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Evaluating asset pricing models: A revised factor model for China

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effectiveness of traditional asset pricing models can partially be attributed to China's unique IPO system. Despite increasing demand for access to public equity markets, IPOs in China are subject to stringent regulatory control (Lee et al., 2021); therefore, limited private firms are approved for the IPO. Li and Zhou (2015) reveal that political connections play an important role in the process of IPO approval in China. This suggests that the market outcome might not be determined solely by economic merit, in sharp contrast to the market-and-disclosure-based system in the U.S. market. Furthermore, Lee et al. (2019) document that China's stringent IPO policies push several firms to seek reverse mergers (RMs). They demonstrate that the entry regulations governing IPOs may be highly restrictive, inducing high-quality but less politically connected firms to pursue costly RM alternatives. Moreover, the revolution of the IPO regulatory system has significant economic consequences for the stock markets, including the primary IPO and secondary stock markets. For example, firms are forbidden from being the RM target in the Chinese growth enterprise market. Unlike the situation in the main board market, Hu et al. (2021) note that IPO firms with prestigious underwriters have lower market-adjusted initial returns on average.

Overall, private firms seek alternative approaches, such as RMs, to expedite the process of going public. During an RM, a private firm targets a publicly listed firm (i.e., the shell) by obtaining its shares. The shell firm then purchases the private firm's assets in exchange for new shares. LSY indicate that the smallest firms are most likely to be the targeting shells. Therefore, a significant part of the value of a typical small listed firm is not related to its fundamentals. Lee et al. (2021) discuss the pervasive effect of China's IPO restrictions, where an important aspect relates to the implications on asset pricing. Lee et al. (2021) construct a new benchmark asset pricing model, which adds a new risk factor (expected shell probability, ESP hereafter), incorporating the targeting shell probability. As an alternative way to mitigate the influence of shell stocks in asset pricing, LSY exploit the earnings-price (EP) ratio to proxy the value of stock and empirically explain the most regular stock returns using the market, size, and value factor (i.e., the CH-3 model) in which they eliminate the smallest 30% of stocks.

In this study, we first document that more firms choose to go public through direct IPO rather than RM induced by the registration-based IPO approvals resumed, the China Securities Regulatory Commission (CSRC) announced to control the pace, which was perceived as a signal to tighten the IPOs (Lee et al., 2021). In 2017, the CSRC began to accelerate the IPO approval process, and the auditing efficiency was significantly improved. The China Securities Issuance Examination Committee approved 380 IPO cases in 2017, and 436 firms went public (note the stark difference from pre-2017). The average annual number of IPOs increased to approximately 307 in the post-2017 period. In addition, the number of delisting firms increased.

Unsurprisingly, the trend of RMs contradicts that of the IPOs. The restrictions on IPOs in pre-2017 rendered obtaining a listing status more difficult. Therefore, private firms wishing to tap into the Chinese stock market needed to resort to different approaches, such as RMs. The number of

Return reactions to earnings surprises across different size and ESP groups.

Size group deciles	Panel A: ESP summary statistics based on size group deciles									
	1	2	3	4	5	6	7	8	9	10
ESP	3.00%	1.68%	1.11%	0.73%	0.48%	0.31%	0.19%	0.10%	0.04%	0.01%
proportion of ESP >1%	77.29%	54.88%	36.81%	20.70%	8.05%	1.81%	0.33%	0.03%	0.00%	0.00%
proportion of ESP >5%	14.91%	3.22%	0.49%	0.06%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Panel B: Return Reactions to Earnings Surprises across Different Size and ESP Groups

