03	−0.05	−1.18	1.44	0.25	−0.55
High *InvA*	−0.02	−0.11	0.19	0.05	−0.21	−1.14	1.16	0.29	−0.13	0.30	0.35	−0.05	−1.37	1.57	2.24	−0.50
	r				*t*(*r*)				*r*				*t*(*r*)			
Low *InvA*	−0.28	0.00	0.35	0.00	−4.40	0.02	1.86	−0.02	−0.76	0.14	−0.12	0.13	−5.52	0.39	−0.66	0.62
2	−0.28	0.15	0.14	0.47	−3.98	1.36	1.61	3.65	−0.85	0.02	0.19	0.67	−3.32	0.12	1.56	2.60
3	−0.11	0.07	0.19	0.49	−0.78	0.69	2.33	4.17	−0.60	−0.59	0.26	0.44	−2.60	−1.77	1.87	3.47
High *InvA*	−0.19	−0.21	0.26	0.39	−1.62	−2.13	1.99	3.47	−1.53	−0.25	−0.06	0.24	−2.90	−1.03	−0.30	1.68
	c				*t*(*c*)				*c*				*t*(*c*)			
Low *InvA*	0.12	0.12	0.52	0.02	1.61	1.04	2.43	0.07	0.19	0.37	0.49	0.36	1.12	0.79	1.34	1.29
2	0.10	0.17	−0.22	0.26	1.04	1.41	−1.79	1.52	−0.10	0.05	0.35	0.28	−0.42	0.25	1.69	0.91
3	0.17	−0.04	0.10	−0.07	0.94	−0.28	0.80	−0.55	0.25	−0.33	0.32	0.08	0.72	−0.95	2.05	0.43
High *InvA*	0.13	−0.27	−0.29	−0.19	0.71	−1.72	−1.66	−1.07	−1.17	−0.23	−0.33	−0.83	−2.18	−0.74	−1.49	−4.71

Table C1
Summary statistics for anomaly decile portfolios: 07/1995–06/2015, 240 months. The table reports average B/M ratio, ROE and InvA of the decile portfolios sorted by E/P, D/P, A/P, A/B, β, ACC, MOM, RD, and FLO.

	E/P	D/P	A/P	A/B	β	ACC	MOM	RD	FLO
Panel A: B/M									
Low	0.35	0.31	0.17	0.35	0.21	0.33	0.35	0.40	0.36
2	0.31	0.34	0.25	0.37	0.27	0.37	0.38	0.41	0.36
3	0.30	0.35	0.30	0.38	0.29	0.38	0.39	0.39	0.34
4	0.32	0.36	0.33	0.36	0.31	0.40	0.40	0.39	0.35
5	0.35	0.38	0.37	0.37	0.31	0.38	0.40	0.38	0.34
6	0.38	0.39	0.42	0.39	0.30	0.38	0.39	0.38	3.92
7	0.41	0.41	0.48	0.38	0.30	0.36	0.38	0.37	0.35
8	0.43	0.42	0.53	0.38	0.30	0.36	0.38	0.35	4.23
9	0.48	0.45	0.60	0.38	0.29	0.34	0.36	0.33	0.38
High	0.64	0.58	0.77	0.35	0.23	0.28	0.33	0.29	0.42
Panel B: ROE									
Low	−0.07	0.08	0.09	0.08	0.03	0.06	0.05	0.10	0.11
2	0.06	0.07	0.06	0.07	0.18	0.06	0.05	0.07	0.05
3	0.07	0.08	0.10	0.08	0.02	0.05	0.05	0.07	0.03
4	0.08	0.08	0.03	0.07	0.05	0.07	0.06	0.07	0.17
5	0.10	0.09	0.02	0.07	0.02	0.06	0.06	0.06	0.01
6	0.11	0.09	0.07	0.07	0.25	0.07	0.07	0.07	0.43
7	0.12	0.09	0.03	0.07	0.02	0.12	0.11	0.07	0.07
8	0.12	0.10	0.00	0.06	0.04	0.08	0.06	0.06	0.96
9	0.13	0.11	0.01	0.04	0.05	0.06	0.06	0.06	0.16
High	0.19	0.12	−0.02	0.21	0.01	0.15	0.11	−0.02	−0.11
Panel C: InvA									
Low	0.26	0.21	0.58	0.51	0.11	0.17	0.73	0.92	1.26
2	0.16	0.23	0.51	0.63	0.13	0.18	0.42	2.90	0.20
3	0.65	0.21	0.33	0.27	0.12	0.20	0.42	0.22	0.17
4	0.25	0.25	0.21	0.23	0.28	0.21	0.27	0.26	0.16
5	0.24	0.18	0.24	0.17	0.16	0.28	0.26	0.19	1.86
6	0.57	0.25	0.21	0.19	0.13	1.19	0.38	0.38	0.20
7	0.37	0.54	0.93	0.34	0.11	0.52	0.28	0.18	2.10
8	0.23	0.20	0.20	0.86	0.13	0.28	0.25	0.25	0.33
9	0.28	2.03	0.32	0.30	0.15	0.20	0.28	0.17	0.41
High	1.58	0.15	0.34	0.65	2.13	0.78	0.53	0.20	0.25

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