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Evaluating asset pricing models: A revised factor model for China

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ABSTRACT

We develop a revised factor model, accounting for unique features of Chinese markets, and evaluate the performance of competing asset pricing models. Extant literature reveals that eliminating the smallest 30% of stocks improves the performance of factor models. The revised factor model excludes firms with a high expected probability of becoming shells, which are companies valued as shells in reverse mergers serving as an alternative way to go public. Our revised model has the smallest model specification errors and the best explanatory power among various constructed portfolios. This new finding suggests that our model offers an effective benchmark model for empirical asset pricing in the Chinese stock market.

1. Introduction

The Chinese stock market has seen extensive growth over the last decades. It has become the world's second-largest market, with an overall market capitalization of more than \$12 trillion and with approximately 4100 listed firms as of 2020. In China, the stock market is largely dominated by retail investors that generate the bulk of trading volumes, whereas institutional investors are increasingly important in price discovery. Furthermore, foreign investors seek active exposure to Chinese A-listed shares using several channels, such as the Qualified Foreign Institutional Investor (QFII) program and Hong Kong Stock Connect (HKC) program. Stimulated by this rapidly growing interest in the Chinese stock market, many scholars seek for better understanding of the relationship between risk and return, by developing empirical asset pricing models applicable to the Chinese market (see Hou et al., 2021; Liu et al., 2019). However, academia has not reached a consensus on appropriate empirical asset pricing models in China. This is largely because the Chinese stock market is facing strict regulatory interventions, such as the registration-based initial public offering (IPO) reforms. This study proposes a benchmark factor model that considers these IPO reforms and examines their performance against several popular factor models proposed in the extant literature.

There exists a longstanding tradition in the financial asset pricing literature that identifies useful factors explaining the risk–return relationship in stock markets. Fama and French (1993) find that three factors (i.e., size, value, and market) can explain cross-sectional stock returns in the U.S. market. Subsequently, other factors extending the three-factor model have been proposed, including the momentum (Carhart, 1997), liquidity (Pástor and Stambaugh, 2003), and profitability (Novy–Marx, 2013), all of which provide additional explanatory power. Over the last decade, competing factor models, such as the investment-based q-factor model (Hou et al., 2015) and Fama and French 5-factor model (Fama and French, 2015), have been inspired partly by theoretical economic models. On the contrary, the mispricing 4-factor (Stambaugh and Yuan, 2017) and behavioral 3-factor models (Daniel et al., 2020) stem from behavioral finance to reconcile the anomalies with the behavioral bias of investors.

However, unlike in developed markets, these empirical asset pricing factor models are less effective in the Chinese stock market. For instance, Hu et al. (2019) find no value premium on the Chinese market when replicating Fama and French's (1993) 3-factor model. They attribute this phenomenon to extreme values in the early years of the market. Liu, Stambaugh, and Yuan (2019; LSY hereafter) argue that small firms at the bottom 30% size quantile act as "shells", allowing private firms to enter the stock exchanges while bypassing an IPO. According to LSY, the market value of these small firms is largely irrelevant to the company's fundamentals. To avoid the shell value contamination, LSY eliminate the smallest 30% of stocks and construct risk factors that can effectively capture the cross-sectional variation of other "regular" stocks that account for approximately 93% of the total Chinese A-share market capitalization.

The discussions presented above indicate that the reduced

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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 reforms in recent years. Throughout 2017 and 2018, the government accelerated the IPO approval process while introducing an essential capital market reform: the registration-based IPO system. These reforms reduced firms' propensity to enter the publicly listed realm through a shell firm. Overall, the average number of IPOs soared to approximately 307 per year, relative to approximately 128 annual IPOs before the reform. During the process, small firms are quite different from shell firms. We argue that we cannot mechanically follow the study of LSY, which eliminates the smallest 30% of stocks. However, not all small firms are necessarily shell firms; therefore, the method proposed by LSY removes potentially valuable information, which may result in a systematic misestimation of risk premiums and alpha. Instead, we propose a method to precisely eliminate stocks with a high ESP, allowing us to maintain as much information as possible while curbing the chance of shell contamination in our sample.

