Size and Value in China

by*

Jianan Liu, Robert F. Stambaugh, and Yu Yuan

First Draft: January 22, 2018

This version: January 29, 2018

Abstract

We construct size and value factors in China. The size factor excludes the smallest 30% of firms, which are companies valued significantly as potential shells in reverse mergers that circumvent tight IPO constraints. The value factor is based on the earnings-price ratio, which subsumes the book-to-market ratio in capturing all Chinese value effects. Our three-factor model strongly dominates a model formed by just replicating the Fama and French (1993) procedure in China. Unlike that model, which leaves a 17% annual alpha on the earnings-price factor, our model explains most reported Chinese anomalies, including profitability and volatility anomalies.

---

* We are grateful for comments from Jules Van Binsbergen, Amir Yaron, and seminar participants at Wharton. We thank Danting Chang, Zhe Geng,and Wenhao Xun for excellent research assistance. Yuan gratefully acknowledges financial support from the NSF of China (71522012). Author affiliations/contact information:

Liu: Ph.D. program, Finance Department, The Wharton School, University of Pennsylvania, email: jiananl@wharton.upenn.edu

Stambaugh: Miller, Anderson & Sherrerd Professor of Finance, The Wharton School, University of Pennsylvania and NBER, phone: 215-898-5734, email: stambaugh@wharton.upenn.edu.

Yuan: Associate Professor of Finance, Shanghai Advanced Institute of Finance, Shanghai Jiao Tong University, and Fellow, Wharton Financial Institutions Center, University of Pennsylvania, phone: +86-21-6293-2114, email: yyuan@saif.sjtu.edu.cn.

1. Introduction

China has the world's second-largest stock market, helping to finance an economy that some predict will be the world's largest within a decade.[1] China also has political and economic environments quite different from those in the US and other developed economies.[2] Moreover, China's market and investors are separated from the rest of the world. China largely prohibits participation by foreign investors in its domestic stock market as well as participation by its domestic investors in foreign markets.[3]

Factor models provide a cornerstone for investigating financial asset pricing and for developing investment strategies. Many studies of China's stock market use a three-factor model constructed by following the Fama and French (1993) procedure for US factors.[4] The advisability of simply replicating a US model in China is questionable, however, given China's separation and the many differences in economic and financial systems.[5] We explore and develop factor models in China, allowing its unique environment to dictate alternative approaches.

We start by examining size and value effects in the Chinese market. These two effects have long been recognized elsewhere as important characteristics associated with expected return: Banz (1981) reports a firm-size effect, and Basu (1983) finds an effect for the earnings-price ratio, a popular value metric. Size and value are the most prominent characteristics used by many institutions to classify investment styles. The most widely used non-market factors in academic research are also size and value, following the influential study by Fama and French (1993). Our study reveals that size and value effects are important in China, but with properties different from the US. We construct size and value factors for China.

[1]According to the World Bank, the 2016 equity values of listed domestic companies, in trillions of US dollars, are 27.4 in the US and 7.3 in China, followed by 5.0 in Japan. For a forecast that China's GDP will reach that of the US by 2028, see Bloomberg (https://www.bloomberg.com/graphics/2016-us-vs-china-economy/).

[2]Numerous studies address such differences. For example, Allen, Qian, and Qian (2003, 2005) compare China to other developed countries along various political, economic, and financial dimensions. Brunnermeier, Sockin, and Xiong (2017) study China's unique government interventions in its trading environment. Bian, Da, Lou, and Zhou (2017) document the special nature of leveraged investors in China's stock market. Allen, Qian, Qian, and Zhao (2009) and Carpenter and Whitelaw (2017) provide broader reviews.

[3]At the end of 2016, 197 foreign institutions were authorized to invest in A-shares, China's domestically traded stocks, but with a quota of just 0.6% of total market value (and even less in earlier years). Chinese domestic investors can invest in international financial markets only through a limited authorized channel.

[4]Examples of such studies include include Wang and Chin (2004), Chen, Kim, Yao, and Yu (2010), and Cheung, Hoguet, and Ng (2015).

[5]Song and Xiong (2017) emphasize the difficulty of analyzing risks in China's financial system without accounting for the economy's uniqueness.

The size factor is intended to capture size-related differences in stock risk and return that arise from size-related differences in the underlying businesses. In China, however, the stock of a small listed firm is typically priced to reflect a substantial component of value related not to the firm's underlying business but instead to the Chinese initial public offering (IPO) process. In China, the IPO market is strictly regulated, and a growing demand for public listing confronts the low processing capacity of the regulatory bureau to approve IPOs.[6] As a consequence, private firms seek an alternative approach, a reverse merger, in order to become public in a timely manner. In a reverse merger, a private firm targets a publicly-traded company, a so-called "shell," and gains control rights by acquiring its shares. The shell then buys the private firm's assets in exchange for newly issued shares.[7] While reverse mergers occur elsewhere, IPO constraints are sufficiently tight in China such that the smallest firms on the major exchanges become attractive shell targets, unlike in the US, for example.

The smallest listed firms are the most likely shells. In fact, 83% of the reverse mergers in China involve shells coming from the smallest 30% of stocks.[8] For a typical stock in the bottom 30%, we estimate that roughly 40% of its market value reflects its potential shell value in a reverse merger. Our estimate combines the empirical probability of being targeted in a reverse merger with the average return accompanying that event. Consistent with the contamination of small-firm stock prices by shell value, we also find that when compared to other firms, the smallest 30% have returns less related to operating fundamentals, proxied by earnings surprises, but more related to IPO activity. Therefore, to avoid shell-value contamination when constructing any of our factors, we delete the bottom 30% of stocks, which account for 7% of the stock market's total capitalization.

The value effect in China is best captured by the earnings-price (EP) ratio, versus other valuation ratios. Following Fama and French (1992), we treat the choice among alternative valuation ratios as an empirical question, asking which variable best captures the cross-sectional variation in average stock returns. As in that study, we run a horserace among all candidate valuation ratios, including EP, book-to-market (BM), asset-to-market, and cash-to-price ratios. In a Fama-MacBeth regression including those four ratios, EP dominates all others, just as Fama and French (1992) find BM dominates in the US market. Relying

[6]Allen, Qian, Shan, and Zhu (2017) study the tug of war between IPO demand and supply.

[7]A number of studies investigate the firm's choice between an IPO and a reverse merger. A commonly accepted reason for choosing the latter is lower cost (Adjei, Cyree, and Walker, 2008 and Floros and Sapp, 2011).

[8]A contemporaneous study by Lee, Qu, and Shen (2017) also concludes that size is the most significant determinant of a company becoming a reverse merger target in China.

on the latter US result, Fama and French (1993) use BM to construct their value factor. Relying on our result for China, we use EP to construct our value factor.

Our three-factor model, CH-3, includes the market factor as well as size and value factors incorporating the above China-specific elements. For comparison, we construct an alternative three-factor model, FF-3, by simply replicating the Fama and French (1993) procedure. We find that CH-3 strongly dominates FF-3. Specifically, FF-3 cannot price the CH-3 size and value factors, which have (significant) FF-3 annualized alphas of 5.64% and 16.80%. In contrast, CH-3 prices the FF-3 size and value factors, which have (insignificant) CH-3 alphas of just 0.12% and 4.32%. A Gibbons, Ross, and Shanken (1989) test of one model's ability to price the other's factors gives a p-value of 0.60 for CH-3's pricing ability but only 10^{-12} for FF-3's ability.

We also investigate the ability of CH-3 to explain previously reported return anomalies in China. A survey of the literature reveals anomalies in nine categories: size, value, profitability, volatility, return-reversal, turnover, investment, accruals, and illiquidity. We find each of the first six categories contains one or more anomalies that produce significant long-short alphas with respect to the single-factor CAPM. CH-3 accommodates all anomalies in the first four of those six categories, including profitability and volatility, whose anomalies fail FF-3 explanations in the US. CH-3 fails only with some of the reversal and turnover anomalies. In contrast, FF-3 leaves significant anomalies in five of the six categories. A total of ten anomalies are unexplained by the CAPM; CH-3 explains eight of them, while FF-3 explains three. The average absolute CH-3 alpha for the ten anomalies is 4.80% annualized, compared to 10% for FF-3 (average absolute t-statistics: 0.99 versus 2.55).[9]

Overall, CH-3 performs well as a factor model in China, and it captures most documented anomalies. In US studies, researchers often supplement the usual three factors (market, size, and value) with a fourth factor, such as the momentum factor of Carhart (1997) or the liquidity factor of Pástor and Stambaugh (2003). We also add a fourth factor, motivated by a phenomenon rather unique to China: a stock market dominated by individuals rather than institutions. Over 101 million individuals have stock trading accounts in China, and individuals own 88% of the market's free-floating shares. This heavy presence of individuals makes Chinese stocks especially susceptible to investor sentiment. To capture sentiment effects, we base our fourth factor on turnover, which previous research identifies as a gauge

[9]Hou, Xue, and Zhang (2015) and Fama and French (2015) add two factors based on investment and profitability measures in their recently proposed factor models, Q-4 and FF-5. Investment does not produce a significant CAPM alpha in China, and profitability is fully explained by CH-3. In an analysis reported in the Appendix, we find that a replication of FF-5 in China is dominated by CH-3.

of both market-wide and stock-specific investor sentiment (e.g. Stein and Baker (2004), Baker and Wurgler (2006), and Lee (2013)). The resulting four-factor model, CH-4, explains the turnover and reversal anomalies in addition to the anomalies explained by CH-3, thereby handling all of China's reported anomalies.

The remainder of the paper proceeds as follows. Section 2 discusses data sources and sample construction. Section 3 addresses the interplay between firm size and China's IPO constraints and explores the importance of shell-value distortions in small-stock returns. Section 4 investigates value effects in China. In Section 5, we construct CH-3 and FF-3 and compare their abilities to price each other's factors. In Section 6, we compare the abilities of those three-factor models to price anomalies. In Section 7, we construct CH-4 by including a turnover factor and then analyze the model's additional pricing abilities. Section 8 summarizes our conclusions.

2. Data source and samples

The data we use, which include data on returns, trading, financial statements, and mergers and acquisitions, are from Wind Information Inc. (WIND), the largest and most prominent financial data provider in China. WIND serves 90% of China's financial institutions and 70% of the Qualified Foreign Institutional Investors (QFII) operating in China.

The period for our main analysis is from January 1, 2000 thorugh December 31, 2016. China's domestic stock market, the A-share market, began in 1990 with the establishment of the Shanghai and Shenzhen exchanges. We focus on the post-2000 period for two reasons. The first is to assure uniformity in accounting data. The implementation of rules and regulations governing various aspects of financial reporting in China did not really take shape until about 1999. Although 1993 saw the origination of principles for fair trade and financial disclosure, firms received little guidance in meeting them. Companies took liberties and imposed their own standards, limiting the comparability of accounting data across firms. Not until 1998 and 1999 were laws and regulations governing trading and financial reporting more thoroughly designed and implemented. For example, detailed guidelines for corporate operating revenue disclosure were issued in December 1998 and implemented in January 1999. Securities laws were passed in December 1998 and implemented in July 1999. Only by 1999 had uniformity in accounting standards been widely accomplished. Accordingly, our post-2000 sample provides accounting data more comparable across firms than in earlier years.[10]

The second reason for beginning our sample in 2000 is to ensure sufficient numbers of observations. Portfolios are used in our study to construct factors and conduct many of the tests. To enable reasonable precision and power, we require at least 50 stocks in all portfolios after imposing our filters, which include eliminating stocks (i) in the bottom 30% of firm size, (ii) listed less than six months, and (iii) having less than 120 trading records in the past year or less than 15 trading records in the past month. This last pair of conditions is intended to prevent our results from being influenced by returns that follow long trading suspensions. Only by 1999 do the numbers of stocks in the market allow these criteria to be met.

WIND's data on reverse mergers begin in 2007, when the China Securities Regulatory Commission identified the criteria of an M&A proposal that classify it as a reverse merger, making such deals easier to trace. In Section 3.2, we use reverse merger data to estimate shell values. Additional details about the data and the construction of empirical measures are provided in the Appendix.

