

Original Paper

Profitability in Asset Pricing Models for Chinese Equities

1996-2016

Dong Liu^{1*}

¹ Graduate School of Faculty of Culture and Information Science, Doshisha University, Kyoto, Japan

* Dong Liu, Graduate School of Faculty of Culture and Information Science, Doshisha University, Kyoto, Japan

Received: February 2, 2018 Accepted: February 13, 2018 Online Published: March 12, 2018

doi:10.22158/jepf.v4n2p118

URL: <http://dx.doi.org/10.22158/jepf.v4n2p118>

Abstract

I follow Novy Marx (2011, 2013) to investigate and compare firms' gross profit, operating leverage as predictors of returns for a cross-section of traded Chinese equities spanning from 1996-2016. I use portfolio tests and Fama-MacBeth regressions, find that gross-profit-to-market-capitalization ratios significantly predict returns on sampled stocks. I also find that sorting portfolios by gross profitability and size outperforms in the Chinese market. Hence, I create a Market-Profitability-Size model that captures profitability and size premium among returns of sampled stocks. Based on Gibbons-Ross-Shanken test and economic value, I demonstrate that my enhanced model outperforms Fama-French multiple-factor model in isolating influences on equity returns.

Keywords

expected return, gross profitability, operating leverage

1. Introduction

The question of what drives stock returns is perennial in modern finance. The Fama-French (1992, 1993) three-factor model has been the benchmark to explain expected returns during the past two decades because the book-to-market ratio (a measure of value) and market capitalization (size) have strong explanatory powers in empirical analysis. Nonetheless, recently more and more researchers have started to question the Fama-French three-factor model (e.g., Chen & Lu, 2010; Hou et al., 2015), because it has been difficult to explain the cross-sectional variation in expected returns recently, especially value factor which is a redundant factor in the US market (Fama and French, 2015a). The value factor also has not reflected fundamentals in the Chinese market (see Wang & Xu, 2004; Chen & Hu, 2015).

Hence, finding a new factor which is closely related to the value factor, and can explain cross-sections of stock returns better is the motivation of this paper.

In this study I have focused on Novy-Marx (2011), who uses real option theory to prove that operating leverage generates a value premium generally, and suggests that operating leverage plays important roles in generating the cross-sectional variation of expected returns (see e.g., Carlson et al., 2004; Kissler, 2014).

Also, Novy-Marx (2013) shows that gross profitability is the other side of the value. Ball et al. (2015) reveals that profitability earns a high positive premium and helps to capture most asset-pricing anomalies that plague the Fama-French (1993) three-factor model.

These studies show that operating leverage and profitability exert power in predicting returns, meanwhile, they can replace value factor among US equities, but scant literature investigates Chinese equities.

First, Liu (2015) finds operating leverage effect in China (2003-2013), I will continue to research operating leverage effects by expanding timeline samples. Second, Liu (2017), Jiang et al. (2018) find that gross profitability is a statistically significant predictor of Chinese equity returns. These studies, however, merely test the factor effects in China, and do not add the new factor into asset-pricing model on Chinese equities. My study resolves this deficiency in the earlier literature section. I characterize the firms' characteristics comprehensively using gross profit, operating leverage to assure robustness in predicting equity returns. I confirm that gross-profit-to-market capitalization is a superior proxy for predicting equity returns. My results endorse those of Novy-Marx (2011, 2013) and support existence of operating leverage and gross profitability premium for Chinese equities. In addition, I mirror Fama-French three-factor (1993) and five-factor models (2015a), delete the redundant factor, and create a new Market-Profitability-Size (MKT-RMW-SMB) model to explain expected returns on Chinese equities, which is more appropriate than the Fama-French three-factor model.

This paper proceeds follows. Section 2 describes our data and variable. Section 3 presents methods and empirical results. Section 4 concludes.

2. Data and Variable

Financial statement data are from the FactSet database (Note 1). Empirical research covers Chinese equities listed on Shanghai A share and Shenzhen A share (SSE and SZSE) that have usable data during 1996-2016 (240 months). Financial firms are excluded for their distinctive high-leverage/low-equity capital structures. Our samples cover 281 companies in 1996, and, adjusted yearly, reaching 2,258 in 2016.