Size group	Panel B1: size group				Panel B2: ESP group				
	CAR[0,0]		CAR[−3,3]		ESP group	CAR[0,0]		CAR[−3,3]	
	coefficient	t-statistics	coefficient	t-statistics		Coefficient	t-statistics	coefficient	t-statistics
1	0.17	5.62	0.32	6.45	1	0.27	11.33	0.49	13.38
2	0.27	8.92	0.51	10.08	2	0.33	11.62	0.58	13.04
3	0.24	7.76	0.52	10.08	3	0.34	11.54	0.60	13.00
4	0.29	9.58	0.57	11.33	4	0.39	12.56	0.67	13.28
5	0.26	8.55	0.55	11.16	5	0.40	12.66	0.75	14.55
6	0.32	10.93	0.68	14.15	6	0.29	9.28	0.61	12.05
7	0.39	13.84	0.62	13.71	7	0.30	9.25	0.56	10.45
8	0.39	14.1	0.67	15.17	8	0.27	8.39	0.44	8.62
9	0.32	12.0	0.61	14.60	9	0.22	7.50	0.39	7.93
10	0.29	13.5	0.50	14.98	10	0.15	5.05	0.31	6.22

Note: Panel A reports ESP mean value and the proportion of ESP greater than 1% and 5% within 10 decile groups formed by sorting individual stocks based on their size. Panel B reports the estimation coefficients (multiplied by 100) and corresponding t-statistics in formula (3). We report the results within 10 decile groups formed by sorting stocks based on size and ESP, respectively.

30% stocks have a lower estimated coefficient than other groups. We report the results of Equation (1) for all groups (in which 10 captures the decile group with the highest stock market value) in Panel B1 of Table 2 for k-values of 0 and 3. It is apparent that the bottom decile group has the lowest estimated -values. However, for the second and third smallest decile groups, the estimation is not smaller than those of decile groups with higher stock market values, thereby indicating that the returns in Deciles 2 and 3 also reflect considerable fundamental information. Thus, eliminating the bottom 30% of stocks omits plethora of useful information.

In Panel B2, we report the results of Equation (1) when sorting the stocks by their ESP (the 10th decile group captures the stocks with the highest ESP value) and find that the top decile group has the lowest value. This finding suggests that to eliminate shell contamination, it is better to filter the sample based on the ESP rather than the size.

Overall, the shrinkage of the reverse merge activities imposes considerable emphasis on revising the original CH-3 model. If we mechanically follow LSY and eliminate the bottom 30% of stocks while constructing factor models, potentially useful information will be removed. Moreover, the obtained risk premium and alpha are misestimated when using the factor model as the benchmark. Therefore, it is necessary to revise the factor model.

We aim to revise the CH-3 model by eliminating shell stocks. Stocks with a high ESP are more likely to get involved in the future RM deals. Therefore, we exclude high ESP stocks based on our replication of Lee et al. (2021). During each period, we construct our factor model and exclude firms with an ESP higher than a threshold value of 1%, but we also use the 0.1% and 5% as alternative threshold measures in robustness tests. The factor construction in our dataset displays similar explaining power. Since the ESP can only be estimated after 2011, we interpret the computed probability model as the rational expectation of a firm being a shell target. Because we cannot establish such a model in the pre-2011 period, it is reasonable to use the full universe of stocks when constructing our factors. We denote the revised CH-3 version as CH-3_R.

We follow LSY to construct the three factors in China. Each month, we segregate the selected sample into two size groups, Small (S) and Big (B), which are split at the median market value of the universe. In addition, we use the earnings-price (EP) ratio as the value proxy. The following three groups are formed: top 30% (value, V), middle 40% (middle, M), and bottom 30% (growth, G). We form the value-weighted portfolios combined with value and size portfolios. Similar to LSY, the small-minus-big (SMB) and value-minus-growth (VMG) are as follows:

$$SMB = \frac{1}{3}\left(S/_V + S/_M + S/_G\right) - \frac{1}{3}\left(B/_V + B/_M + B/_G\right), \tag{3}$$

and

$$VMG = \frac{1}{2}\left(S/_V + B/_V\right) - \frac{1}{2}\left(S/_G + B/_G\right) \tag{4}$$

The market factor (MKT) is the value-weighted return of the entire universe over the one-year deposit rate. In addition, LSY augment their CH-3 with a turnover factor (PMO) to explain trading-related anomalies effectively and denote it as CH-4 (CH-3 + PMO). Similarly, we construct our revised CH-4 (CH-4_R) incorporating this turnover factor. We also replicate all the factors exploited in LSY for benchmark purposes.