3. Small stocks and IPO constraints

As discussed earlier, market values of the smallest firms in China include a significant component reflecting the firms' potential to be shells in reverse mergers. Private firms often employ reverse mergers to become publicly traded, rather than pursue the constrained IPO process. Subsection 3.1 describes that IPO process, while subsection 3.2 describes reverse mergers and presents a notable example of one in China. In subsection 3.3, we compute a simple estimate of the fraction of firm value associated with being a shell for a potential reverse merger, and we find the fraction to be substantial for the smallest stocks. Consistent with that result, we show in subsection 3.4 that the returns on those stocks exhibit significantly less association with their underlying firms' fundamentals.

3.1. The IPO process

In China, the IPO market is controlled by the China Securities Regulatory Commission (CSRC). As a central planner, the CSRC constrains the IPO process to macro-manage the

[10] Portfolios formed in 2000 use accounting data for 1999

total number of listed firms.[11] Unlike the US, where an IPO can clear regulatory scrutiny in a matter of weeks, undertaking an IPO in China is long and tedious, easily taking three years and presenting an uncertain outcome. The process involves seven administrative steps, and three bureau departments, and a select 25-member committee that votes on each application.[12] The committee meets for both an initial review and a final vote, with those meetings separated by years. As of November 2017, the CSRC reported 538 firms being processed, with just 31 having cleared the initial review. The IPOs approved in early 2017 all entered the process in 2015.

The long waiting time can impose significant costs. During the review process, firms are discouraged from any sort of expansion and must produce consistent quarterly earnings. Any change in operations can induce additional scrutiny and further delay. A firm undertaking an IPO may thus forgo substantial investment opportunities during the multi-year approval process. Moreover, policy changes could prolong the process even more. In 2013, the CSRC halted all reviews for nearly a year to cool down the secondary market.

3.2. Reverse mergers

Facing the lengthy IPO process, private firms wishing to become public often opt for an alternative: reverse merger. A reverse merger, which is regulated as a merger and acquisition (M&A), involves fewer administrative steps and is much faster. We illustrate the process via a real-life case involving the largest delivery company in China, SF Express (SF).

In 2016, SF decided to become public through a reverse merger. To be its shell firm, SF targeted the small public company, DT Material (DT), with market value of about $380 million. SF and DT agreed on merger terms, and in May 2016 DT officially announced the deal to its shareholders. At the same time, DT submitted a detailed M&A proposal to the CSRC. The plan had DT issuing more than three billion shares to SF in exchange for all of SF's assets. The intent was clear: three billion shares would account for 97% of DT's stock upon the shares' issuance. With those shares, SF would effectively be the sole owner of DT, which would in turn be holding all of SF's assets. DT would become essentially the same old SF company but with publicly-traded status. The M&A authorization went smoothly. By October 2016, five months after the application, the CSRC gave its conditional approval, and final authorization came two months later. The merged company was trading as SF on

[11] Allen, Qian, Shan, and Zhao (2014) illustrate this point in the context of state-owned bank IPOs.

[12] Details of the steps in the IPO process are provided in the Appendix.

the Shenzhen Stock Exchange by February 2017. That same month, IPO applicants in the 2015 cohort had just begun their initial reviews.

The entire SF-DT process took less than a year, fairly typical for a reverse merger. The greater speed of a reverse merger comes with a price tag, however. In addition to regular investment banking and auditing fees, the private firm bears the cost of acquiring control of the public shell firm. In the SF-DT case, DT kept 3% of the new public SF's shares, worth about $938 Million. In the course of the deal, DT's original share holders made about 150%.

Reverse mergers are not unfamiliar to the US market. As in China, they have long been recognized as an IPO alternative. From 2000 through 2008, the US averaged 148 reverse mergers annually (Floros and Sapp, 2011). There is, however, a fundamental difference between reverse mergers in the US versus China: Because IPOs are less constrained in the US, the value of being a potential shell is much lower. In the US, the median shell's equity market value is only $2 million (Floros and Sapp, 2011), versus an average of $200 million in China. Nearly all shell companies in the US have minimal operations and few non-cash assets. Their Chinese counterparts are typically much more expensive operating businesses. As a result, while small stocks on China's major exchanges are attractive shell targets, small stocks on the major US exchanges are not. Consistent with this difference, Floros and Sapp (2011) observe that their US reverse-merger sample includes almost no shell targets listed on the three major exchanges.

3.3. Small stocks with large shell values

A private firm's price tag for acquiring a reverse-merger shell depends essentially on the shell's market value. Not surprisingly, shells are most often small firms.[13] Figure 1 displays the size distribution of public shells in our sample of reverse mergers covering the 2007–2016 period. Of the 133 reverse mergers, 83% come from the bottom 30%, and more than half come from the bottom 10%. Given this evidence, we eliminate the bottom 30% when constructing factors, to avoid much of the contamination of stock prices reflecting the potential to be targeted as shells.[14]

What fraction of a firm's market value owes to the firm potentially becoming a reverse-

[13] While other firm characteristics can affect the likelihood of being targeted as a shell, Lee et al. (2017) confirm our focus on size. Their logistic regression indicates size is more important than profitability and other characteristics.

[14] Although the 30% cutoff is somewhat arbitrary, our results are robust to using 25%, 35%, and 40% as cutoffs.

merger shell? A back-of-the-envelope calculation suggests the fraction equals roughly 40% for the stocks we eliminate (the bottom 30%). Let p denote the probability of such a stock becoming a reverse-merger shell in any given period, and let G denote the stock's gain in value if it does become a shell. We can then compute the current value of this potential lottery-like payoff on the stock as

$$S = \frac{pG + (1-p)S}{1+r} = \frac{pG}{r+p}, \tag{1}$$

where r is the discount rate. We take p to be the annual rate at which stocks in the bottom 30% become reverse-merger shells, and we take G to be the average accompanying increase in stock value. Both quantities are estimated over a two-year rolling window. The annual discount rate, r, is set to 3%.

Panel A of Figure 2 plots the estimated daily ratio of shell value to market value, S/V, where V is the median market value of stocks in the bottom 30%. Over the 2009–2016 sample period, the average value of S/V is 40%, while the series fluctuates between 10% and 60%. Equation (1) implicitly assumes the stock remains a potential shell in perpetuity, until becoming a shell. In other words, the role of small stocks in reverse mergers is assumed to be rather permanent in China, as the IPO regulatory environment shows no overall trend toward loosening. Even if we reduce the horizon to 20 years, though, the average S/V remains about half as large as the series plotted.

Panel B of Figure 2 plots the estimated shell value, S, expressed in RMB. This value exhibits a fivefold increase over the eight-year sample period, consistent with the significant premium earned over the period by stocks in the bottom 30% of the size distribution. Recall, however, that these stocks account for just 7% of the stock market's total capitalization. As we demonstrate later, constructing factors that include these stocks, whose returns are distorted by the shell component, impairs the ability of those factors to price "regular" stocks constituting the other 93% of the stock market's value.[15]

3.4. Return variation of small stocks

Given that the shell component contributes heavily to the market values and average returns of the smallest stocks, we ask whether this component also contributes to variation in their returns. If it does, then when compared to other stocks, returns on the smallest stocks

[15] Alternatively, if the objective is to price the shell stocks, they can be treated separately as is in Lee et al. (2017).

should be explained less by shocks to underlying fundamentals but more by shocks to shell values. We explore both implications.

To compare responses to fundamentals, we analyze returns accompanying earnings announcements. We divide the entire stock universe into three groups, using the 30th and 70th size percentiles. Within each group, we estimate a panel regression of earnings-window abnormal return on standardized unexpected earnings (SUE),

$$R_{i,t-k,t+k} = a + b\, SUE_{i,t} + e_{i,t}, \tag{2}$$

where earnings are announced on day t, and $R_{i,t-k,t+k}$ is the cumulative return on stock i, in excess of the market return, over the surrounding trading days from $t-k$ through $t+k$. We compute $SUE_{i,t}$ using a seasonal random-walk, where $SUE_{i,t} = \Delta_{i,t}/\sigma(\Delta_i)$, $\Delta_{i,t}$ equals the year-over-year change in stock i's quarterly earnings, and $\sigma(\Delta_i)$ is the volatility of $\Delta_{i,t}$ for the last eight quarters.

Under the hypothesis that the shell component is a significant source of return variation for the smallest stocks, we expect those stocks to have a lower b in equation (2) and a lower regression R^2 than the other groups. The first three columns of Table 1 report the regression results, which confirm our hypothesis. Panel A contains results for $k = 0$ in equation (2), and Panel B has results for $k = 3$. In both panels, the smallest stocks have the lowest values of b and R^2. For comparison, we conduct the same analysis in the US and report the results in the last three columns of Table 1.[16] In contrast to the results for China, the smallest stocks in the US have the *highest* values of b and R^2.

We also compare stocks' return responses to shell-value shocks, using two proxies for such shocks. One is the average return that public stocks experience upon becoming shells in reverse mergers. Our rationale is that the higher is this return, the greater is the potential value of becoming a shell. The other proxy is the log of the total number of IPOs, with the rationale that a greater frequency of IPOs could be interpreted by the market as a relaxing of IPO constraints. Consistent with the importance of the shell component for the smallest stocks, only that group's returns covary both positively with the reverse-merger premium and negatively with the log IPO number. The results are presented in the Appendix.

[16] The US returns data are from CRSP and the earnings data are from COMPUSTAT. The sample period is 1/1/1980–6/30/2016, before which the quality of quarterly data is lower.

4. Value effects in China

A value effect is a relation between expected return and a valuation metric that scales the firm's equity price by an accounting-based fundamental. The long-standing intuition for value effects (e.g., Basu, 1983, and Ball, 1992) is that a scaled price is essentially a catch-all proxy for expected return: a higher (lower) expected return implies a lower (higher) current price, other things equal.

Our approach to creating a value factor in China follows the same path established by the two-study sequence of Fama and French (1992, 1993). Following Fama and French (1992), the first step is to select the valuation ratio exhibiting the strongest value effect among a set of candidate ratios. The valuation ratios Fama and French (1992) consider include EP, BM, and assets-to-market (AM). The authors find BM exhibits the strongest value effect, subsuming the other candidates. Based on that result, the subsequent study by Fama and French (1993) uses BM to construct the value factor (HML).

In this section we conduct the same horse race among valuation ratios. Our entrants are the same as in Fama and French (1992), plus cash-flow-to-price (CP). As in that study, we estimate cross-sectional Fama and MacBeth (1973) regressions of individual monthly stock returns on the valuation ratios, with a stock's market capitalization and estimated CAPM beta (β) included in the regression. For the latter variable we use the beta estimated from the past year's daily returns, applying a five-lag Dimson (1979) correction. Following Fama and French (1992), we use EP to construct both EP^+ and a dummy variable, where EP^+ equals EP when EP is positive and zero otherwise, and the dummy variable, $D(EP < 0)$, equals one when EP is negative and zero otherwise. In the same manner, we construct CP^+ and $D(CP < 0)$ from CP. Due to the shell-value contamination of returns discussed earlier, we exclude the smallest 30% of stocks.

Table 2 reports average slopes from the month-by-month Fama-MacBeth regressions. Similar to results in the US market, we see from column (1) that β does not enter significantly. Also as in the US, the size variable, $log(ME)$, enters with a significantly negative coefficient that is insensitive to including β: in columns (2) and (3), without and with β beta included, the size slopes are -0.0049 and -0.0046 with t-statistics of -2.91 and -2.69. These results confirm a significant size effect in China.

Columns (4) through (7) of Table 2 report results when each valuation ratio is included individually in its own regression. All four valuation ratios exhibit significant explanatory power for returns. When the four valuation ratios are included in the regression simultaneously, as reported in column (8), EP dominates the others. The t-statistic for the coefficient on EP^+ is 4.14, while the t-statistics for $\log BM$, $\log AM$, and CP^+ are just 1.22, 0.90, and 1.40. In fact, the coefficient and t-statistic for EP^+ in column (8) are very similar to those in column (6), where EP is the only valuation ratio in the regression. The estimated EP effect in column (8) is also economically significant. A one-standard-deviation difference in EP^+ implies a difference in expected monthly return of 0.51%.