To construct factors that might influence equity returns, we assemble annual financial statement data for sales (SALE), cost of goods sold (COGS), sales-general-administrative expenses (SGA), book value of total assets (AT), and book equity (BE) measured as AT minus total liabilities (LT). LOG (ME) is the log of market capitalization (ME). B/M indicates the book-to-market ratio (BE/ME). Gross profit

(GP) is SALE minus COGS. Operating costs (OL) is SALE plus COGS. Based on Novy-Marx (2011, 2013), I define operating leverage as operating costs divided by market capitalization, gross profitability as gross profit divided by market capitalization.

3. Methods and Empirical Results

3.1 Fama-MacBeth Univariate Regressions

I use monthly Fama and MacBeth (1973) cross-sectional regressions to examine whether profitability convincingly forecasts stock returns.

Table 1. Fama-MacBeth Univariate Regressions of Firm Returns 1996-2016

<i>variables</i>	1	2	3	4
<i>OL</i>	0.48			
<i>(t)</i>	2.51			
<i>GP</i>		1.70		
<i>(t)</i>		3.24		
<i>B/M</i>			0.03	
<i>(t)</i>			0.27	
<i>log(ME)</i>				-0.33
<i>(t)</i>				-1.85

Slope coefficients ($\times 100$) β and (t-statistics) from regressions are shown. The sample period starts in April 1996 and ends in March 2016.

Table 1 shows regressed monthly returns of individual stocks on lagged operating leverage, profitability, market capitalization, the book-to-market ratio. I focus on t-values to compare the explanatory power of variables. Gross profitability and operating leverage have significantly predicted power, while size ($\log(ME)$), book-to-market ratio (B/M) have no significant predicting power. Gross profitability has the most power, with a test-statistic of 3.24.

3.2 Fama-MacBeth Multivariate Regression

Table 2. Fama-MacBeth Multivariate Regressions of Firm Returns 1996-2016

<i>variables</i>	1	2	3	4
<i>OL</i>		0.53		0.04
<i>(t)</i>		2.98		0.23
<i>GP</i>			2.16	2.12
<i>(t)</i>			4.62	4.14
<i>B/M</i>	-0.06	-0.04	-0.04	-0.03
<i>(t)</i>	-0.63	-0.34	-0.36	-0.32
<i>Log (ME)</i>	-0.36	-0.33	-0.40	-0.40
<i>(t)</i>	-1.98	-1.83	-2.26	-2.22

Multivariate slope coefficients ($\times 100$) β s and (t-statistics) from regressions are shown. I estimate regressions monthly spanning from April 1996 to March 2016. t-statistics are based on the time-series variability of slope estimates, incorporating a white adjust for possible autocorrelation in the slopes.

Table 2 reports model (1)-(4) specifications for multivariate regressions including controls for book-to-market ratio (B/M), size (log(ME)). When controlled accordingly, model (1) implies Fama-French's.

Size-B/M is not an ideal combination. Although size effect is effective, value effect sheds predictive power. Model (2), model (3) reveal that operating leverage and gross profitability effects are strong for the sampled equities. Model (4) shows that when controlled operating leverage, gross profitability still shows strongest effect, with a test-statistic of 4.14. However, operating leverage loses much of its power to predict returns. Based on Novy-Marx's (2013) explanation, the operating leverage on its power is absorbed by profitability. Hence, I abandon operating leverage as an investigative variable.

Overall, I reconfirm the existence of strong gross profitability effects among Chinese equities per Jiang et al. (2018). Size premium still have power. However, Due to the speculative nature of the Chinese capital markets and low quality in the accounting information, the value factor shows no effect on returns of sampled equities, consistent with prior study.

3.3 Construction of Mimicking Factors

I perform portfolio tests as a more predictive exercise that escapes biased results of Fama and MacBeth (1973) regression. I can explore the performance of portfolios double-sorted by profitability and size to generate more excess return. For comparison, I sort Size-B/M portfolios, Size-GP portfolios, and GP-B/M portfolios for the sampled equities. Average excess portfolio returns appear.