Subsequently, we conduct formal asset pricing tests for model comparison across various popular factor models through the Hansen–Jagannathan (HJ) distance (Hansen and Jagannathan, 1997; Hodrick and Zhang, 2001) and Gibbons–Ross–Shanken (GRS) test (Gibbons et al., 1989). The empirical evidence demonstrates that our revised model performs the best among the competing factor models in the asset pricing tests. In addition, we follow Hou et al. (2015) and LSY to investigate the capability of the model to explain a broad range of 122 reported anomalies in the Chinese market (Hou et al., 2021). Our results reveal that the revised model is better equipped to explain liquidity anomalies than LSY. Hou et al. (2021) indicate that liquidity is the most critical anomaly in the Chinese stock market, which sets itself apart from the U.S., and is likely driven by retail investors. Therefore, we claim that our revised factor model may serve as a more effective pricing model in the Chinese context.

Our study contributes to the literature on asset pricing in Chinese equity markets in the following three points. First, we emphasize the limitation of the CH-3 factor model (proposed by LSY) in light of the presence of a structural break in the Chinese IPO market induced by the policy and regulation changes after 2017. Removing the bottom 30% of stocks may result in a systematically overestimated alpha when evaluating the portfolio performance. We circumvent these issues by proposing and implementing an improved asset pricing model that includes the bottom 30% of stocks contingent on the activity of reverse merges in constructing factor models.

Second, we perform a series of rigorous model comparisons that include the most commonly used factor models. Unlike the comparison of asset pricing factor models in Sha and Gao (2019) and Ma et al. (2021), we examine 11 competing factor models based on various testing assets and methods to investigate model specification errors and pricing ability. Compared with the model of LSY, our revised model has the smallest pricing error measured through the HJ distance and can elucidate more liquidity anomalies. Portfolio managers may develop strategies to harvest the size premium, which contains "small" stocks in the bottom 30%. Thus, the proposed revised model is a more appropriate benchmark to evaluate portfolio performance.

Finally, our research can also play a role in improving market efficiency. An effective factor model can distinguish the source of systematic risk and provide a proper benchmark to compute the risk-adjusted return. Our study finds that following LSY's proposal to construct factor models will lead to misestimating alpha in the portfolio evaluation. LSY's research is quite influential; academics and financial practitioners may use the factor model to identify fund managers with active management ability. In that case, the capital might not be allocated to those skilled fund managers. As well known, active fund managers play an important role in correcting the mispricing in the security market and improving the degree of market efficiency. Therefore, we hold that our finding is beneficial for investment practice and capital allocation.

The remainder of the paper is structured as follows. Section 2 briefly introduces the institutional background of the Chinese IPO market. Section 3 discusses the shell value and its implication for asset pricing models. Section 4 proposes our revised CH-3/4 models. Section 5 compares the pricing ability of our revised models with the alternatives. Finally, Section 6 concludes the study.

2. Institutional background

We obtain financial data and stock returns from Wind Information Inc., China's largest and leading financial data provider, from January 2000 to June 2021. Consistent with LSY, we focus on the post-2000 period for two reasons. First, regulations on trading and disclosures are intensively published by the regulators during the late 1990s, rendering accounting information less comparable across firms. Since 2000, we have more reliable accounting data for A-share listed companies. Second, we start our sample in 2000 to ensure a sufficient number of observations. Our portfolios need to comprise at least 50 stocks, after excluding stocks that have been listed for less than six months, those with less than 120 trading records in the past year, and those with less than 15 trading records in the past month. Before 2000, the data did not fit these portfolio construction criteria. We further obtain data on RMs from the iFinD database by Tong Hua Shun, a prominent financial data service provider. It is a comprehensive sample comprising 318 RM transactions in China, announced between January 2007 and June 2021. We primarily emphasize the post-2007 period because RM transactions became legally tenable.

Table 1 reports the yearly number of IPOs and RMs in China alongside relevant policy changes. The initial years of the sample period are characterized by imbalanced IPO demand and supply. For instance, the IPO approval was suspended for a year in 2013. However, while the IPO

Table 1
Number of IPOs and RM in each year with important policy change.