Because BM likely enters the horse race as favorite, we also report in column (9) the results when BM and EP are the only valuation ratios included. The results are very similar, with the coefficient and t-statistic for EP^+ quite close to those in column (8), and with the coefficient on $\log BM$ still insignificant.

In sum, we see that EP emerges as the most effective valuation ratio, subsuming the other candidates in a head-to-head contest. Therefore, in the next section we construct our value factor for China using EP. The dominance of EP over BM is further demonstrated in the next section, where we show that our CH-3 model with the EP-based value factor prices a BM-based value factor, whereas the BM-based model, FF-3, cannot price the EP-based value factor.

5. A three-factor model in China

In this section we present our three-factor model, CH-3, with factors for size, value, and the market. Our approach incorporates the features of size and value in China discussed in the previous sections. Subsection 5.1 provides details of the factor construction. We then compare our approach to one that ignores the China-specific insights. Subsection 5.2 illustrates the problems with including the smallest 30% of stocks, while subsection 5.3 shows that using EP to construct the value factor dominates using BM.

5.1. Size and value factors

Our model has two distinct features tailored to China. First, we eliminate the smallest 30% of stocks, to avoid their shell-value contamination, and we use the remaining stocks to form factors. Second, we construct our value factor based on EP. Otherwise, we follow the procedure used by Fama and French (1993). Specifically, each month we separate the remaining 70% of stocks into two size groups (Small and Big), split at the median market value of that universe. We also break that universe into three EP groups: top 30% (Value), middle 40%(Middle), and bottom 30%(Growth).[17] We then use the intersections of those groups to form value-weighted portfolios for the six resulting size-EP combinations: S/V, S/M, S/G, B/V, B/M, and B/G. Our size and value factors, denoted as SMB (Small-minus-Big) and VMG (Value-minus-Growth), combine the returns on these six portfolios as follows:

$$SMB = \frac{1}{3}(S/V + S/M + S/G) - \frac{1}{3}(B/V + B/M + B/G),$$
$$VMG = \frac{1}{2}(S/V + B/V) - \frac{1}{2}(S/G + B/G).$$

The market factor, MKT, is the return on the value-weighted portfolio of our universe, the top 70% of stocks, in excess of the one-year deposit interest rate.

Table 3 reports summary statistics for the three factors. SMB and VMG have averages of 1.03% and 1.11% per month, and their volatilities are 4.42% and 3.81%. Given the 204-month sample period, the respective implied t-statistics for the size and value premia are 3.32 and 4.16. In contrast, the market factor over this period has a 0.66% mean and 8.09% volatility per month, yielding an implied t-statistic of just 1.16. Clearly, size and value are important factors in China over our sample period.

5.2. Including shell stocks

If we construct our three factors without eliminating the smallest 30% of stocks, the monthly size premium increases to 1.36% while the value premium shrinks to 0.86%. As observed earlier, the value of being a potential reverse-merger shell has grown significantly over time, creating a shell premium that accounts for a substantial portion of the smallest stocks' average returns. Consequently, a size premium that includes shell stocks is distorted upward by the shell premium.[18] At the same time, the shell premium distorts the value premium downward. Market values of small firms with persistently poor or negative earnings nevertheless include significant shell value, so those firms' resulting low EP ratios classify them as growth firms. Misidentifying shell firms as growth firms then understates the value premium due to the shell premium in returns on those "growth" firms.

[17]We keep negative EP stocks in our sample and categorize them as growth stocks, observing that negative-EP stocks comove with growth stocks. They load negatively on a value factor constructed using just the positive-EP sample, with a slope coefficient of -0.30, with t-statistics: -4.08. As a robustness check, we exclude negative EP stocks and find all our results hold. On average across months, negative-EP stocks account for 15% of the stocks in our universe.

[18]Lee et al. (2017) also offer consistent evidence.

Including shell stocks also impairs the resulting factor model's explanatory power. When the three factors include the bottom 30% of stocks, they fail to price SMB and VMG from CH-3, which excludes shells: shell-free SMB produces an alpha of -20 basis points (bps) per month (t-statistic: -2.78), and VMG produces an alpha of 26 bps (t-statistic: 2.90). These results further confirm that the smallest 30% of stocks are rather different animals. Although they account for just 7% of the market's total capitalization, including them significantly distorts the size and value premia and impairs the resulting model's explanatory ability. Therefore, excluding shells is important if the goal is to build a model that prices regular stocks.

5.3. Comparing size and value factors

The obvious contender to CH-3 is FF-3, which follows Fama and French (1993) in using BM instead of EP as the value metric.[19] In this subsection, we compare CH-3 to FF-3, asking whether one model's factors can explain the other's. Using the same stock universe as CH-3, we construct the FF-3 model's size and value factors, combining the six size-BM value-weighted portfolios (S/H, S/M, S/L, B/H, B/M, B/L). The size groups are again split at the median market value, and the three BM groups are the top 30% (H), middle 40% (M), and bottom 30% (L). The returns on the resulting six portfolios are combined to form the FF-3 size and value factors as follows:

$$FFSMB = \frac{1}{3}(S/H + S/M + S/L) - \frac{1}{3}(B/H + B/M + B/L),$$

$$FFHML = \frac{1}{2}(S/H + B/H) - \frac{1}{2}(S/L + B/L).$$

The market factor is the same as in the CH-3 model.

Our CH-3 model outperforms FF-3 in China by a large margin. Panel A of Table 4 reports the alphas and corresponding t-statistics of each model's size and value factors with respect to the other model. CH-3 prices the FF-3 size and value factors quite well. The CH-3 alpha of $FFSMB$ is just 1 bps per month, with a t-statistic of 0.22, while the alpha of $FFHML$ is 36 bps, with a t-statistic of 1.0. In contrast, FF-3 prices neither the size nor the value factor of CH-3. FF-3 removes only about half of our model's 103 bps size premium, leaving an SMB alpha of 47 bps with a t-statistic of 6.59. Most strikingly, the alpha of our value factor, VMG, is 140 bps per month (16.8% annually), with a t-statistic of 7.94.

[19] Previous studies of China's factor models use the Chinese replication of Fama and French (1993) for their three-factor model (e.g., Yang and Chen, 2003, Fan and Shan, 2004, and Chen, Hu, Shao, and Wang, 2015).

Panel B of Table 4 reports GRS tests of whether both of a model's size and value factors jointly have zero alphas with respect to the other model. The results tell a similar story as above. The test of zero CH-3 alphas for both $FFSMB$ and $FFHML$ fails to reject that null, with a p-value of 0.60. In contrast, the test strongly rejects jointly zero FF-3 alphas for SMB and VMG, with a p-value less than 10^{-12}.

The above analysis takes a frequentist approach in comparing models' abilities to explain each other's factors. Another approach to making this model comparison is Bayesian, proposed by Barillas and Shanken (2017) and also applied by Stambaugh and Yuan (2017). This approach compares factor models in terms of posterior model probabilities across a range of prior distributions. Consistent with the above results, this Bayesian comparison of FF-3 to CH-3 also heavily favors the latter. Details of the analysis are presented in the Appendix.

In the US, two additional factors, profitability and investment, appear in recently proposed models by Hou et al. (2015) and Fama and French (2015). We find in China that the investment effect is weak, yielding no significant excess return spread or CAPM alpha. A profitability spread has a significant CAPM alpha but does not survive CH-3. Accordingly, in the same tests as above, CH-3 dominates these models' Chinese replications.[20] A detailed comparison is presented in the Appendix.

6. Anomalies and factors

A factor model is often judged by its ability not only to price another model's factors but also to explain return anomalies. In this section we explore the latter ability for CH-3 versus FF-3. We start by compiling a set of anomalies in China that are reported in the literature. For each of those anomalies, we compute a long-short return spread in our sample, and we find ten anomalies that produce significant alphas with respect to a CAPM benchmark. Our CH-3 model explains eight of the ten, while FF-3 explains three.

6.1. Anomalies in China

Our survey of the literature reveals 14 anomalies reported for China. The anomalies fall into nine categories: size, value, profitability, volatility, reversal, turnover, investment, accruals,

[20]Guo, Zhang, Zhang, and Zhang (2017) examine a Fama-French five-factor model in the A-share market and also find that the investment factor is very weak while the profitability factor is significant when benchmarked against the CAPM.

and illiquidity. The literature documenting Chinese anomalies is rather heterogeneous with respect to sample periods, data sources, and choice of benchmarking model (e.g., one factor, three factors, or no factors). Our first step is to re-examine all of the anomalies using our data and sample period. As discussed earlier, our reliance on post-2000 data and our choice of WIND as the data provider offer the most reliable inferences. We also use one model, the CAPM, to classify all the anomalies as being significant or not. Unlike the previous literature, we also evaluate the anomalies within our stock universe that eliminates the smallest 30%, so that shell values do not contaminate anomaly effects.

For our later analysis of the pricing abilities of the three-factor models, we retain only the anomalies that generate significant CAPM alphas in either unconditional or size-neutral sorts. We conduct the latter sort because correlation between an anomaly variable and size could obscure an anomaly's effect in an unconditional sort, given China's large size premium of 12.36% annually. For each of the 14 anomalies, the two sorting methods are implemented as follows: The unconditional sort forms deciles by sorting on the anomaly variable. (For EP and CP, we sort only the positive values.) We then construct a long-short strategy using the extreme deciles, forming a value-weighted portfolios within each decile. The long leg is the higher-performing one, as reported by previous studies and confirmed in our sample. For the size-neutral version, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort.

Our procedure reveals significant anomalies in six categories: size, value, profitability, volatility, reversal, and turnover. Almost all of the anomalies in these categories produce significant CAPM-adjusted return spreads from both unconditional and size-neutral sorts. Although investment, accrual, and illiquidity anomalies produce significant CAPM alphas in the US, they do not in China, for either unconditional or size-neutral sorts. Also unlike the US, there is no momentum effect in China. There is, however, a reversal effect, as past losers significantly outperform past winners.

Reversal effects in China are especially strong. Past performance over any length window tends to reverse in the future. In contrast, past returns in the US correlate in different directions with future returns, depending on the length of the past-return window. That is, past one-month returns correlate negatively with future returns, past two-to-twelve-month returns correlate positively (the well-documented momentum effect), and past three-to-five-year returns correlate negatively. In China, past returns over various windows all predict future reversals. In untabulated results, we find that past returns over windows of one, three, six, and twelve months, as well as five years, all negatively predict future returns, in monotonically weakening magnitudes. For a one-month window of past return, the decile of biggest losers outperforms the biggest winners with a CAPM alpha of 18% annually (t-statistic: 2.96). The alpha drops to 6% and becomes insignificant (t-statistic: 0.90) when sorting by past one-year return. In this section, we choose one-month reversal for the anomaly in the reversal category.

Altogether we find ten significant anomalies.[21] Table 5 reports their average excess returns along with their CAPM alphas and betas. The results for the unconditional sorts appear in Panel A. The monthly CAPM alphas range from 0.53%, for 12-month turnover, to 1.49%, for one-month reversal, and most display significant t-statistics. The average alpha for the ten anomalies is 0.98%, and the average t-statistic is 2.04.

Panel B of Table 5 reports the corresponding results for the size-neutral sorts. Two differences from Panel A emerge. First, size-neutralization substantially increases the alphas of several anomalies. For example, the EP monthly alpha increases by 0.81%, and the alpha for twelve-month turnover increases by 0.21% bps. Second, for almost all of the long-short spreads, standard deviations decrease and thus t-statistics increase. The decrease in standard deviations confirms that size is an important risk factor. The size-neutral sorting essentially gives the long-short spreads a zero SMB loading and thus smaller residual variance in the single-factor CAPM regression. Panel B conveys a similar message as Panel A, just more strongly: all ten anomalies generate significant CAPM-adjusted return spreads. The average monthly CAPM alpha for the size-neutral sorts is 1.15%, and the average t-statistic is 2.80.