Table 3 Panel A. Double Sort by Size and B/M

<i>Panel A</i>	<i>Low</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>High</i>		
<i>Size</i>	<i>B/M quintiles</i>					<i>H-L</i>	<i>T</i>
<i>Small</i>	2.22	2.16	2.05	1.80	1.56	-0.66	-2.62
<i>2</i>	1.41	1.72	1.78	1.69	1.25	-0.16	-0.71
<i>3</i>	1.47	1.47	1.66	1.40	1.28	-0.16	-0.62
<i>4</i>	0.91	1.16	1.46	1.32	1.21	0.25	0.68
<i>Big</i>	0.75	1.04	0.86	0.90	0.86	0.10	0.21
<i>S-B</i>	1.46	1.12	1.16	0.88	0.77		
<i>T</i>	2.79	2.16	2.49	1.68	1.32		

Panel A shows average excess returns for 25 value-weighted (VW) portfolios from independent (5x5 B/M-Size sorting). The “H-L” profitability spread portfolio is computed as long the highest B/M decile and short the lowest decile. The “S-B” profitability spread portfolio is computed as short the biggest size decile and long the smallest decile. I sort stocks into deciles based on Shanghai A share and Shenzhen A share (SSE and SZSE) breakpoints at the end of each December and hold the portfolio for the April. My sample period starts in April 1996 and ends in March 2016.

In the Size-B/M formulation, holding B/M roughly constant, average return typically falls as size increases. The S-B portfolios (size premium) in column 1, 2, 3 are significant. Holding size roughly constant, only R-W portfolios in row 4, 5 increases with B/M. No R-W portfolio is significant. The finding reveals size quintiles outperform B/M quintiles.

Table 3 Panel B. Double Sort by Size and GP

<i>Panel B</i>	<i>Weak</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Robust</i>		
<i>Size</i>	<i>GP quintiles</i>					<i>R-W</i>	<i>T</i>
<i>Small</i>	1.93	1.95	1.83	2.05	2.16	0.23	0.94
<i>2</i>	1.23	1.52	1.61	1.63	1.85	0.62	2.83
<i>3</i>	1.16	1.33	1.48	1.58	1.73	0.70	2.53
<i>4</i>	0.92	0.83	1.16	1.34	1.84	0.71	2.54
<i>Big</i>	0.42	0.82	0.64	1.04	1.36	0.96	2.55
<i>S-B</i>	1.51	1.13	1.26	0.97	0.90		
<i>T</i>	3.22	2.23	2.61	1.76	1.54		

Panel B shows average excess returns for 25 value-weighted (VW) portfolios from independent (5x5 Size-GP sorting). The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. The “S-B” profitability spread portfolio is computed as

short the biggest size decile and long the smallest decile. I sort stocks into deciles based on Shanghai A share and Shenzhen A share (SSE and SZSE) breakpoints at the end of each December and hold the portfolio for the April. My sample period starts in April 1996 and ends in March 2016.

In the Size-GP formulation, holding GP roughly constant, average return typically falls as size increases. The S-B portfolios (size premium) in column 1, 2, 3 are significant. Holding size roughly constant, average return typically increases with GP, R-W portfolios (gross profitability premium) in row 2, 3, 4, 5 are significant. Small size and robust profitability portfolio performs best with 2.16% monthly returns. The finding reveals GP quintiles outperform size quintiles.

Table 3 Panel C. Double Sort by GP and B/M Ratio

<i>Panel C</i>	<i>Weak</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Robust</i>		
<i>B/M</i>		<i>GP quintiles</i>				<i>R-W</i>	<i>T</i>
<i>Low</i>	0.58	0.74	0.86	0.71	1.11	0.53	1.16
<i>2</i>	0.85	0.93	0.94	1.27	1.49	0.63	1.68
<i>3</i>	0.90	0.92	0.95	1.18	1.50	0.58	1.55
<i>4</i>	0.92	0.95	1.20	1.30	1.89	0.97	2.29
<i>High</i>	0.92	0.80	0.95	0.82	1.14	0.17	0.43
<i>H-L</i>	0.33	0.06	0.08	0.13	0.04		
<i>T</i>	0.87	0.16	0.18	0.29	0.09		

Panel C shows average excess returns for 25 value-weighted (VW) portfolios, from independent (5x5 GP-B/M sorting). The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. The “H-L” profitability spread portfolio is computed as long the highest B/M decile and short the lowest decile. I sort stocks into deciles based on Shanghai A share and Shenzhen A share (SSE and SZSE) breakpoints at the end of each December and hold the portfolio for the April. My sample period starts in April 1996 and ends in March 2016.