We report the summary statistics for the related factors in Table 3. CH-4_R presents the factor premiums that flexibly exclude the smallest firms based on their ESP. We present the mean, standard deviation, and t-statistics for each factor model. Furthermore, Table 3 displays the correlation between the raw CH-4 and the corresponding revised CH-4 factors. The inclusion of the smallest stocks drives the SMB from

Summary statistics for the related factors.

Factor Models	Factor	Mean	Std	t-statistics	Correlations
CH-4	MKT	0.61	7.58	1.07	–
	SMB	0.46	4.42	1.60	–
	VMG	1.12	3.65	5.74	–
	PMO	0.74	3.48	3.77	–
CH-4_R	MKT	0.65	7.60	1.37	1.00
	SMB	0.68	4.73	2.30	0.98
	VMG	1.04	3.71	4.50	0.96
	PMO	0.79	3.35	3.78	0.96

Note: Mean and std are expressed in percent per month. For comparison purposes, we also report the correlation between the revised factors and corresponding raw factors.

0.46% per month to 0.74% (CH-4_R). Our revised MKT, VMG, and PMO factors are comparable to the raw CH-4 factors for the entire sample.

We follow Hodrick and Zhang (2001) and Hou et al. (2015) to conduct formal asset pricing tests for model comparison. This comparison includes our revised model and a series of popular factor models proposed by finance

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Summary statistics for the competing factor models.

Factor Models	Factors	Mean	Std	t-statistics	Factor Models	Factors	Mean	Std	t-statistics
CAPM	MKTRF	0.79	7.53	1.35	HXZ-4	MKTRF	0.96	7.81	1.44
FF-3	MKTRF	0.79	7.53	1.35		ME	0.77	4.34	2.58
	SMB	0.46	4.84	1.46		INV	0.04	2.03	0.32
	HML	0.20	3.81	0.90	PTX-4	ROE	0.72	3.56	3.51
Carhart-4	MKTRF	0.79	7.53	1.35		MKTRF	0.67	7.63	1.41
	SMB	0.46	4.84	1.46		SMB	1.16	5.22	3.57
	HML	0.20	3.81	0.90		VMG	1.21	2.89	6.71
	UMD	0.05	4.01	0.24	SY-4	ATR	1.59	2.85	8.95
FF-5	MKTRF	0.79	7.53	1.35		MKTRF	0.79	7.69	1.25
	SMB	0.48	4.66	1.61		SMB	0.59	5.63	1.60
	HML	0.20	3.81	0.90		MGMT	−0.01	3.19	−0.06
	RMW	0.24	3.39	1.20	DHS-3	PERF	0.57	4.53	2.14
	CMA	−0.18	2.30	−1.29		MKTRF	0.79	7.69	1.25
NM-4	MKTRF	0.79	7.53	1.35		FIN	0.31	2.69	1.87
	HML	0.22	1.86	2.04		PEAD	0.25	2.07	1.65
	UMD	−0.22	2.75	−1.13					
	PMU	0.12	1.73	1.21					

Note: MKTRF means MKT minus the risk-free rate (we use the one-year deposit rate as the proxy). The sample period is from January 2000 to June 2021, and the mean/std are in %. However, HXZ-4 ranges from October 2003 to June 2021, and SY-4 and DHS-3 are from May 2002 to June 2021.

Summary statistics of the 25 Fama–French portfolios.