6.2. Factor models' abilities to explain anomalies

Table 6 reports CH-3 alphas and factor loadings for the ten anomalies that survive the CAPM, the same anomalies as in Table 5. For the most part, our CH-3 model explains the anomalies well. Panel A of Table 6 reports results for the unconditional sorts. Not surprisingly, CH-3 explains the size anomaly. More noteworthy is that the model explains all the value anomalies (EP, BM, and CP), which all load positively on our value factor. The monthly CH-3 alphas of the three value anomalies are 0.5% or less, and the highest t-statistic is just 0.91. These findings echo the earlier Fama-MacBeth regression results, where

[21] The Appendix provides details for all 15 anomalies considered as well as a literature summary.

EP subsumes both BM and CP in terms of cross-sectional abilities to explain average returns.

Perhaps unexpectedly, given the US evidence, CH-3 fully explains the profitability anomaly, ROE. In the US, profitability's strong positive relation to average return earns it a position as a factor in the models recently advanced by Hou et al. (2015) and Fama and French (2015). In China, however, profitability is captured by our three-factor model. The ROE spread loads heavily on the value factor (t-statistic: 9.68), and the CH-3 monthly alpha is -0.36%, with a t-statistic of just -0.90.

CH-3 also performs well on the volatility anomalies. It produces insignificant alphas for return spreads based on the past month's daily volatility and the past month's maximum daily return (MAX). The CH-3 monthly alphas for both anomalies are 0.25% or less, with t-statistics no higher than 0.93. We also see that both of the anomalies load significantly on the value-factor. That is, low (high) volatility stocks behave similarly to value (growth) stocks.

CH-3 encounters its limitations with anomalies in the reversal and turnover categories. While the reversal spread loads significantly on SMB, its monthly alpha is nevertheless 0.84% (t-statistic:1.63). In the turnover category, CH-3 accommodates twelve-month turnover well but has no success with abnormal one-month turnover. The latter anomaly's return spread has only small loadings on SMB and VMG, and its CH-3 monthly alpha is 1.14%, nearly identical to its CAPM alpha (t-statistic: 2.47).

The size-neutral sorts, reported in Panel B of Table 6, deliver the same conclusions as the unconditional sorts in Panel A. CH-3 again explains all anomalies in the size, value, profitability, and volatility categories. The monthly alphas for those anomalies have absolute values of 0.53% or less, with t-statistics less than 0.93 in magnitude. For the reversal and turnover categories, CH-3 displays the same limitations as in Panel A. The CH-3 monthly alpha for reversal is 1.04%, with a t-statistic of 1.90. Abnormal turnover has an alpha of 1.17%, with a t-statistic of 2.81.

In the same format as Table 6, Table 7 reports the corresponding results for the FF-3 model. These results clearly demonstrate that FF-3 performs substantially worse than CH-3, leaving significant anomalies in five of the six categories—all categories except size. Consider the results in Panel A, for example. Similar to FF-3's inability to price our EP-based value factor, FF-3 fails miserably with the EP anomaly, leaving a monthly alpha of 1.39% (t-statistic: 5.34). Moreover, as in the US, FF-3 cannot accommodate profitability. The ROE anomaly leaves a monthly alpha of 1.77% (t-statistic: 5.84). Finally, for all anomalies in the volatility, reversal and turnover categories, FF-3 leaves both economically and statistically significant alphas.

Table 8 compares models' anomaly-explaining abilities by reporting the average absolute alphas for the anomaly long-short spreads, the corresponding average absolute t-statistics, and GRS tests of whether a given model produces jointly zero alphas across anomalies. The competing models include unconditional means (i.e., zero factors), the single-factor CAPM, and both of the three-factor models, CH-3 and FF-3. As in Tables 6 and 7, Panel A reports results for the unconditional sorts, and Panel B reports the size-neutral sorts. First, in both panels, observe that CH-3 produces much smaller absolute alphas than do the other models: 0.4% for CH-3 versus at least 0.9% for the other models. In Panel A, for the unconditional sorts, the GRS p-value of 0.22 for CH-3 fails to reject the joint hypothesis that all ten anomalies produce zero CH-3 alphas. In contrast, the corresponding p-values for the other models are all less than 10^{-6}. For the size-neutral sorts (Panel B), a similar disparity occurs for a test of jointly zero alphas on nine anomalies (size is omitted). The CH-3 p-value is 0.04 versus p-values less than 10^{-9} for the other models. Because size, EP, and BM are used to construct factors, we also eliminate those three anomalies and conduct the GRS test using the remaining seven. As shown in the last two rows of each panel, the results barely change—CH-3 again dominates.

7. A four-factor model in China

Notwithstanding the impressive performance of CH-3, the model does leave significant alphas for reversal and turnover anomalies, as noted earlier. We therefore explore the addition of a fourth factor based on turnover. In subsection 7.1, we discuss this factor's sentiment-based motivation, describe the factor's construction, and explain how we also modify the size factor when building this four-factor model, CH-4. Subsection 7.2 then documents CH-4's ability to explain all of China's reported anomalies.

7.1. Turnover as a sentiment factor

A potential source of high trading intensity in a stock is heightened optimism toward the stock by sentiment-driven investors. This argument is advanced by Baker and Stein (2004), for example, and Lee (2013) uses turnover empirically as a sentiment measure at the individual-stock level. High sentiment toward a stock can affect its price, driving it higher than justified by fundamentals and thereby lowering its expected future return. Two assumptions underly such a scenario. One is a substantial presence in the market of irrational, sentiment-driven traders. The other is the presence of short-sale impediments that constrain arbitrage-driven price correction.

China's stock market is especially suited to both assumptions. First, individual retail investors are the most likely sentiment traders, and individual investors are the major participants in China's stock market. As of year-end 2015, over 101 million individuals had trading accounts, and individuals held 88% of all free-floating shares (Jiang, Qian, and Gong, 2016). Second, shorting is extremely costly in China (China Securities Regulatory Commission, 2008).

To construct our fourth factor, reflecting investor sentiment, we use abnormal turnover, which is the past month's share turnover divided by the past year's turnover. We construct this factor in precisely the same manner as our value factor, again neutralizing with respect to size. That is, abnormal turnover simply replaces EP, except the factor goes long the low-turnover stocks, about which investors are relatively pessimistic, and goes short the high-turnover stocks, for which greater optimism prevails. We denote the resulting factor PMO (Pessimistic Minus Optimistic). We also construct a new SMB, taking a simple average of the EP-neutralized version of SMB from CH-3 and the corresponding turnover-neutralized version. The latter procedure for modifying SMB when adding additional factors essentially follows Fama and French (2015). The new size and turnover factors have annualized averages of 11% and 12%. The market and value factors in CH-4 are the same as in CH-3.

7.2. Explaining all anomalies with four factors

For model CH-4, Table 9 reports results of the same analyses conducted for models CH-3 and FF-3 and reported in Tables 6 and 7. Adding the fourth factor produces insignificant alphas not just for the abnormal-turnover anomaly but also for reversal. In Panel A, for the unconditional sorts, the CH-4 monthly alphas for those anomalies are -0.06% and 0.47%, with t-statistics of -0.24 and 0.84. The size-neutral sorts in Panel B produce similar results.

CH-4 accommodates the above two anomalies, thus now explaining all ten, while also lowering the average magnitude of all the alphas. For the unconditional sorts, the average absolute alpha drops to 0.29%, versus 0.40% for CH-3, and the average absolute t-statistic drops to 0.75, versus 0.99 for CH-3. The GRS test of jointly zero alphas for all ten anomalies produces a p-value of 0.53, versus 0.22 for CH-3, thereby moving even farther from rejecting the null. Similar improvements occur for the size-neutral sorts.

8. Conclusions

Size and value are important factors in the Chinese stock market, with both having average premiums exceeding 12% per year. Capturing these factors well, however, requires that one not simply replicate the Fama and French (1993) procedure developed for the US.

Unlike small listed stocks in the US, China's tight IPO constraints cause returns on the smallest stocks in China to be significantly contaminated by fluctuations in the value of becoming corporate shells in reverse mergers. To avoid this contamination, before constructing factors we eliminate the smallest 30% of stocks, which account for just 7% of the market's total capitalization. Eliminating these stocks yields factors that perform substantially better than using all listed stocks to construct factors, as the Fama and French (1993) procedure essentially does in the US.

Value effects in China are captured much better by the earning-price ratio (EP) than by the book-to-market ratio (BM) used in the US by Fama and French (1993). The superiority of EP in China is demonstrated at least two ways. First, in an investigation paralleling Fama and French (1992), cross-sectional regressions reveal that EP subsumes other valuation ratios, including BM, in explaining average stock returns. Second, our three-factor model, CH-3, with its EP-based value factor, dominates the alternative FF-3 model, with its BM-based value factor. In a head-to-head model comparison, CH-3 prices both the size and value factors in FF-3, whereas FF-3 prices neither of the size and value factors in CH-3. In particular, FF-3 leaves a 17% annual alpha for our value factor.

We also survey the literature that documents return anomalies in China, and we find ten anomalies with significant CAPM alphas in our sample. Our CH-3 model explains eight of the anomalies, including not just all value anomalies but also profitability and volatility anomalies not explained in the US by the three-factor Fama-French model. In contrast, the only two anomalies in China that FF-3 explains are size and BM. The two anomalies for which CH-3 fails, return reversal and abnormal turnover, are both explained by a four-factor model that adds a sentiment-motivated turnover factor.

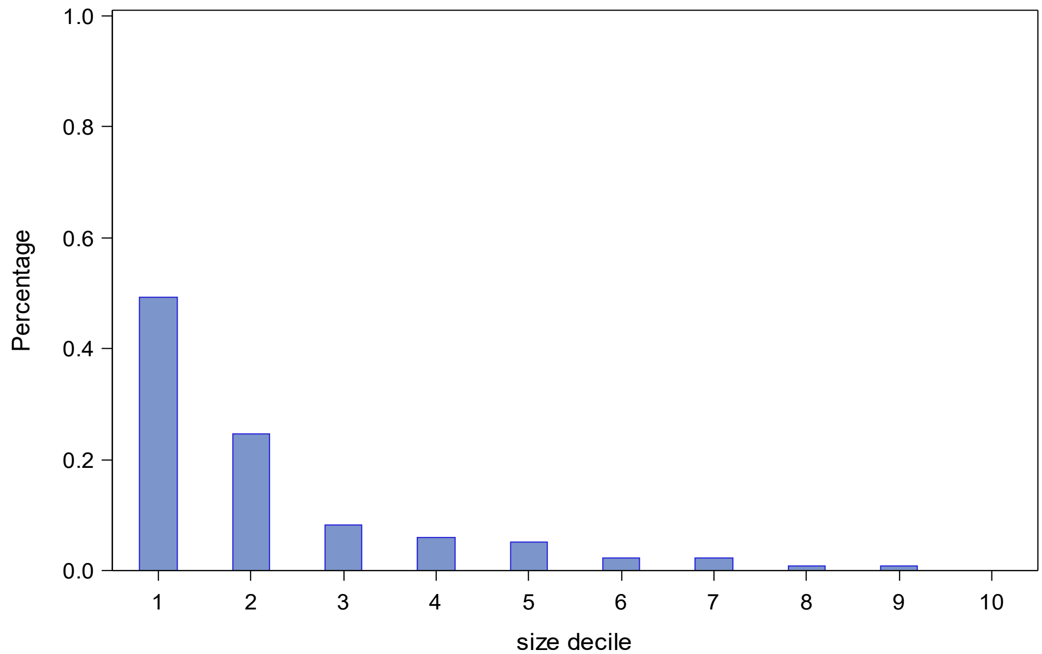
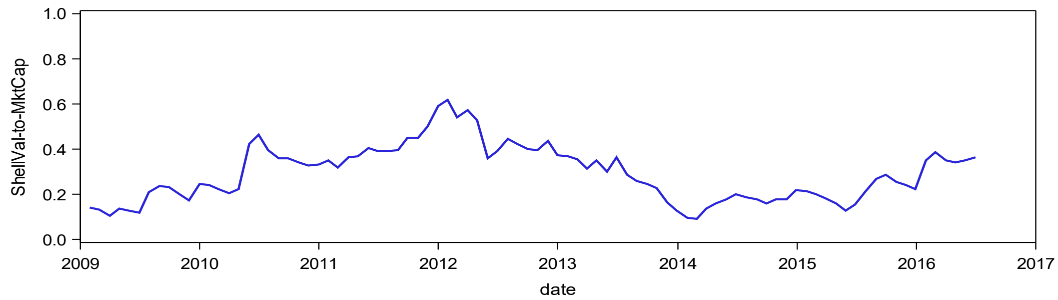


Figure 1. Firm Size Distribution of Reverse-Merger Shells. The figure displays the size distribution of firms acquired in reverse-merger deals from January 2007 through June 2016. A total of 133 reverse-merger deals occurred, and the fraction of those deals falling into a given firm size decile is displayed in the bar chart. Size deciles reflect month-end market values three months before the deal month.