Year	# IPOs	# Main Board	# GEM	# STAR	# RM	# Delisted	Important Policy Change
2000	132	132	–	–		0	–
2001	77	77	–	–		3	–
2002	70	70	–	–		7	–
2003	67	67	–	–		4	–
2004	100	100	–	–		8	–
2005	15	15	–	–		12	–
2006	66	66	–	–		4	–
2007	125	125	–	–	10	5	The RM transactions became legally tenable.
2008	77	77	–	–	32	0	–
2009	99	63	36	–	31	1	–
2010	347	230	117	–	23	2	–
2011	282	154	128	–	20	0	–
2012	155	81	74	–	23	0	–
2013	0	0	0	–	36	2	IPO approval was suspended for one year.
2014	125	74	51	–	38	0	The CSRC announced to control the pace of IPOs, which was perceived as a signal to tighten the IPOs.
2015	219	133	86	–	43	2	–
2016	227	149	78	–	18	1	CSRC released *The Revised Regulations on the Assets-restructuring of Listed Firms*.
2017	436	295	141	–	6	2	The auditing efficiency of the IPO process was highly improved.
2018	105	76	29	–	11	4	President Xi Jinping announced the establishment of STAR and registration-based IPO system trial.
2019	201	79	52	70	12	9	–
2020	394	142	107	145	10	17	The registration-based IPO system was extended to GEM.
2021H1	245	74	85	86	5	13	The Registration-based IPO system is scheduled to be extended to all boards.

Note: Table 1 reports the numbers of IPOs and RMs with related yearly policy changes. RM denotes the reverse merger as an alternative way to go public. GEM represents the growth enterprise market; STAR indicates the Science and Technology Innovation Board.

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 RMs peaked in 2013–2015 but subsequently began to fall. In June 2016, the CSRC released *The Revised Regulations on the Assets-restructuring of Listed Firms*, which came into power after three months. After issuing this document, an acquisition was deemed equivalent to an RM, which makes the RM process more scrutinized. The 2017 policy change on IPOs substantially reduced the attractiveness of RMs as a means of entering the stock market.

In November 2018, President Xi Jinping further announced that the Shanghai Stock Exchange would establish the Science and Technology Innovation Board (STAR) and introduced a registration-based IPO system trial. This system was extended to the growth enterprise market (GEM) in 2020 and was scheduled to be extended to all boards in 2021. This new IPO system is a capital market reform aiming to raise the proportion of direct financing, thereby substantially decreasing the scarcity and value of public listing status.

3. Shell value and its implication for asset pricing

To measure the ex-ante probability of a firm being a shell firm, we follow Lee et al. (2021) and calculate the ESP. Shell firms are public companies with high ESP. To eliminate shell firms, it is straightforward to drop the high ESP firms. LSY drop the bottom 30% of stocks to avoid incorporating RMs into their sample. However, these stocks are not necessarily shell stocks. Shell and small firms are not the same. For instance, all stocks from the GEM are prohibited from being taken over for shell purposes. Throughout our sample, a nontrivial part of the bottom 30% of stocks—that is, 17.5%—stems from the GEM. This already indicates that simply removing those observations may distort our sample.

To give a further illustration, we report ESP summary statistics of 10 decile groups formed on size in Panel A of Table 2. Even though the average ESP decreases from 3% in the bottom size group to 0.01% in the top size group, there is large ESP variation in each group. Furthermore, we report the proportion of ESP greater than 1% and 5% within each group. Considering the bottom size group an example, only 77.29% of firms have an ESP greater than 5%, and 14.91% of firms have an ESP greater than 1%. Concurrently, shell firms do not only exist in the smallest three groups but also in other groups. For example, 20.70% and 8.05% of the firms have an ESP greater than 1% in groups 4 and 5, respectively. This suggests that small firms are not the same as shell stocks.

Shell firms are believed to respond less to firm fundamentals but more to IPO policy shocks. In contrast, small firms are regular firms with small market capitalization. Moreover, we test how the return variation of stocks responds to firm fundamentals. Following standard practice, we divide the stock universe into 10 decile groups according to the stock market value. Within each group, we estimate a panel regression of the earnings-window abnormal return on standardized unexpected earnings (SUE) as follows:

$$CAR_{i,t-k,t+k} = a + bSUE_{i,t} + e_{i,t}, \tag{1}$$

where $CAR_{i,t-k,t+k}$ represents the cumulative abnormal return on stock i over the market return between time $t-k$ and $t+k$. We compute $SUE_{i,t}$ using a seasonal random walk:

$$SUE_{i,t} = \frac{\Delta_{i,t}}{\sigma(\Delta_i)}, \tag{2}$$

where $\Delta_{i,t}$ indicates the year-over-year change in stock i's quarterly earnings, and $\sigma(\Delta_i)$ represents the standard deviation of $\Delta_{i,t}$ over the last eight quarters.