In the GP-B/M formulation, GP and average return are positively related in all rows. R-W portfolio (gross profitability premium) in row 4 is significant. Value premium has no evidence in columns 1 through 5. The finding reveals GP quintiles outperform B/M quintiles.

Overall, I confirm that controlling GP improves performance of size strategies and controlling for size improves performance of profitability strategies. Results in Table 3 suggest sorting of gross profitability and size portfolios outperform among the sampled equities.

3.5 Summary of Factor Model

Following Fama-French (1993, 2015a), to construct factor, I sort independently to assign stocks to two size groups, three B/M groups, and three profitability groups (GP). The size breakpoint is a median market cap. B/M or GP breakpoints are the 30th and 70th percentiles.

MKT (Rm-Rf) is the value-weighted return on the market portfolio of all sampled stocks minus the risk-free rate. SMB is the return on a diversified portfolio of small-cap stocks minus the return on a diversified portfolio of big-cap stocks. HML is the difference between returns on diversified portfolios of high and low B/M stocks. In addition, RMW is the difference between returns on diversified portfolios of stocks with robust and weak gross profitability.

First, analyzing the correlation among the factor premium. That is MKT (market premium), SMB (size premium), HML (value premium) and RMW (profitability premium).

Table 4. Correlation among the Factor Premiums 1996-2016

	MKT	RMW	SMB	HML
Mean	1.00	0.54	0.62	-0.01
STD	9.51	2.44	3.46	2.68
CORR	MKT	RMW	SMB	HML
MKT	1.00	-0.26	0.06	-0.10
RMW	-0.26	1.00	-0.58	-0.18
SMB	0.06	-0.58	1.00	-0.27
HML	-0.10	-0.18	-0.27	1.00

Table 4 reports factor premiums conditions. Mean stands for average of the factor premiums. STD stands for standard deviation of the factor premiums. CORR stands for the Pearson correlation between the factor premiums. My sample period starts in April 1996 and ends in March 2016.

RMW has a negative relation with MKT, HML, SMB, this is consistent with US equities. The strong negative relationship between RMW and SMB is interesting for any kind of investment strategy. Value premium (HML) is almost zero, Hence, I eliminate redundant factors to boost the model's explanatory power. Based on Fama-MacBeth regressions and tests of combination portfolios, I define two main factor premiums: SMB (small minus big size) and RMW (robust minus weak GP).

If a characteristic is significant in cross-sectional regressions, I hypothesize that its factor will be significant in time-series regressions. Hence, I create a new model MKT-RMW-SMB model for the sampled equities and compare time-series regressions with the Fama-French three-factor model. Test factor models are

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_iSMB_t + h_iHML_t + e_{it} \quad (1)$$

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_iSMB_t + r_iRMW_t + e_{it} \quad (2)$$

where: R_{it} is the return of portfolio in month t. a_i is the intercept, b_i s_i h_i r_i are factor coefficients for time-series regression, e_{it} is the error term.