Panel A. Ratio of Estimated Shell Value to Market Cap



Panel B. Estimated Shell Value (RMB)

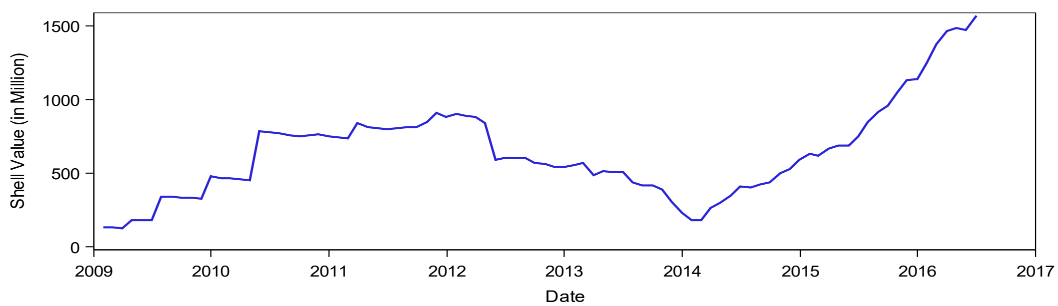


Figure 2. Shell Values Over Time. Panel A displays the time series of the ratio of estimated shell value to firm market capitalization. Panel B displays the time series of the estimated shell value (in RMB). The sample period is January 2009 through June 2016.

Table 1
Return Reactions to Earnings Surprises across Different Size Groups in the Chinese and US Markets

The table reports slope estimates and R-squares in a panel regression of earnings-window returns on earnings surprises,

$$R_{i,t-k,t+k} = a + b\, SUE_{i,t} + e_{i,t},$$

where earnings are announced on day t, $R_{i,t-k,t+k}$ is the cumulative return on stock i, in excess of the market return, over the surrounding trading days from $t-k$ through $t+k$, $SUE_{i,t} = \Delta_{i,t}/\sigma(\Delta_i)$, $\Delta_{i,t}$ equals the year-over-year change in stock i's quarterly earnings, and $\sigma(\Delta_i)$ is the volatility of $\Delta_{i,t}$ for the last eight quarters. Panel A contains results for $k=0$; Panel B contains results for $k=3$. The regression is estimated within each of three size groups in both the China and US markets. The groups are formed based on the top 30%, middle 40% and bottom 30% of the previous month's market capitalizations. The sample periods are January 2000 through December 2016 for China and January 1980 through December 2016 for the US. White (1980) heteroscedasticity-consistent t-statistics are reported in parentheses.

	China			US		
	Smallest	Middle	Largest	Smallest	Middle	Largest
			Panel A: $k=0$			
b	0.001	0.002	0.002	0.002	0.001	0.001
	(7.87)	(14.22)	(18.62)	(41.03)	(18.95)	(12.04)
R^2	0.003	0.010	0.017	0.005	0.003	0.002
			Panel B: $k=3$			
b	0.004	0.006	0.006	0.005	0.002	0.001
	(10.64)	(17.91)	(20.56)	(64.00)	(25.25)	(15.00)
R^2	0.006	0.016	0.021	0.012	0.005	0.003

Table 2

Fama-MacBeth Regressions of Stock Returns on Beta, Size, and Valuation Ratios

The table reports average slope coefficients from month-by-month Fama-MacBeth regressions. Individual stock returns are regressed cross-sectionally on stock characteristics as of the previous month. The columns correspond to different regression specifications, with non-empty rows indicating the included regressors. The regressors include: preranking CAPM β_t estimated using past 12 months of daily returns with five-lag Dimson (1979) correction, log month-end market cap ($\log M$), book-to-market ($\log BM$), assets-to-market ($\log AM$), EP^+, which equals the positive values of earnings-to-price and zero otherwise, $D(EP < 0)$, which equals one if earnings are negative and zero otherwise, CP^+, and $D(CP < 0)$ (with the last two similarly defined). The last row reports the average adjusted R-squared for each specification. The sample period is January 2000 through December 2016. The t-statistics based on Newey and West (1987) standard errors with four lags are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0148	0.0581	0.0571	0.0672	0.0640	0.0705	0.0566	0.0738	0.0748
	(1.94)	(3.32)	(3.19)	(4.00)	(3.82)	(4.13)	(3.21)	(4.56)	(4.55)
β	−0.0002		−0.0010	−0.0019	−0.0017	0.0002	−0.0010	−0.0002	−0.0004
	(−0.09)		(−0.37)	(−0.73)	(−0.68)	(0.07)	(−0.37)	(−0.07)	(−0.15)
$logME$		−0.0049	−0.0046	−0.0047	−0.0050	−0.0069	−0.0048	−0.0068	−0.0066
		(−2.91)	(−2.69)	(−2.87)	(−3.11)	(−4.43)	(−2.83)	(−4.68)	(−4.61)
$logBM$				0.0055				0.0020	0.0032
				(3.22)				(1.22)	(1.64)
$logAM$					0.0044			0.0013	
					(3.06)			(0.90)	
EP^+						0.8490		0.6845	0.6986
						(4.79)		(4.14)	(4.91)
$D(EP < 0)$						0.0002		−0.0010	−0.0006
						(0.09)		(−0.62)	(−0.36)
CP^+							0.0574	0.0204	
							(3.52)	(1.40)	
$D(CP < 0)$							0.0019	0.0015	
							(3.15)	(2.26)	
R^2	0.0196	0.0277	0.0441	0.0651	0.0676	0.0609	0.0456	0.0827	0.0769

Table 3
Summary Statistics for the CH-3 Factors

This table reports the means, standard deviations, and pairwise correlations for the three factors in the CH-3 model. The means and standard deviations are expressed in percent per month. The sample period is January 2000 through December 2016 (204 months).

			Correlations		
Factor	Mean	Std. Dev.	MKT	SMB	VMG
MKT	0.66	8.09	1	0.12	−0.27
SMB	1.03	4.42	0.12	1	−0.62
VMG	1.11	3.81	−0.27	−0.62	1

Table 4
Abilities of Models CH-3 and FF-3 to Explain Each Other's Size and Value Factors

Panel A reports a factor's estimated monthly alpha (in percent) with respect to the other model (with White, 1980, heteroscedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken(1989) F-test of whether a given model produces zero alphas for the factors of the other model (p-value in parentheses). The sample period is January 2000 through December 2016.

	Alphas with respect to:	
Factors	CH-3	FF-3
Panel A: Alpha (t-statistic)		
$FFSMB$	0.01	-
	(0.22)	-
$FFHML$	0.36	-
	(1.00)	-
SMB	-	0.47
	-	(6.59)
VMG	-	1.40
	-	(7.94)
Panel B: GRS F-statistics (p-value)		
$FFSMB$, $FFHML$	0.52	-
	(0.60)	-
SMB, VMG	-	33.03
	-	(4.11×10^{-13})

Table 5
CAPM Alphas and Betas for Anomalies

For each of ten anomalies, the table reports the monthly long-short return spread's, average ($\bar{R}$), CAPM alpha (α), and CAPM beta (β). In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort. Our sample period is January 2000 through December 2016 (204 months). All t-statistics are based on the heteroscedasticity-consistent standard errors of White (1980).

Category	Anomaly	$\bar{R}$	α	β	$t(\bar{R})$	$t(\alpha)$	$t(\beta)$
			Panel A: Unconditional Sorts				
Size	Market Cap	1.09	0.97	0.18	1.92	1.82	1.90
Value	EP	0.97	1.10	−0.20	1.98	2.38	−2.69
Value	BM	1.04	1.06	−0.04	1.96	2.08	−0.47
Value	CP	0.68	0.66	0.03	1.51	1.54	0.33
Profitability	ROE	0.83	0.93	−0.15	1.77	2.11	−2.08
Volatility	1-Month Vol.	0.81	1.03	−0.34	1.64	2.31	−5.54
Volatility	MAX	0.57	0.81	−0.36	1.26	2.03	−6.39
Reversal	1-Month Return	1.47	1.49	−0.02	2.96	3.07	−0.23
Turnover	12-Month Turn.	0.33	0.53	−0.29	0.63	1.09	−3.46
Turnover	1-Mo. Abn. Turn.	1.14	1.27	−0.19	2.44	2.92	−2.66
			Panel B: Size-Neutral Sorts				
Value	EP	1.78	1.90	−0.18	4.16	4.67	−2.89
Value	BM	0.92	0.93	−0.02	1.87	1.93	−0.21
Value	CP	0.80	0.80	-0.00	2.38	2.41	-0.00
Profitability	ROE	1.45	1.50	−0.07	3.90	4.10	−1.29
Volatility	1-Month Vol.	0.66	0.90	−0.37	1.41	2.19	−6.19
Volatility	MAX	0.39	0.60	−0.32	0.93	1.61	−6.14
Reversal	1-Month Return	1.67	1.66	0.02	3.65	3.68	0.32
Turnover	12-Month Turn.	0.51	0.74	−0.34	1.06	1.75	−4.94
Turnover	1-Mo. Abn. Turn.	1.29	1.39	−0.15	3.19	3.68	−2.56

Table 6
CH-3 Alphas and Factor Loadings for Anomalies

For each of ten anomalies, the table reports the monthly long-short return spread's CH-3 alpha and factor loadings. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{VMG} VMG_t + \epsilon_t,$$

where R_t is the anomaly's long-short return spread in month t, MKT_t is the excess market return, SMB_t is CH-3's size factor, and VMG_t is the EP-based value factor. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort. Our sample period is January 2000 through December 2016. All t-statistics are based on the heteroscedasticity-consistent standard errors of White (1980).

Category	Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$
				Panel A: Unconditional Sorts					
Size	Market Cap	0.23	0.01	1.45	−0.58	1.55	0.66	39.11	−11.81
Value	EP	0.01	−0.00	−0.48	1.31	0.06	−0.02	−6.64	14.43
Value	BM	0.53	0.04	−0.14	0.57	0.91	0.52	−0.73	2.46
Value	CP	0.08	0.13	−0.25	0.70	0.17	1.85	−1.723	3.87
Profitability	ROE	−0.36	0.03	−0.27	1.30	−0.90	0.76	−2.16	9.68
Volatility	1-Month Vol.	0.25	−0.24	−0.10	0.74	0.48	−3.86	−0.60	3.75
Volatility	MAX	0.18	−0.29	−0.00	0.53	0.42	−4.51	−0.02	2.80
Reversal	1-Month Return	0.84	−0.05	0.60	0.04	1.63	−0.65	3.34	0.22
Turnover	12-Month Turn.	0.33	−0.14	−0.81	0.83	1.00	−3.57	−8.42	8.00
Turnover	1-Mo. Abn. Turn.	1.14	−0.22	0.24	−0.09	2.47	−2.69	1.17	−0.40
				Panel B: Size-Neutral Sorts					
Value	EP	0.27	−0.02	0.07	1.31	0.84	−0.50	0.67	10.78
Value	BM	0.53	0.06	−0.19	0.49	0.93	0.79	−1.06	2.26
Value	CP	0.22	0.07	−0.04	0.52	0.64	1.43	−0.29	4.11
Profitability	ROE	−0.32	0.05	0.43	1.17	−0.90	1.22	4.19	9.42
Volatility	1-Month Vol.	0.16	−0.28	−0.05	0.66	0.35	−4.91	−0.30	3.48
Volatility	MAX	−0.09	−0.26	0.10	0.50	−0.21	−4.33	0.57	2.75
Reversal	1-Month Return	1.04	0.01	0.45	0.14	1.90	0.16	2.79	0.77
Turnover	12-Month Turn.	0.13	−0.22	−0.37	0.81	0.36	−4.89	−3.31	6.01
Turnover	1-Mo. Abn. Turn.	1.17	−0.18	0.29	−0.05	2.81	−2.74	1.69	−0.25

Table 7
FF-3 Alphas and Factor Loadings for Anomalies

For each of ten anomalies, the table reports the monthly long-short return spread's CH-3 alpha and factor loadings. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} FFSMB_t + \beta_{HML} FFHML_t + \epsilon_t,$$

where R_t is the anomaly's long-short return spread in month t, MKT_t is the excess market return, SMB_t is FF-3's size factor, and $FFHML_t$ is the BM-based value factor. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort. Our sample period is January 2000 through December 2016. All t-statistics are based on the heteroscedasticity-consistent standard errors of White (1980).