Under LSY's hypothesis that the return variation of the bottom 30% stocks is mainly driven by shell values, we would expect that the bottom

Table 2
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 b 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 b-values. However, for the second and third smallest decile groups, the b 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 b 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.

4. Improved CH-3/4 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

Table 3
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.

5. Model comparison

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 literature. A brief introduction to these models is presented as follows.

5.1. Competing factor models

The list of competing models includes the capital asset pricing model (CAPM, hereafter), Fama–French 3-factor model (FF-3, hereafter), and Carhart 4-factor model (Carhart-4, hereafter), which are arguably the most influential asset pricing models developed over the last three decades. We further include the Fama-French 5-factor model (FF-5, hereafter) that add investment (conservative-minus-aggressive, CMA) and profitability (robust-minus-weak, RMW) factor in FF-3.

Novy-Marx (2013) proposes a profitability factor (profitability-minus-unprofitability, PMU), which is measured by gross profits-to-assets, in a four-factor model that further includes market (MKT), book-to-market ratio (high-minus-low, HML), momentum (up-minus-down, UMD). Their model explains most earning-related anomalies. Hou et al. (2015) build on investment-based asset pricing theory and construct a new empirical model, including MKT, size (market equity), investment, and profitability.[1] Their q-factor model empirically outperforms FF-3 and Carhart-4 with a few exceptions. Building on the Chinese context, Pan et al. (2016) define the abnormal turnover ratio (ATR) by isolating speculative trading from other components in the trading volume. Combined with other three popular factors, ATR can serve as a risk factor in the Chinese market.

Additionally, we include two popular models based on the behavioral finance theory. Stambaugh and Yuan (2017) propose two mispricing factors that capture the overconfidence and inattention of investors. Their four-factor model, augmented with market and size, explains a large set of anomalies. Daniel et al. (2019) further augment the market factor with two additional factors capturing long- and short-horizon mispricing. Furthermore, their three-factor model works effectively in explaining a variety of anomalies. Finally, we include CH-3 and CH-4 in LSY. Table 4 summarizes all these factor models.

Table 5 reports the summary statistics for the competing factor models. The factor war website (www.factorwar.com) generously replicates these factors in China, which have widely been discussed in academia. These factor models provide a competing benchmark in evaluating the pricing ability of our revised model in the Chinese stock market.

5.2. The 25 Fama–French portfolios

To evaluate the pricing ability for each factor model, a fair playing field must be established. We follow Fama and French (1993) and construct the 25 Fama–French portfolios. The deadline for Chinese listed firms to file annual reports is April 30. Therefore, we sort the stocks into quintiles based on size and E/P ratios at the end of April. The portfolio will be rebalanced until April of the subsequent year. The following filters are used when constructing the Fama–French portfolios: (i) the stock needs to be listed less than six months to avoid newly-issued firms and (ii) we remove any stocks with less than 120 trading records in the past year or less than 15 trading records in the past month to avoid trading suspension firms.

[1] Note that the investment-based asset pricing theory is built on the neoclassical q-theory of investment.

Table 4
List of competing models.

Factor Models	Factors	Reference
CAPM	MKT	Sharpe (1964)
FF-3	MKT, SMB, HML	Fama and French (1993)
Carhart-4	MKT, SMB, HML, UMD	Carhart (1997)
FF-5	MKT, SMB, HML, CMA, RMW	Fama and French (2015)
NM-4	MKT, HML, UMD, PMU	Novy-Marx (2013)
PTX-4	MKT, SMB, VMG, ATR	Pan et al. (2016)
HXZ-4	MKT, ME, I/A, ROE	Hou et al. (2015)
SY-4	MKT, SMB, MGMT, PERF	Stambaugh and Yuan (2017)
DHS-3	MKT, FIN, PEAD	Daniel et al. (2020)
CH-3	MKT, SMB, VMG	Liu et al. (2019)
CH-4	MKT, SMB, VMG, PMO	Liu et al. (2019)