Portfolios	EP1	EP2	EP3	EP4	EP5
anel ean					
SIZE1	1.38	1.51	1.44	1.72	1.51
SIZE2	1.03	1.02	1.18	1.33	1.63
SIZE3	0.59	0.76	0.92	1.19	1.39
SIZE4	0.44	0.55	0.79	1.05	1.24
SIZE5	0.16	0.44	0.54	0.46	0.85
anel B Standard eviation					
SIZE1	10.46	10.50	10.46	10.11	10.14
SIZE2	10.55	10.48	10.14	9.28	9.04
SIZE3	10.01	10.00	9.54	9.20	8.77
SIZE4	10.00	10.03	9.21	8.83	8.55
SIZE5	9.37	8.98	8.31	7.69	7.40
anel t statistics					
SIZE1	2.12	2.31	2.21	2.73	2.39
SIZE2	1.56	1.56	1.86	2.31	2.90
SIZE3	0.95	1.23	1.55	2.07	2.55
SIZE4	0.70	0.89	1.39	1.92	2.33
SIZE5	0.28	0.79	1.04	0.96	1.84

Note: The table shows the mean, standard deviation and t-statistics of 25 Fama-French portfolios' excess return. The time period is January 2000 to June 2021. We use the one-year deposit rate as the risk-free rate to calculate the excess return. Portfolios are numbered *ij* with *i* indicating size increasing from 1 to 5 and *j* indicating the earnings-to-price increasing from 1 to 5.

Results of model comparison.

	HJ distance					GRS test	
	HJ	p-HJ	Max. Err	p-Wald-b	p-GMM	F-stat	P-value
Const	0.57	0.00	11.34	0.00	0.10	2.98	0.00
CAPM	0.56	0.00	11.12	0.00	0.07	2.88	0.00
FF-3	0.55	0.00	11.01	0.00	0.05	2.78	0.00
FF-5	0.40	0.08	8.09	0.00	0.30	2.68	0.00
Carhart-4	0.52	0.00	10.36	0.00	0.17	2.06	0.00
HXZ-4	0.43	0.09	8.69	0.00	0.43	2.97	0.00
NM-4	0.55	0.00	10.93	0.00	0.04	1.33	0.15
SY-4	0.40	0.42	8.10	0.00	0.57	2.27	0.00
DHS-3	0.55	0.00	11.10	0.00	0.10	2.46	0.00
PTX-4	0.40	0.06	8.01	0.00	0.31	2.48	0.00
CH-3	0.44	0.02	8.90	0.00	0.19	2.93	0.00
CH-4	0.43	0.03	8.60	0.00	0.29	2.74	0.00
CH-3_R	0.42	0.03	8.45	0.00	0.25	1.66	0.03
CH-4_R	0.40	0.11	7.93	0.00	0.44	1.55	0.05

Note: p-HJ denotes the corresponding p-value. Max. Err is the maximum pricing error for the testing assets. p-Wald-b is the p-value with the null hypothesis. p-GMM is the p-value corresponding to J-statistics that all the portfolio pricing errors are equal to zero under optimal GMM. Panel B summarizes the GRS F-statistics and the corresponding p-value for each competing factor model.

can be described as the maximum pricing error for one specific portfolio. Table 7 reports that the maximum error can be computed by the δ times of the portfolio standard deviation. Herein, we assume that the portfolio standard deviation is 20%. Furthermore, we report the p-value of the Wald test, whose null hypothesis is that the estimated value from the SDF is zero. In addition, we show the p-value corresponding to the J-statistics in which all the portfolio pricing errors are equal to zero under optimal GMM.

In Table 7, CH-4_R cannot reject the null hypothesis that the HJ distance is equal to zero. This finding indicates that CH-4_R can price the 25 Fama–French portfolios. Even though other factor models (e.g., SY-4) also have the pricing ability, CH-4_R has the smallest HJ distance value among the factor models, and its maximum errors is 7.93%. Overall, the HJ distance test confirms that CH-4_R is the best performing factor model.

Additionally, we conduct the GRS test. Most models fail to price the testing assets under the 95% confidence interval, whereas CH-4_R and HXZ-4 can explain the testing assets with zero alpha. These results highlight that the CH-4_R has the best pricing performance.