Category	Anomaly	α	β_{MKT}	β_{SMB}	β_{HML}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{HML})$
				Panel A: Unconditional Sorts					
Size	Market Cap	0.14	0.03	1.54	−0.18	1.15	1.59	34.70	−3.96
Value	EP	1.39	−0.09	−1.00	0.46	5.34	−2.40	−15.04	6.05
Value	BM	−0.07	0.01	0.04	1.53	−0.38	0.17	0.75	35.15
Value	CP	0.58	0.08	−0.45	0.50	1.31	1.18	−3.70	2.72
Profitability	ROE	1.77	−0.07	−1.04	−0.27	5.84	−1.42	−12.80	−3.01
Volatility	1-Month Vol.	0.85	−0.29	−0.35	0.56	2.17	−5.33	−2.74	4.73
Volatility	MAX	0.75	−0.33	−0.25	0.29	1.90	−5.67	−1.58	2.20
Reversal	1-Month Return	0.94	−0.06	0.56	0.28	1.97	−0.78	3.79	1.58
Turnover	12-Month Turn.	0.81	−0.18	−1.03	0.50	3.01	−5.15	−12.50	5.06
Turnover	1-Mo. Abn. Turn.	1.29	−0.21	0.16	−0.17	2.77	−2.76	0.93	−0.82
				Panel B: Size-Neutral Sorts					
Value	EP	1.80	−0.12	−0.50	0.56	5.71	−2.39	−6.72	6.46
Value	BM	−0.05	0.03	−0.02	1.37	−0.27	0.74	−0.26	26.09
Value	CP	0.54	0.03	−0.17	0.51	1.84	0.71	−2.13	6.68
Profitability	ROE	2.03	−0.04	−0.41	−0.39	5.90	−0.82	−4.11	−4.15
Volatility	1-Month Vol.	0.77	−0.33	−0.29	0.43	2.09	−6.00	−2.27	4.13
Volatility	MAX	0.47	−0.29	−0.14	0.30	1.24	−5.58	−0.91	2.81
Reversal	1-Month Return	1.22	−0.00	0.37	0.28	2.59	−0.03	2.83	1.76
Turnover	12-Month Turn.	0.76	−0.27	−0.63	0.51	2.44	−6.03	−5.95	5.26
Turnover	1-Mo. Abn. Turn.	1.33	−0.17	0.21	−0.09	3.17	−2.81	1.41	−0.55

Table 8
Comparing Models' Abilities to Explain Anomalies

The table reports measures summarizing the degree to which anomalies produce alphas under three different factor models: CAPM, FF-3, and CH-3. Also reported are measures for "unadjusted" return spreads (i.e., for a model with no factors). For each model, the table reports the average absolute monthly alpha (in percent), average absolute t-statistic, the Gibbons, Ross, and Shanken (1989) "GRS" F-statistic with associated p-value, and the number of anomalies for which the model produces the smallest absolute alpha among the four models. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort. Two versions of the GRS test are reported. In Panel A, GRS_{10} uses all ten anomalies, while GRS_7 excludes the anomalies for size, BM, and EP, which are variables used to construct factors. In Panel B, the market cap anomaly is excluded throughout. The sample period is from January 2000 through December 2016 (204 months).

Measure	Unadjusted	CAPM	FF-3	CH-3
		Panel A: Unconditional Sorts		
Average $\|\alpha\|$	0.89	0.98	0.86	0.40
Average $\|t\|$	1.80	2.04	2.55	0.99
GRS_{10}	6.86	5.82	5.82	1.33
p_{10}	3.73×10^{-9}	2.66×10^{-9}	1.22×10^{-7}	0.22
GRS_7	4.08	4.17	6.66	1.36
p_7	3.00×10^{-4}	3.00×10^{-4}	4.49×10^{-7}	0.22
		Panel B: Size-Neutral Sorts		
Average $\|\alpha\|$	1.05	1.15	1.00	0.43
Average $\|t\|$	2.50	2.80	2.79	0.97
GRS_9	8.08	8.02	8.05	1.98
p_9	3.72×10^{-10}	4.65×10^{-10}	4.28×10^{-10}	0.04
GRS_7	8.47	8.44	9.14	2.32
p_7	4.75×10^{-9}	5.20×10^{-9}	9.50×10^{-10}	0.03

Table 9
Anomaly Alphas under a Four-Factor Model

For each of ten anomalies, the table reports the monthly long-short return spread's CH-4 alpha and factor loadings. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{VMG} VMG_t + \beta_{PMO} PMO_t + \epsilon_t,$$

where R_t is the anomaly's long-short return spread in month t, MKT_t is the excess market return, SMB_t is CH-3's size factor, VMG_t is the EP-based value factor, and PMO_t (Pessimistic minus Optimistic) is the sentiment factor based on abnormal turnover. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort. Our sample period is January 2000 through December 2016. All t-statistics are based on the heteroscedasticity-consistent standard errors of White (1980).

Category	Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	β_{UMO}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$	$t(\beta_{UMO})$
Panel A: Unconditional Sortings											
Size	Market Cap	0.28	0.04	1.49	−0.45	0.00	1.63	2.78	36.27	−6.75	0.04
Value	EP	−0.11	−0.03	−0.53	1.28	0.05	−0.49	−0.96	−6.74	12.97	0.50
Value	BM	0.55	0.02	−0.15	0.54	−0.04	0.80	0.25	−0.79	2.15	−0.17
Value	CP	0.16	0.09	−0.23	0.70	−0.16	0.26	1.36	−1.64	3.56	−0.86
Profitability	ROE	−0.36	−0.02	−0.31	1.31	−0.10	−0.87	−0.43	−2.77	8.94	−0.93
Volatility	1-Mon Vol.	−0.27	−0.16	−0.26	0.58	0.72	−0.50	−2.65	−1.71	3.14	5.07
Volatility	MAX	−0.56	−0.18	−0.13	0.42	0.88	−1.58	−3.07	−0.92	3.08	7.73
Reversal	1-Month Return	0.47	0.02	0.55	0.05	0.45	0.84	0.28	3.35	0.23	2.46
Turnover	12-Month Turn.	−0.10	−0.10	−0.89	0.72	0.43	−0.30	−3.15	−10.46	5.92	3.85
Turnover	1-Mo. Abn. Turn.	−0.06	−0.01	0.09	−0.23	1.43	−0.24	−0.30	0.83	−2.26	16.05
Panel B: Size-Neutral Sorts											
Value	EP	0.32	−0.06	0.01	1.30	−0.06	0.89	−1.32	0.05	9.98	−0.48
Value	BM	0.48	0.05	−0.20	0.45	0.05	0.71	0.69	−1.17	1.90	0.22
Value	CP	0.26	0.04	−0.03	0.54	−0.10	0.70	0.83	−0.25	3.99	−0.91
Profitability	ROE	−0.29	0.03	0.37	1.21	−0.05	−0.70	0.65	3.47	8.41	−0.38
Volatility	1-Month Vol.	−0.29	−0.21	−0.18	0.52	0.64	−0.64	−3.86	−1.20	2.88	4.84
Volatility	MAX	−0.73	−0.16	0.00	0.42	0.74	−1.97	−2.86	0.01	3.05	5.69
Reversal	1-Month Return	0.68	0.07	0.42	0.14	0.42	1.23	1.16	2.80	0.79	2.58
Turnover	12-Month Turn.	−0.25	−0.18	−0.46	0.71	0.44	−0.67	−4.06	−4.15	4.77	3.51
Turnover	1-Mo. Abn. Turn.	0.14	−0.00	0.17	−0.15	1.21	0.59	−0.06	1.84	−1.79	15.06

APPENDIX

Section A1 provides details of the data sources and the filters we apply. Section A2 details the anomalies and their construction. Section A3 provides further details about China's IPO review process. Section A4 explains the reverse-merger data and the shell-value estimation, while section A5 examines the hypothesis that the smallest 30% of stocks covary more with shell-value proxies. Section A6 presents additional comparisons of model CH-3 to models FF-3 and FF-5.

A.1. Data sources and filters

Our stock trading data and firm financial data all come from WIND. Our sample includes all A-share stocks from the main boards of the Shanghai and Shenzhen exchanges as well as the board of the GEM (Growth Enterprises Market), essentially the Chinese counterpart of NASDAQ. In China, stock tickers for listed firms are non-reusable unique identifiers. The ticker contains six digits, of which the first two indicate the exchange and the security type. We include stocks whose first two digits are 60, 30, and 00. Our sample period is January 2000 through December 2016.

We also impose several filters: First, we exclude stocks that have become public within the past six months. Second, we exclude stocks having less than 120 days of trading records during the past 12 months. We also exclude stocks having less than 15 days of trading records during the most recent month. The above filters are intended to prevent our results from being influenced by returns that follow long trading suspensions. Third, for the reason explained in Section 3, we eliminate the bottom 30% of stocks ranked by market capitalization at the end of the previous month. Market capitalization is calculated as the closing price times total shares outstanding, including non-tradable shares.

When we use financial-statement information to sort stocks, in constructing either factors or anomaly portfolios, the sort at the end of a given month uses the information in a firm's financial report having the most recent public release date prior to that month's end. (The WIND data include release dates.) Firms' financial statement data are from quarterly reports beginning January 1, 2002, when public firms were required to report quarterly. Prior to that date, our financial statement data are from semi-annual reports.

A.2. Firm characteristics and anomaly portfolios

We survey the literature documenting anomalies in China, and we compile here, to our knowledge, an exhaustive list of stock characteristics identified as cross-sectional predictors of future returns. The list comprises nine categories: size, value, profitability, volatility, investment, accruals, illiquidity, reversal, and turnover. Within each category, one or more firm-level characteristics are identified as return predictors. The anomalies, by category, are as follows;

1. Size. The stock's market capitalization is used in this category. It is computed as the previous month's closing price times total shares outstanding, including non-tradable shares.
2. Value. Three variables are used.

- Earnings-price ratio (EP). Earnings equals the most recently reported annualized net profit excluding non-recurrent gains/losses. A stock's EP is the ratio of earnings to the previous month's size.
- Book-to-market ratio (BM). Book equity equals total shareholder equity minus the book value of preferred stocks. A stock's BM is the ratio of book equity to size.
- Cash-flow-to-price (CP). Cash flow equals the net change in cash or cash equivalents between the two most recent cash-flow statments.[22] A stock's CP is the ratio of cash flow to size.