Note: Summary of the competing factor models proposed by finance literature. MKT is market. SMB is small -minus-big. HML is high-minus-big. UMD is up-minus-down. CMA is conservative-minus-aggressive. RMW is robust-minus-weak. PMU is profitability-minus-unprofitability. VMG is value-minus-growth. ATR is abnormal turnover ratio. ME is market equity. I/A is investment. ROE is profitability. PMO is perssimistic-minus-optimistic. MGMT denote the factor arising from six anomaly variables all represent quantities that firms' managements can affect rather directly. PERF denote the factor arising from five anomaly variables related more to performance and less directly controlled by management. One can see Stambaugh and Yuan (2017) for more details. FIN is a financing factor to capture longer-horizon mispricing. PEAD is based on post-earnings announcement drift to capture shorter-horizon mispricing. One can see Daniel et al. (2020) for more details.

We report the mean, standard deviation, and t-statistics of the 25 Fama–French portfolios in Table 6. The average annualized returns range from 16.56% for the smallest firms with the lowest EP ratio to 18.12% for the smallest firms with the highest EP ratio. A nearly monotonic increase in average returns within a size quintile is observed as EP increases, barring the smallest size group. The average returns to the smallest firms are greater than those to the largest firms within the EP quintiles.

5.3. Model comparison based on the HJ distance and GRS test

We use two methods used to test the pricing ability of each factor model. The first method is the HJ distance, which is used to evaluate the pricing error of model specification. Hodrick and Zhang (2001) indicate that a large HJ distance results in a less precise model specification. Another method is the GRS (1989) F-statistic, which is often used to jointly test whether the 25 Fama–French portfolios can be priced with zero alpha by the factor models.

We first provide a brief introduction to the theoretical background of the HJ distance. Under the assumption of the arbitrage-free condition, the stochastic discount factor (SDF) exists for the N assets return vector R_t.

$$E(m_t R_t) = P. \tag{5}$$

The price vector should be 0 when R_t denotes the excess return of risk-free rates. In reality, the actual discount factor m_t remains unknown. We assume that the discount factor y_t satisfies the linear form, according to the specification of factor models:

$$y_t = b' F = b_0 + b_1 f_t. \tag{6}$$

Hansen and Jagannathan (1997) define the distance between two items when y_t is not the actual m_t:

$$\delta = \min E y_t - m_t \Big) \left(y_t - m_t\right)\left(y_t - m_t\right)^2 \Big]^{1/2} s.t. E(R_t m_t) = p. \tag{7}$$

The generalized method of moments (GMM) can be used to estimate the HJ distance. Jagannathan and Wang (1996) provide the distribution of the HJ distance; thus, we can give the corresponding p-value under the null hypothesis that δ is equal to zero. If the model can correctly price the risk-free rate, that is $E(y_t) = E(m_t) = R_f^{-1}$, then the HJ distance

Table 5
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.

Table 6
Summary statistics of the 25 Fama–French portfolios.

Portfolios	EP1	EP2	EP3	EP4	EP5
Panel A: Mean					
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
Panel B: Standard Deviation					
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
Panel C: 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.

Table 7
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 $R_f\delta$ 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 b 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.

5.4. Comparing the capabilities of models to explain anomalies

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

Table 8
The number of unexplained anomalies.

Factor Models	Trading-related Anomalies			Accounting-related Anomalies				
Panel A: cut-off is $\lvert t\rvert > 1.96$	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 $\lvert t\rvert > 2.85$	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.

Table 9
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.

Table 10
Capability to explain liquidity anomalies among the factor models.

Anomaly names		CH-4		CH-4_R	
		alpha	t-statistics	alpha	t-statistics
abturn_daily	Abnormal turnover	0.08	0.43	0.10	0.47
Ami1_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
dtv6_daily	Dollar trading volume of the past six months	0.44	2.32	0.18	0.97
dtv12_daily	Dollar trading volume of the past 12 months	0.66	3.70	0.40	2.31
Lm1_daily	Turnover-adjusted number of zero daily volume of past one month	0.03	0.11	0.06	0.18
tacap	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
vdtv6_daily	Variation in the dollar trading volume of the past 6 months	0.51	2.69	0.19	0.99
vdtv12_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
vturn6_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.

5.5. Robust checks

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.

6. Conclusion

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.

Declaration of competing interest

The authors have no conflicts of interest to disclose.

Data availability

Data will be made available on request.

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