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We also examine the capability of factor models to explain anomalies. This study collects 122 anomalies explored in Hou et al. (2021) in the Chinese stock market. We divide these anomalies into two categories: trading-related and accounting-related anomalies. The trading-related anomalies can further be categorized into liquidity, risk, and past return. The accounting-related anomalies are also categorized into profitability, value, investment, and others (Hou et al., 2021).[2] We compute a value-weighted long-short portfolio for each of these anomalies by monthly rebalancing from January 2000 to June 2021. Following Hou et al. (2015), we only keep 46 anomalies with positive significant raw returns at the 5% significance level in the cross-section.

[2] For additional details regarding the construction and grouping of the anomaly categories, we refer the reader to the Appendix of Hou et al. (2021).

In constructing market-wide anomalies, we only introduce two common filters; that is, we remove (i) stocks listed less than six months ago to avoid newly-issued firms and (ii) stocks that have less than 120 trading records in the past year or less than 15 trading records in the past month. However, we are cautious that our 21-year period is substantially shorter than that of typical US studies. Therefore, our statements regarding the statistical insignificance of anomalies may need to be interpreted cautiously.

Among the 46 significant anomalies, 31 are trading-related (approximately half are liquidity-related), and 15 are accounting-related. Therefore, it appears that trading-related anomalies, which are likely driven by the high presence of retail investors, are more critical in the Chinese market than in the US market. This finding corresponds to that of Hou et al. (2021). Subsequently, we run the long-short portfolios of 46 anomalies on the factor models and investigate the number of anomalies that cannot be explained.

Panel A of Table 8 reports the number of unexplained anomalies if we set the cut-off $|t| > 1.96$. The original CH-3 and CH-4 can explain approximately half of the 46 anomalies, but the CH-3_R and CH-4_R can provide additional explanations. For example, 21 anomalies survive from the CH-4, whereas 19 survive from the CH-4_R. The difference is attributed to the powerful capability to explain more liquidity anomalies (only 7 liquidity anomalies survive from the CH-4_R, whereas 10 from the CH-4). In addition, we list the results of other competing models. In stark contrast, the remaining models cannot explain most of the 46 significant anomalies. Only PTX-4 performs somewhat competitively with CH-4_R.

Since studies in the asset pricing literature have been emphasizing multiple testing to avoid false discoveries stemming from data-snooping biases (see Harvey et al., 2016), Hou et al. (2021) propose that the multiple t-cutoff on the Chinese stock market should be 2.85. Therefore, we also set the cut-off $|t| > 2.85$ and examine the number of unexplained anomalies in Panel B of Table 8. The original CH-3 and CH-4 cannot explain approximately 1/3 and 1/7 of these anomalies, respectively, whereas the numbers of unexplained anomalies in CH-3_R and CH-4_R are even smaller. Consistent with Panel A, the difference mainly stems from the strong capability to explain liquidity anomalies. Again, other popular factor models are still substantially weak, as demonstrated by the high rate of survival of anomalies (again, PTX-4 is the exception).

Subsequently, we compare the factor models by summarizing the magnitude to which anomalies produce alphas. We follow LSY and report the average absolute alpha (in %) for the long–short spreads and the corresponding average absolute t-statistics in Table 9. The sample period ranges from January 2000 to June 2021. The average absolute alphas produced by the original CH-3 and CH-4 are 0.63% and 0.56% monthly, respectively, approximately 7% annually, with corresponding average absolute t-statistics (Newey–West t-statistics with four lags) of 2.25 and 1.96. Our revised model reduces the magnitude of the average absolute alpha by approximately 0.10% monthly, which does not appear as a substantially significant improvement at first glance. However, the average absolute t-statistics are all well below 1.96. Among these findings, CH-4_R demonstrates the best performance, producing an average absolute alpha of 0.51% monthly (the average absolute t-statistics is only 1.66). Furthermore, we present the results of other competing factor models. The produced average absolute alphas range from 0.66% to 1.03% monthly (8%–12% annually), which are approximately twice the value obtained using our revised model. Moreover, their t-statistics are much larger.

Table 10 presents additional details regarding the strength of the CH-4_R factor model in explaining liquidity anomalies compared with the

The number of unexplained anomalies.