3. Profitability. Firm-level ROE at the quarterly frequency is used. ROE equals the ratio of a firm's earnings to book equity, with earnings and book equity defined above.
4. Volatility. Two variables are used.
   - One-month volatility. A firm's one-month volatility is calculated as the standard deviation of daily returns over the past 20 trading days.
   - MAX. MAX equals the highest daily return over the previous month.
5. Investment. As in Fama and French (2015), a firm's investment is measured by its annual asset growth rate. Specifically, a firm's asset growth equals total assets in the most recent annual report divided by total assets in the previous annual report.
6. Accruals. Two variables are used.
   - Accruals. We construct firm-level accruals following Sloan (1996). Specifically, a firm's accruals in year t can be expressed as:
   $$Accrual = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep$$
   where ΔCA equals the most recent year-to-year change in current assets, $\Delta Cash$ equals the change in cash or cash equivalents, ΔCL equals the change in current liabilities, ΔSTD equals the change in debt included in current liabilities, ΔTP equals the change in income taxes payable, and Dep equals the most recent year's depreciation and amortization expenses.
   - Net-operating-assets (NOA). We construct firm-level NOA, following Hirshleifer, Hou, Teoh, and Zhang (2004). Specifically, a firm's NOA is calculated as:
   $$NOA = (Operating\ Asset_t - Operating\ Liability_t)/Total\ Asset_{t-1}$$
   where $Operating\ Asset_t$ equals total assets minus cash and short-term investment, $Operating\ Liability_t$ equals total assets minus short-term debt, long-term debt, minority interest, book preferred stock, and book common equity.
7. Illiquidity. We compute a stock's average daily illiquidity over the past 20 trading days. Following Amihud (2002), a stock's illiquidity measure for day t is calculated as
   $$Illiq_t = |ret_t|/volume_t$$
   where $|ret_t|$ is the stock's absolute return on day t, and $volume_t$ is the stock's dollar trading volume on day t.

[22] Prior to January 2002, cash flow equals half the net change between the two most recent semi-annual statements.

8. Turnover. Two variables are used.

    - Twelve-month turnover. We measure twelve-month turnover as the average daily share turnover over the past 250 days. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.
    - One-month abnormal turnover. A firm's abnormal turnover is calculated as the ratio of its average daily turnover over the past 20 days to its average daily turnover over the past 250 days.

9. Reversal. The sorting measure used is the stock's one-month return, computed as the cumulative return over the past 20 trading days.

For every anomaly except one-month return reversal, we sort the stock universe each month using the most recent month-end measures and then hold the resulting portfolios for one month. Because one-month return reversal is a short-term anomaly, we sort the stock universe each day based on the most recently available 20-day cumulative return. Using this sort, we rebalance a one-fifth "slice" of the total portfolio that is then held for five trading days. Each day we average the returns across the five slices. Those resulting daily returns are then compounded across days to compute the reversal anomaly's monthly return. For all anomalies, value-weighted portfolios of stocks within the top and bottom deciles are formed using the most recent month-end market capitalizations as weights.

A.3. The IPO review process in China

The process of IPO review by the CSRC involves seven steps:

1. Confirmation of application receipt. The reception department in the bureau organizes all of the application packages, confirms with each applicant firm the receipt of all materials, and makes the offering proposals public.

2. Application material pre-check (feedback provided). In this step, the offering administration department assigns a team to pre-check all application materials and prepare a written report indicating whether more material/information is needed and suggesting the potential concerns or issues with the offering for further reviews. After receiving the written report, the applicant firm can work with investment bankers to revise the application package.

3. Communication meeting. The applicant's IPO team meets with the offering administration department, but no material issues are discussed.

4. Update disclosed offering proposal. After revising the application package and upon receiving the offering administration team's approval, the applicant's team can revise the initially disclosed offering proposal.

5. Initial review meeting. An offering committee team and the offering administrative department attend the meeting to review thoroughly whether the applicant firm's current condition and growth prospects satisfy IPO criteria.

6. Final offering review meeting. A different offering committee team votes on whether or not to approve the firm's IPO application based on the results of the initial review meeting discussion.

7. Offering. The applicant firm may still need to revise its application package based on the decision in the Final Offering Review Meeting. Following that, the firm can prepare the offering.

A.4. Reverse-merger data and shell-value estimation

Our reverse merger data are from WIND and cover the 2007 to 2016 period. In July 2007, the CSRC issued a ruling that formed a special committee in its Public Offering Department to strengthen the review process for M&A applications. Subsequently, the CSRC took a more active role in the M&A review process, increasing reporting transparency and quality. In the same ruling, the CSRC identified several characteristics of M&A cases that classify them as reverse mergers, to be handled with more scrutiny. The improved reporting transparency and CSRC's specification of reverse mergers made it possible to trace reverse-merger cases.

To construct the daily series of estimated shell values, we first estimate p and G in equation (1) as follows:

1. Probability of becoming a shell (p). Each day, we calculate the fraction of stocks, among those in the bottom 30%, involved in reverse merger deals during the past 730 calendar days. We use that fraction as the empirical probability estimate of becoming a shell within in a two-year window, converting the value to a one-year probability (essentilly by halving it).

2. Value appreciation upon becoming a shell (G). For each reverse merger case among the bottom 30%, the value appreciation equals the change in market value over a time window beginning 60 days before the board's announcement of a proposed deal proposal and ending 60 days after the deal's CSRC approval. On each day, the estimated value of G is the average value appreciation in all reverse-merger deals whose windows end during the past 730 calendar days.

A.5. Return variation related to shell value

Here we investigate the sensitivity of the returns on the smallest stocks to two variables that proxy for fluctuations in shell values. The first variable reflects variation in the reverse-merger premium. For each reverse-merger event, we define an event window beginning 60 days before the shell firm's board meeting announcing the proposal and ending 60 days after CSRC approval. Each day we compute the average return of all stocks that are within their event window, and then we compound those daily average returns to form a reverse-merger return for month t, RM_t. We associate a relatively high value of RM_t with an increase in shell value during that month. Our hypothesis is that returns on stocks in the bottom 30% of the size distribution are more sensitive to RM_t than are other stocks. For each of three size groups, formed by dividing the universe of all listed stocks at the 30th and 70th percentiles, we estimate the regression,

$$R_t = a + bRM_t + \gamma F_t + \epsilon_t \tag{A1}$$

where R_t is the size group's value-weighted monthly return, and the vector F_t contains the other two size groups' returns. For example, when the regression has the return on the smallest stocks on the left-hand side, F_t includes the returns on the middle- and large-cap groups. We expect b to be positive for the smallest stocks but not for the other two size groups. Panel A of Table A2 reports the regression results. We see that indeed the estimate of b is significantly positive for the smallest stocks but is negative for the other two size groups.

The second proxy for capturing fluctuations in shell value is the log of the total number of IPOs in month t, with the rationale that a greater frequency of IPOs could be interpreted by the market as a relaxing of IPO constraints and thus a reduction in reverse-merger shell value. Under our shell-value hypothesis, we expect stock returns to covary negatively with IPO numbers for the smallest stocks but not for the other two size groups. The regression is the same as regression (A1) except that RM_t is replaced by the log IPO number, $log(NIPO_t)$. Panel B of Table A2 reports the results. Consistent with our hypothesis, the estimate of b is negative for the smallest stocks, although the t-statistic of -1.51 falls somewhat short of significance. In contrast, the estimate of b is insignificant and positive (t-statistic: 1.18) for the middle group, while it has a t-statistic of just -0.50 for the large-cap group.

The results from both sets of regressions are consistent our hypothesis that the returns on stocks in the bottom 30% reflect, in substantial part, variation in the value of being a potential reverse-merger shell. In other words, the values of these "small" stocks reflect more than the businesses of the underlying small firms.

A.6. Additional model comparisons

Model CH-3 dominates FF-3 not only in the frequentist comparisons reported in Table 4 but also in a Bayesian comparison that follows the Stambaugh and Yuan (2017) procedure in applying the analysis of Barillas and Shanken (2017). Suppose we compare two models, M_1 and M_2, and before observing the data we assign probabilities $p(M_1)$ and $p(M_2)$ to each model being the right one, with $p(M_1)+p(M_2) = 1$. After observing the data, D, the posterior probability of model i is given by

$$p(M_i|D) = \frac{p(M_i) \cdot p(D|M_i)}{p(M_1) \cdot p(D|M_1) + p(M_2) \cdot p(D|M_2)}, \tag{A2}$$

where model i's marginal likelihood is given by

$$p(D|M_i) = \int_{\theta_i} p(\theta_i)p(D|\theta_i)d\theta_i, \tag{A3}$$

where $p(\theta_i)$ is the prior distribution for model i's parameters, and $p(D|\theta_i)$ is the likelihood function for model i. As shown by Barillas and Shanken (2017), when D includes observations of the factors in both models (including the market) as well as a common set of "test" assets, the latter drop out of the computation in Equation (A2). Moreover, that study also shows that when $p(\theta_i)$ follows a form as in Pástor and Stambaugh (2000), then $p(D|M_i)$ can be computed analytically. The key feature of the prior, $p(\theta_i)$, is that it is informative about how large a Sharpe ratio can be produced by combining a given set of assets, in this case the assets represented by the model's factors. Specifically, the prior implies a value for the expected maximum squared Sharpe ratio, relative to the (observed) Sharpe ratio of the market. We use the Barillas and Shanken (2017) analytical results here to compute posterior model probabilities in the above two-way model comparison. Prior model probabilities of each model are set to one-half.

Figure 3 displays posterior model probabilities in the comparison of CH-3 to FF-3. The value on the horizontal axis is the square root of the prior expected maximum squared Sharpe ratio achievable by combining the model's factors, $[\mathrm{E}_{\mathrm{prior}}\{S^2_{MAX}\}]^{1/2}$, divided by the observed Sharpe ratio of the market, S_{MKT}. We see that the data strongly favor CH-3 over FF-3. In fact, the posterior probability of CH-3 essentially equals one if the Sharpe-ratio multiplier on the horizontal axis exceeds only 1.05 or so, corresponding to a prior expectation that the market's Sharpe ratio can be improved only very modestly.

We also find that CH-3 dominates the frequentist comparisons reported in Table 4 when FF-3 is replaced by FF-5, the replication in China of the five-factor model in Fama and French (2015). Table A3 reports those results. As with FF-3, FF-5 fails to explain either SMB or VMG from model CH-3, leaving those factors' FF-3 alphas with t-statistics of 2.54 and 3.54 and producing a GRS p-value of just 0.0007. In contrast, the CH-3 alphas for the four non-market factors in FF-5 are all insignificant, having t-statistics of 1.04 or less in magnitude and producing a large GRS p-value of 0.88.

Table A1
Chinese Anomalies in the Literature

The table provides a compilation of the anomalies reported by one or more studies as being significant in China. The studies analyzing each anomaly are listed, including those reporting an anomaly to be insignificant (identified as such in the table). For each anomaly variable, we also report CAPM alphas for both unconditional and conditional sorts. For the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, where a high value of the measure is associated with lower return. For the conditional sorts, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form ten value-weighted anomaly portfolios, where each portfolio pools the stocks in a given anomaly decile across the size groups. The remaining steps follow those for the unconditional sort. Our sample period is January 2000 through December 2016 (204 months). All t-statistics (in parentheses) are based on the heteroscedasticity-consistent standard errors of White (1980).