Table 5. Time Series Regressions for 25 Size-GP Portfolios

<i>Panel A</i>	<i>Weak</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Robust</i>	<i>Weak</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Robust</i>
<i>Size</i>			α		<i>GP quintiles</i>					$t(\alpha)$
<i>Small</i>	-0.09	-0.51	-0.52	-0.44	-0.55	-0.47	-3.34	-3.48	-2.33	-2.93
<i>2</i>	-0.15	-0.18	-0.30	-0.56	-0.23	-0.90	-1.15	-1.90	-3.31	-1.56
<i>3</i>	0.07	0.07	0.01	-0.08	-0.10	0.45	0.50	0.04	-0.52	-0.66
<i>4</i>	0.36	0.04	0.02	0.04	0.18	2.37	0.25	0.11	0.24	1.49
<i>Big</i>	0.30	0.34	0.48	0.84	0.94	2.18	2.06	2.26	3.93	4.35
			β							$t(\text{MKT})$
<i>Small</i>	1.08	1.09	1.10	1.11	1.10	56.46	68.85	70.60	57.08	56.53
<i>2</i>	1.04	1.05	1.05	1.04	1.00	60.86	66.00	63.54	59.35	66.60
<i>3</i>	1.01	1.05	1.08	1.04	1.00	61.06	73.06	62.73	62.66	65.32
<i>4</i>	1.02	1.05	1.03	1.07	0.97	64.19	65.81	64.33	63.50	76.27
<i>Big</i>	1.00	1.05	1.04	0.96	0.94	69.78	61.85	47.31	43.39	41.90
			s							$t(\text{SMB})$
<i>Small</i>	1.62	1.33	1.12	0.66	0.04	29.72	29.44	25.19	11.97	0.65
<i>2</i>	1.56	1.19	0.93	0.66	-0.21	32.19	26.32	19.86	13.29	-5.01
<i>3</i>	1.35	0.98	0.67	0.46	-0.32	28.72	23.91	13.64	9.85	-7.33
<i>4</i>	1.22	0.91	0.57	0.25	-0.48	26.96	20.16	12.55	5.16	-13.22
<i>Big</i>	1.19	0.60	0.23	-0.12	-0.97	29.24	12.58	3.73	-1.96	-15.26
			h							$t(\text{HML})$
<i>Small</i>	0.06	0.06	0.04	0.05	0.24	0.82	1.09	0.65	0.68	3.29
<i>2</i>	-0.08	-0.06	-0.06	-0.08	0.22	-1.28	-0.98	-0.94	-1.18	4.00
<i>3</i>	-0.21	-0.12	-0.37	-0.16	0.11	-3.51	-2.22	-5.90	-2.63	1.99
<i>4</i>	-0.26	-0.14	-0.29	-0.24	-0.04	-4.51	-2.47	-4.96	-3.90	-0.82
<i>Big</i>	-0.08	-0.26	-0.45	-0.46	-0.16	-1.45	-4.21	-5.50	-5.65	-1.99
			R^2							
<i>Small</i>	0.96	0.97	0.97	0.95	0.94					
<i>2</i>	0.96	0.96	0.96	0.95	0.96					
<i>3</i>	0.96	0.97	0.96	0.95	0.96					
<i>4</i>	0.96	0.96	0.96	0.95	0.97					
<i>Big</i>	0.97	0.95	0.92	0.91	0.91					
<i>Average</i>	0.95									

<i>Panel B</i>	<i>Weak</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Robust</i>	<i>Weak</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Robust</i>
	0.17	-0.17	-0.19	0.08	0.17	0.87	-1.08	-1.21	0.44	0.97
<i>2</i>	-0.08	-0.06	-0.10	-0.21	0.16	-0.45	-0.38	-0.62	-1.22	1.02
<i>3</i>	-0.10	0.03	-0.24	-0.13	0.11	-0.54	0.21	-1.27	-0.71	0.69
<i>4</i>	0.06	-0.14	-0.22	-0.11	0.05	0.35	-0.84	-1.25	-0.62	0.34
<i>Big</i>	0.13	-0.16	-0.36	0.02	0.31	0.90	-0.93	-1.74	0.10	1.45
			β					t(MKT)		
<i>Small</i>	1.07	1.07	1.08	1.07	1.04	54.83	69.27	71.39	59.38	61.92
<i>2</i>	1.03	1.04	1.03	1.02	0.97	58.51	63.69	61.85	59.49	64.85
<i>3</i>	1.03	1.06	1.10	1.04	0.98	58.60	70.00	58.03	59.80	62.84
<i>4</i>	1.04	1.06	1.05	1.08	0.98	62.80	64.32	60.92	60.29	75.43
<i>Big</i>	1.01	1.08	1.11	1.02	0.98	69.04	65.83	54.27	48.92	47.08
			s					t(SMB)		
<i>Small</i>	1.49	1.16	0.95	0.41	-0.33	23.56	23.03	19.36	6.97	-6.05
<i>2</i>	1.54	1.14	0.84	0.51	-0.43	26.71	21.43	15.51	9.12	-8.68
<i>3</i>	1.46	1.01	0.84	0.51	-0.43	25.59	20.59	13.51	8.89	-8.46
<i>4</i>	1.39	1.02	0.72	0.35	-0.41	25.77	18.87	12.84	6.02	-9.63
<i>Big</i>	1.28	0.87	0.69	0.32	-0.65	26.78	16.26	10.40	4.76	-9.57
			r					t(RMW)		
<i>Small</i>	-0.30	-0.39	-0.39	-0.60	-0.80	-3.19	-5.35	-5.45	-6.99	-9.98
<i>2</i>	-0.09	-0.14	-0.24	-0.42	-0.41	-1.12	-1.84	-3.03	-5.18	-5.77
<i>3</i>	0.16	0.03	0.23	0.02	-0.22	1.94	0.35	2.58	0.27	-3.01
<i>4</i>	0.31	0.19	0.23	0.14	0.16	3.96	2.35	2.76	1.63	2.51
<i>Big</i>	0.18	0.54	0.92	0.88	0.71	2.65	6.83	9.42	8.88	7.19
			R^2							
<i>Small</i>	0.96	0.97	0.97	0.96	0.96					
<i>2</i>	0.96	0.96	0.96	0.96	0.96					
<i>3</i>	0.96	0.97	0.95	0.95	0.96					
<i>4</i>	0.96	0.96	0.95	0.95	0.97					
<i>Big</i>	0.97	0.96	0.94	0.92	0.92					
<i>Average</i>	0.96									