Factor Models	Trading-related Anomalies			Accounting-related Anomalies				
Panel A: cut-off is $|t| > 1.96$	Liquidity	Risk	Past return	Profitability	Value	Investment	Others	Total
	15	11	5	10	0	0	5	46
CH-3	12	2	2	4	0	0	3	23
CH-4	10	2	1	4	0	0	4	21
CH-3_R	10	2	2	4	0	0	3	21
CH-4_R	7	2	2	4	0	0	4	19
CAPM	15	10	5	10	0	0	4	44
FF-3	15	8	3	10	0	0	5	41
Carhart-4	15	8	4	10	0	0	4	41
FF-5	15	8	8	10	0	0	8	41
NM-4	14	5	4	9	0	0	4	36
HXZ-4	13	9	3	0	0	0	2	27
PTX-4	7	4	2	4	0	0	2	19
SY-4	10	7	3	8	0	0	4	32
DHS-3	11	5	4	6	0	0	4	30
Panel B: cut-off is $|t| > 2.85$	Liquidity	Risk	Past return	Profitability	Value	Investment	Others	Total
	10	10	3	3	0	0	3	29
CH-3	11	1	1	0	0	0	2	15
CH-4	6	1	1	3	0	0	1	7
CH-3_R	8	1	1	0	0	0	1	11
CH-4_R	2	2	1	0	0	0	1	6
CAPM	9	8	1	3	0	0	3	24
FF-3	14	8	1	10	0	0	3	36
Carhart-4	15	7	2	9	0	0	4	37
FF-5	15	7	2	7	0	0	2	33
NM-4	9	2	2	4	0	0	4	21
HXZ-4	8	7	1	0	0	0	1	17
PTX-4	3	2	2	0	0	0	1	8
SY-4	7	7	0	8	0	0	4	26
DHS-3	8	2	3	3	0	0	4	20

Note: The long leg of an anomaly is the value-weighted portfolio of stocks in the highest decile of the anomaly measure, and the short leg contains the stocks in the lowest decile, with a lower decile being associated with lower return.

Comparing the capabilities of models to explain the anomalies.

Factor Models	Absolute Alpha Average	Absolute t-statistics Average
CH-3	0.63	2.25
CH-4	0.56	1.96
CH-3_R	0.58	1.93
CH-4_R	0.51	1.66
CAPM	1.02	2.95
FF-3	1.03	4.04
Carhart-4	1.03	4.29
FF-5	0.92	3.54
NM-4	0.98	3.06
HXZ-4	0.81	2.37
PTX-4	0.66	1.85
SY-4	0.96	3.27
DHS-3	0.97	2.63

Note: For each model, the table reports the absolute alpha (in %, monthly) and accompanying t-statistics (Newey–West t-statistics with four lags) of the 46 significant anomalies. The long leg of an anomaly is the value-weighted portfolio of stocks in the highest decile of the anomaly measure, and the short leg contains the stocks in the lowest decile, with a lower decile being associated with lower return.

Capability to explain liquidity anomalies among the factor models.

Anomaly names		CH-4		CH-4_R	
		alpha	t-statistics	alpha	t-statistics
a turn daily	Abnormal turnover	0.08	0.43	0.10	0.47
i1 daily	Amihud illiquidity of the past one month	0.52	3.59	0.29	2.11
cvdtv daily	Coefficient of variation in the dollar trading volume	0.93	2.35	0.94	2.52
cvturn daily	Coefficient of variation in the share turnover	0.89	2.72	0.92	2.73
dtv1 daily	Dollar trading volume of the past one month	0.53	3.49	0.22	1.44
dtv daily	Dollar trading volume of the past six months	0.44	2.32	0.18	0.97
dtv1 daily	Dollar trading volume of the past 12 months	0.66	3.70	0.40	2.31
1 daily	Turnover-adjusted number of zero daily volume of past one month	0.03	0.11	0.06	0.18
taca	Market Capitalization	1.14	5.97	0.87	5.92
turn1 daily	Daily turnover of the past one month	0.13	0.50	0.16	0.50
vdtv1 daily	Variation in the dollar trading volume of the past one month	0.66	4.13	0.35	2.19
vdtv daily	Variation in the dollar trading volume of the past 6 months	0.51	2.69	0.19	0.99
vdtv1 daily	Variation in the dollar trading volume of past 12 months	0.81	4.77	0.52	3.02
vturn1 daily	Variation in the share turnover of the past one month	0.39	1.37	0.43	1.27
vturn daily	Variation in share turnover of in the past six months	0.16	0.50	0.14	0.43
Mean		0.53	2.58	0.39	1.80