			CAPM alpha (monthly %)	
Category	Anomaly	References	Unconditional	Size-neutral
Size	Market Cap	Wang and Xu (2004), Eun and Huang (2007), Cheung et al. (2015), Chen et al. (2015), Cakici, Chan, and Topyan (2015), Hsu, Viswanathan, Wang, and Wool (2017), and Carpenter, Lu, and Whitelaw (2017). Reported insignificant: Chen et al. (2010) and Cheung et al. (2015).	0.97 (1.82)	—
Value	EP	Cakici et al. (2015) and Hsu et al. (2017). Reported insignificant: Chen et al. (2010) and Chen et al. (2015).	1.10 (2.38)	1.90 (4.67)
Value	BM	Wang and Xu (2004), Eun and Huang (2007), Chen et al. (2010), Cheung et al. (2015), Cakici et al. (2015), Hsu et al. (2017), and Carpenter et al. (2017). Reported insignificant: Chen et al. (2015).	1.06 (2.08)	0.93 (1.93)
Value	CP	Cakici et al. (2015). Reported insignificant: Wang and Di Iorio (2007) and Chen et al. (2010).	0.66 (1.54)	0.80 (2.41)
Profitability	ROE	Guo et al. (2017). Reported insignificant: Li, Yao, and Pu (2007).	0.93 (2.11)	1.50 (4.10)
Volatility	1-Mo. Vol.	Cheung et al. (2015), Cakici et al. (2015), and Hsu et al. (2017). Reported insignificant: Chen et al. (2010).	1.03 (2.31)	0.90 (2.19)
Volatility	MAX	Carpenter et al. (2017).	0.81 (2.03)	0.60 (1.61)

Table A1
Anomalies List (Continued)

Category	Anomaly	References	CAPM alpha (monthly %) Unconditional	Size-neutral
Reversal	1-Month Return	Cakici et al. (2015), Hsu et al. (2017), and Carpenter et al. (2017). Reported insignificant: Cheung et al. (2015).	1.49 (3.07)	1.66 (3.68)
Turnover	12-Mo. Turn.	Zhang and Liu (2006) and Eun and Huang (2007). Reported insignificant: Chen et al. (2010).	0.53 (1.09)	0.74 (1.75)
Turnover	1-Mo. Abn. Turn.	Li (2004) and Zhang and Liu (2006).	1.27 (2.92)	1.39 (3.68)
Investment	Asset Growth	Chen et al. (2010). Reported insignificant: Hsu et al. (2017), Guo et al. (2017), and Lin (2017).	0.22 (0.72)	−0.05 (−0.20)
Accruals	Accruals	Li, Niu, Zhang, and Largay (2011) and Hsu et al. (2017). Reported insignificant: Chen et al. (2010).	0.08 (0.39)	−0.15 (−0.70)
Accruals	NOA	Chen et al. (2010) and Hsu et al. (2017).	0.38 (1.03)	0.42 (1.22)
Illiquidity	Amihud-Illiq.	Carpenter et al. (2017) and Chen et al. (2010).	0.83 (1.62)	0.63 (1.55)

Table A2
Sensitivities of Size-Group Returns to Proxies for Fluctuations in Shell Values

For each of three size groups, formed by dividing the universe of all listed stocks at the 30th and 70th percentiles, the table reports the estimate of b in the regression,

$$R_t = a + bShell_t + \gamma F_t + \epsilon_t,$$

where R_t is the value-weighted return for the size group, $Shell$ is a proxy for fluctuations in the value of potentially becoming a reverse-merger shell, and the vector F_t contains the returns on the other two size groups. In Panel A, $Shell_t$ is the average return of shell stocks experiencing reverse mergers, RM_t. In Panel B, $Shell_t$ is the log number of IPOs, $\log(NIPO_t)$. The sample period is January 2007 through December 2016. All t-statistics (in parentheses) are based on the heteroscedasticity-consistent standard errors of White (1980).

Smallest Stocks	Middle	Largest Stocks
Panel A. $Shell_t = RM_t$		
0.963	−1.267	−0.330
(2.19)	(−3.02)	(−4.65)
Panel B. $Shell_t = \log(NIPO_t)$		
−0.023	0.013	−0.001
(−1.53)	(1.18)	(−0.50)

Table A3
Abilities of Models CH-3 and FF-5 to Explain Each Other's Factors

Panel A reports a factor's estimated monthly alpha (in percent) with respect to the other model (with White, 1980, heteroscedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken(1989) F-test of whether a given model produces zero alphas for the factors of the other model (p-value in parentheses). The sample period is January 2000 through December 2016.

	Alphas with respect to:	
Factors	CH-3	FF-5
Panel A: Alpha (t-statatistics)		
SMB	-	0.20
	-	(2.54)
VMG	-	0.40
	-	(3.45)
$FFSMB$	0.00	-
	(-0.43)	-
$FFHML$	0.40	-
	(1.04)	-
$FFRMW$	-0.10	-
	(-0.78)	-
$FFCMA$	0.10	-
	(0.52)	-
Panel B: GRS F-statistics (p-value)		
SMB, VMG	-	7.52
	-	(0.0007)
$FFSMB$, $FFHML$,	0.30	-
$FFRMW$, $FFCMA$	(0.88)	-

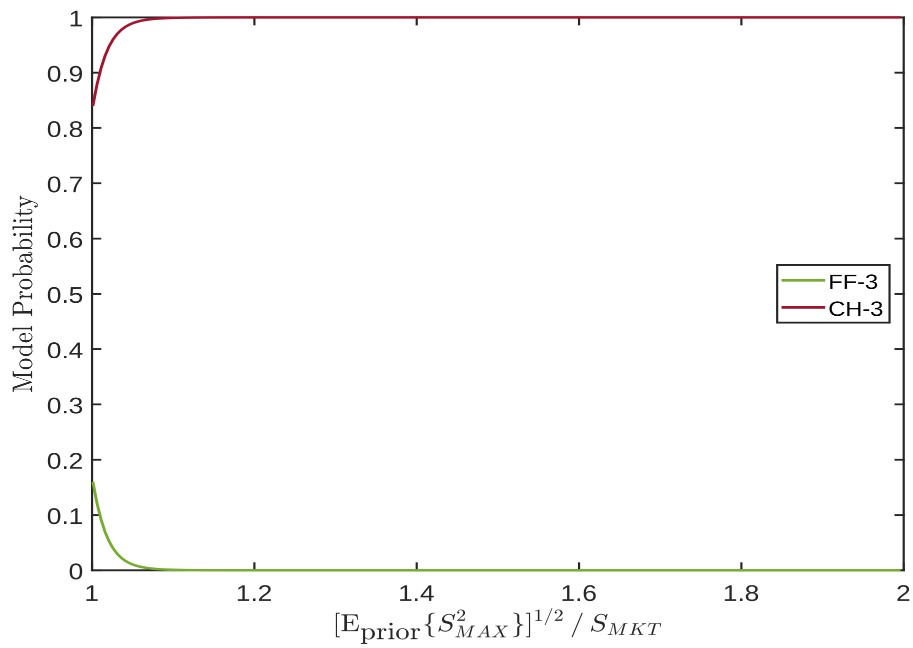


Figure A.1. Model probabilities comparing model CH-3 to model FF-3 The figure displays Bayesian posterior model probabilities for the two-way model comparison. The value on the horizontal axis is the square root of the prior expected maximum Sharpe ratio achievable by combining the model's factors, divided by the observed Sharpe ratio of the market. Prior model probabilities are equal. The sample period is from January 2000 through December 2016 (204 months)

References

Adjei, F., Cyree, K. B., Walker, M. M., 2008. The determinants and survival of reverse mergers vs IPOs. Journal of Economics and Finance 32, 176–194.

Allen, F., Qian, J., Qian, M., 2003. Comparing China' s financial system. China Journal of Finance 1, 1–28.

Allen, F., Qian, J., Qian, M., 2005. Law, finance, and economic growth in China. Journal of Financial Economics 77, 57–116.

Allen, F., Qian, J., Qian, M., Zhao, M., 2009. A review of China's financial system and initiatives for the future. In: *China's emerging financial markets*, Springer, Boston, MA, pp. 3–72.

Allen, F., Qian, J., Shan, C., Zhao, M., 2014. The IPO of industrial and commercial bank of China and the 'Chinese Model' of privatizing large financial institutions. European Journal of Finance 20, 599–624.

Allen, F., Qian, J., Shan, C., Zhu, J. L., 2017. Dissecting the long-term performance of the Chinese stock market. Unpublished Working Paper.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Baker, M., Stein, J. C., 2004. Market liquidity as a sentiment indicator. Journal of Financial Markets 7, 271–299.

Ball, R., 1992. The earnings-price anomaly. Journal of Accounting and Economics 15, 319–345.

Banz, R. W., 1981. The relationship between return and market value of common stocks. Journal of Financial Economics 9, 3–18.

Barillas, F., Shanken, J., 2017. Comparing asset pricing models. Journal of Finance, forthcoming .

Basu, S., 1983. The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. Journal of Financial Economics 12, 129–156.

Bian, J., Da, Z., Lou, D., Zhou, H., 2017. Leverage network and market contagion. Unpublished Working Paper.

Brunnermeier, M. K., Sockin, M., Xiong, W., 2017. China's model of managing the financial system. Unpublished Working Paper.

Cakici, N., Chan, K., Topyan, K., 2015. Cross-sectional stock return predictability in China. European Journal of Finance .

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance 52, 57.

Carpenter, J. N., Lu, F., Whitelaw, R. F., 2017. The real value of China's stock market. Unpublished Working Paper.

Carpenter, J. N., Whitelaw, R. F., 2017. The development of China's stock market and stakes for the global economy. Annu. Rev. Financ. Econ 9, 233–57.

Chen, C., Hu, X., Shao, Y., Wang, J., 2015. Fama-French in China: size and value factors in Chinese stock returns. Unpublished Working Paper.

Chen, X., Kim, K. A., Yao, T., Yu, T., 2010. On the predictability of Chinese stock returns. Pacific-Basin Finance Journal 18, 403–425.

Cheung, C., Hoguet, G., Ng, S., 2015. Value, size, momentum, dividend yield, and volatility in China's A-share market. The Journal of Portfolio Management 41, 57–70.

China Securities Regulatory Commission, 2008. Chinese Capital Market Developmental Report (Translated from Mandarin).

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics 7, 197–226.

Eun, C. S., Huang, W., 2007. Asset pricing in China's domestic stock markets: Is there a logic? Pacific Basin Finance Journal 15, 452–480.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Fan, L., Shan, Y., 2004. Trading volume, valuation ratio, momentum and a three-factor model (Translated from Mandarin). Journal of Management Science 7, 13–22.

Floros, I. V., Sapp, T. R. A., 2011. Shell games: On the value of shell companies. Journal of Corporate Finance 17, 850–867.

Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57, 1121.

Guo, B., Zhang, W., Zhang, Y., Zhang, H., 2017. The five-factor asset pricing model tests for the Chinese stockmarket. Pacific-Basin Finance Journal 43, 84–106.

Hirshleifer, D., Hou, K., Teoh, S., Zhang, Y., 2004. Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

Hsu, J. C., Viswanathan, V., Wang, C., Wool, P., 2017. Anomalies in Chinese A-shares. Unpublished Working Paper.

Jiang, J., Qian, K., Gong, F., 2016. Institutional holdings' structure analysis in China (Translated from Mandarin). Tech. rep., Shenwan Hongyuan Research CO.

Lee, C., Qu, Y., Shen, T., 2017. Reverse mergers, shell value, and regulation risk in Chinese equity markets. Unpublished Working Paper.

Lee, E., 2013. Individual stock investor sentiment, stock issuance, and financial market anomalies. Ph.D. thesis, University of Pennsylvania.

Li, Y., 2004. An empirical analysis of the liquidity premium in China (Translated from Mandarin). Ph.D. thesis.

Li, Y., Niu, J., Zhang, R., Largay, J. A., 2011. Earnings management and the accrual anomaly: Evidence from China. Journal of International Financial Management & Accounting 22, 205–245.

Li, Z., Yao, Z., Pu, J., 2007. What is the economics of ROE in China's stock market? (Translated from Mandarin). Chinese Accounting Review 3, 305–314.

Lin, Q., 2017. Noisy prices and the Fama-French five-factor asset pricing model in China. Emerging Markets Review 31, 141–163.

Newey, W. K., West, K. D., 1987. A simple positive-definite heteroskedasticity and autocorrelation-consistent covariance matrix. Econometrica 55, 703–708.

Pástor, L., Stambaugh, R. F., 2000. Comparing asset pricing models: An investment perspective. Journal of Financial Economics 56, 335–381.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Accounting Review 71, 289–315.

Song, Z., Xiong, W., 2017. Risks in China's financial system. Unpublished Working Paper.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing factors. Review of Financial Studies 30, 1270–1315.

Wang, C., Chin, S., 2004. Profitability of return and volume-based investment strategies in China's stock market. Pacific Basin Finance Journal 12, 541–564.

Wang, F., Xu, Y., 2004. What determines Chinese stock returns? Financial Analysts Journal 60, 65–77.

Wang, Y., Di Iorio, A., 2007. The cross section of expected stock returns in the Chinese A-share market. Global Finance Journal 17, 335–349.

White, H., 1980. A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. Econometrica 48, 817–838.

Yang, X., Chen, Z., 2003. An empirical analysis of the three-factor model in China (Translated from Mandarin). Quantitative Economics Review 12.

Zhang, Z., Liu, L., 2006. Turnover Premium: Is it a liquidity premium or bubble? (Translated from Mandarin). Quarterly Economics Journal 3, 871–892.