Table 5 shows coefficient from time series regressions for monthly percent excess returns on (5*5) size and GP portfolios. The t-statistics are provided on the right-hand side. Panel A model is Fama-French-three-factor (MKT-SMB-HML) model. Panel B model is MKT-SMB-RMW factor model. My sample

period starts in April 1996 and ends in March 2016.

Table 5 shows results from time series regressions for monthly percent excess returns on 25 Size-GP portfolios. The test models include a Fama-French three-factor model (Panel A) and MKT-RMW-SMB factor model (Panel B). The test sample is Size-GP portfolios.

In Panel A, R^2 s vary from 91% to 97% with an average of 95%. In Panel B, R^2 s vary from 92% to 97% with an average of 96%. Using visual comparison methods R^2 s, MKT-RMW-SMB model outperforms Fama-French three-factor model.

3.6 Evaluating Model Performance

Gibbons, Ross and Shanken (1989) propose the most widely used statistical test of empirical validity for asset-pricing models (GRS test). It tests for the null hypothesis that the intercept terms of empirical asset-pricing model portfolios jointly equal 0. Failure to reject the null hypothesis is evidence the model adequately captures portfolio returns. Meanwhile, considering its predictive power properties, I follow Kim and Shamsuddin (2016), add to Economic value to evaluate model performance.

The test models include a Fama-French three-factor model and MKT-RMW-SMB factor model. The test samples include GP-B/M portfolios, Size-GP portfolios, and Size-B/M portfolios.

Table 6. Gibbons-Ross-Shaken Test (Gibbons et al., 1989; Kim & Shamsuddin, 2016)

Test portfolios	Model	GRS P value	Economic value
B/M and GP	Fama-French-three-factor	0.01	0.37
	MKT-RMW(GP)-SMB(Size)	0.22	0.73
Size and GP	Fama-French-three-factor	0.00	0.32
	MKT-RMW(GP)-SMB(Size)	0.82	0.81
Size and B/M	Fama-French-three-factor	0.00	0.32
	MKT-RMW(GP)-SMB(Size)	0.00	0.60

Table 6 reports results from the Gibbons-Ross-Shaken test (Gibbons et al., 1989). Comprehensively, the GRS P value indicates statistical significance. The bigger the P value, the greater the model performance. Economic value indicates proportion between the maximum Sharpe ratio of the three factor portfolios and the slope of the efficient frontier based on all assets. The bigger the economic value, the greater the dual economic and market efficiency. My sample period starts in April 1996 and ends in March 2016. Test models are Fama-French- three-factor (MKT-SMB-HML) model and MKT-SMB-RMW factor model.

For GRS P value, MKT-RMW-SMB factor model outperforms the Fama-French three-factor model. For economic value, MKT-RMW-SMB factor model obviously provides optimum. Overall, I show MKT-RMW-SMB factor model outperforms both the statistical and economic significance for the sampled equities.