Note:Alphas (in %, monthly) and t-statistics (Newey–West t-statistics with four lags) reported under the CH-4 and CH-4_R for each of the 15 significant liquidity anomalies in Table 8. The long leg of an anomaly is the value-weighted portfolio of stocks in the highest decile of the anomaly measure, and the short leg contains the stocks in the lowest decile with a lower decile being associated with lower return.

original CH-4. We report the alphas and t-statistics for each of the 15 significant liquidity anomalies in Table 8 using the CH-4 and CH-4_R. Ten liquidity anomalies produce a significant alpha for the original CH-4 with an absolute mean of 0.53% monthly and an absolute t-statistics of 2.58. Meanwhile, only seven survive for the CH-4_R, with an absolute mean of 0.39% monthly and the absolute t-statistics of 1.80. More specifically, the improvement stems from the CH-4_R's ability to explain Ami1_daily (Amihud illiquidity for the past one month), dtv1/6/12_daily (dollar trading volume for the past 1/6/12 months), and vdtv1/6_daily (variation in the dollar trading volume for the past 1/6 month), which are shown to be distinctive anomalies in the Chinese market (Hou et al., 2021).

Altogether, the formal model comparison tests in this section reveal that our revised factor models outperform the original CH-3/4 models by LSY and other popular factor models. In particular, they outperform when (i) considering the model specification error, (ii) providing explanatory power for 25 Fama–French portfolios, and (iii) attempting to explain a variety of 122 anomalies in the Chinese stock market. The overarching results highlight the importance of approximating shell value contamination when constructing factor models to conduct empirical studies.

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We perform several robust tests. The 1% probability filter for the model construction is somewhat arbitrary, and our results are robust to using 0.5% and 5% cut-offs. Owing to the data limit, the revised CH-3 model can only impose the shell probability filter after 2011. Therefore, we use the subsample between January 2011 and June 2021 to evaluate the factor models. Our revised CH-3 and CH-4 models have comparable explaining power compared with the competing factor models.

This study proposes a revised factor model for the Chinese stock market in light of the IPO policy reform. Liu, Stambaugh, and Yuan (2019) eliminate the bottom 30% of stocks to avoid shell stocks when constructing their CH-3/4 models. This study demonstrates that the propensity of firms to engage in reverse mergers has sharply decreased in recent years. Therefore, mechanically following the procedure of Liu et al. (2019) may result in the loss of valuable information in asset pricing studies. Our study makes a unique contribution to this strand of literature by proposing an alternative filter, which excludes the stocks with a high estimated shell probability when constructing factor models.

When examining the performance of our proposed models, we reconstruct the 25 Fama–French portfolios based on the size and EP double-sorting to form testing assets in model comparison. Hansen–Jagannathan distance and Gibbons–Ross–Shanken test are used to investigate the capability of the factor models to explain the 25 Fama–French portfolios. We find that both tests favor our revised model. Finally, we examine the capability of our proposed model to explain a range of anomalies observed in the Chinese stock market. The results lend further support to the improved performance of our revised model because it can explain most of the Chinese stock anomalies reported in Hou et al. (2021). In particular, the revised model can explain more liquidity anomalies than the original CH-4. Overall, our study provides an effective benchmark model for empirical asset pricing in the Chinese stock market.

The authors have no conflicts of interest to disclose.

Data will be made available on request.

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