4. Conclusion

McLean and Pontiff (2016) argue that some stock market anomalies are less anomalous after being published. Repeatedly cited size and value factors naturally are less anomalous over time which also impels me to seek new effective factors and new-factor models.

The conclusions are as follows.

Gross-profit-to-market-capitalization explains the sampled cross-section of expected returns better than other variables on Chinese equities. Value premium for the sampled equities sheds predictive power over time and becomes redundant. Operating leverage premium loses powers when adding to profitability factor. Size premium remains strong among our sampled equities. Hence, I create a new MKT-RMW-SMB factor model and investigate the applicability of a Fama-French three factor model on my sampled equities. Tests reveal that the model featuring gross profitability outperforms the Fama-French three factor model.

Acknowledgements

The authors are grateful to the Mizuho Securities Endowment, also thank the participants at the 23th and 25th meetings of the Japan Finance Association. Any errors are our own.

References

- Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. V. (2015). Deflating profitability. *Journal of Financial Economics*, *117*(2), 225-248. <https://doi.org/10.1016/j.jfineco.2015.02.004>
- Carlson, M., Fisher, A., & Giammarino, R. (2004). Corporate Investment and Asset Price Dynamics: Implications for the Cross Section of Returns. *Journal of Finance*, *59*, 2577-2603. <https://doi.org/10.1111/j.1540-6261.2004.00709.x>
- Chen, L., & Zhang, L. (2010). A better three-factor model that explains more anomalies. *Journal of Finance*, *65*(2), 563-595.
- Fama, E. F., & French, K. R. (1992). The Cross Section of Expected Stock Returns. *Journal of Finance*, *47*, 427-465. <https://doi.org/10.1111/j.1540-6261.1992.tb04398.x>
- Fama, E. F., & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, *33*, 3-56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5)
- Fama, E. F., & French, K. R. (2015a). A five-factor asset-pricing model. *Journal of Financial Economics*, *116*, 1-22. <https://doi.org/10.1016/j.jfineco.2014.10.010>
- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), 607-636. <https://doi.org/10.1086/260061>
- Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica*, *57*, 1121-1152. <https://doi.org/10.2307/1913625>
- Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, *28*(3), 650-705. <https://doi.org/10.1093/rfs/hhu068>

- Hu, G. X., Chen, C., Shao, Y., & Wang, J. (2015). Fama-French in China: Size and value factors in Chinese stock returns. *International Review of Finance*.
- Jiang, F., Qi, X., & Tang, G. (2018). Q-theory, mispricing, and profitability premium: Evidence from China. *Journal of Banking & Finance*, 87, 135-149. <https://doi.org/10.1016/j.jbankfin.2017.10.001>
- Jiang, F., Qi, X., & Tang, G. (2018). Q-theory, mispricing, and profitability premium: Evidence from China. *Journal of Banking & Finance*, 87, 135-149.
- Kim, J. H., & Shamsuddin, A. (2016). *Reappraising Empirical Validity of Asset-Pricing Models with consideration of Statistical Power* (Working Paper).
- Kisser, M. (2014). *What explains the gross profitability premium*.
- Liu D. (2017). *Profitability effect in Japanese and Chinese Asset Pricing Models* (Japan Finance Association 2015 working paper).
- Liu, D. (2015). *What determines Chinese stock return* (Japan Finance Association 2015 working paper).
- McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1), 5-32. <https://doi.org/10.1111/jofi.12365>
- Novy-Marx, R. (2011). Operating leverage. *Review of Finance*, 15, 103-134. <https://doi.org/10.1093/rof/rfq019>
- Novy-Marx, R. (2013). The other side of the value: The gross profits-to-assets premium. *Journal of Financial Economics*, 108, 1-28. <https://doi.org/10.1016/j.jfineco.2013.01.003>
- Wang, F. H., & Xu, Y. X. (2004). What determines the Chinese stock market. *Financial Analysts Journal*, 58, 215-260.

Note

Note 1. FactSet integrates third-party data for 16,000+ active companies. It provides financial information and analytical applications to global buy and sell-side professionals. FactSet is popular among Chinese financial analysts and portfolio managers and the world's third-largest provider of financial data behind Bloomberg and Thomson Reuters.