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Forthcoming Management Science

Replicating and Digesting Anomalies in the Chinese A-share Market*

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Abstract

We replicate 469 anomaly variables similar to those studied by Hou, Xue, and Zhang (2020) using Chinese A-share data and a reliable testing procedure with mainboard breakpoints and value-weighted returns. We find that 83.37% of the anomaly variables do not generate significant high-minus-low quintile raw return spreads. Further adjusting risk increases the failure rate slightly to 84.22% based on CAPM alphas and 86.99% based on Fama–French 3-factor alphas. We show that the conventional procedure using all A-share breakpoints with equal-weighted returns for the anomaly test is indeed problematic, as it assigns too much weight to microcaps and has a very limited investment capacity. The CH3-factor, CH4-factor, and *q*-factor models show the best performance over the whole sample period. The *q*-factor model is the best performer in the post-2007 subsample period, after significant improvements occurred in China's financial market environment, such as the completion of the split-share structure reform and the implementation of new accounting standards conforming to the IFRS. The non-SOE subsample in the post-2007 period is a cleaner sample, in which the CH4-factor and *q*-factor models are the best performers.

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Abstract

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JEL Classification: G11; G12; G15

Keywords: Replication; Chinese A-share market; Anomalies; Factor models; SOEs vs. non-SOEs

1. Introduction

In the years since Ioannidis (2005) argued that most research results are not replicable, replication research has attracted extensive attention in various fields; only recently, however, has it become a major topic in the field of finance. Harvey et al. (2016) and Hou et al. (2020, HXZ hereafter) find that there is a high replication failure rate for stock market anomalies identified in the finance and accounting literature.[1] HXZ (2020) summarize 452 anomalies in the U.S. market and find that 65% of them cannot be replicated. In this paper, we replicate 469 anomalies similar to those studied by HXZ, using Chinese data and incorporating the special features of the Chinese stock market. In addition, we test the performance of the Chinese versions of seven prominent factor models in terms of explaining the significant anomalies that we find. These include five models originally developed for the U.S. market, namely the CAPM, the Fama–French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (Car4), the Fama–French (2015) five-factor model (FF5), and the HXZ (2015) *q*-factor model (*q*-factor), as well as two models designed specifically for the Chinese stock market, namely the CH3-factor (CH3) and CH4-factor (CH4) models proposed by Liu et al. (2019).

The Chinese stock market is the world's second largest after the U.S. market, based on market capitalization and trading volume. However, whereas many studies have provided factor model comparison evidence from the U.S. market (e.g., HXZ 2015; Hou et al. 2019, 2021, HMXZ hereafter; Cooper and Maio 2019a, 2019b; Ahmed et al. 2019), few studies have explored which factor model performs best in the Chinese market. Liu et al. (2019) propose a new three-factor model (i.e., the CH3-factor model) that considers the special features of the Chinese stock market and find that this model performs well. Most of the Chinese stock market literature focuses on only a few anomaly variables; thus, large-scale anomaly tests in the Chinese stock market are warranted. In this paper, we attempt to provide the largest anomaly test to

[1] The terms "anomaly" and "anomalies" are used loosely in the finance literature. Cochrane (2011) and Harvey et al. (2016) use the term "factor" in place of "anomaly." For instance, Cochrane (2011) describes the discovery of many new anomalies as "the factor zoo" (p. 1063) or "the zoo of new variables" (p. 1061). Strictly speaking, an anomaly should be defined based on a particular benchmark model such as the CAPM. However, there is no consensus on the right benchmark model. We follow the literature (e.g., HXZ 2015, 2020) and loosely define an anomaly variable based on a high-minus-low decile or quintile sorted on a particular firm characteristic (e.g., firm size) that has been found in the literature to generate a significant raw return spread.

date in the Chinese stock market.

One major issue in connection with the Chinese stock market is whether it is market-oriented and efficient. Fortunately, this became less of an issue in 2007 after the completion of the split-share structure reform and the implementation of new accounting standards. The split-share structure reform made all shares tradable and brought the interests of controlling and minority shareholders into closer alignment, significantly reducing agency problems. The new accounting standards are of much higher quality (Ho et al. 2015) and have helped to standardize the interpretation of accounting variables across countries. Importantly, Carpenter et al. (2021) find that stock prices in China were not informative before 2004, but have since become as informative as those in the U.S., as evidenced by the positive relation between corporate investment efficiency and stock price informativeness. As a result of these notable events, and on the strength of the evidence from Carpenter et al. (2021), we expect the post-2007 subsample period to provide a better playing field for asset-pricing tests in China. We conduct empirical tests for both the whole sample period (2000–2019) and the post-2007 subsample period, and we believe that the post-2007 subsample period is more appropriate for asset-pricing tests in China. Another special feature of the Chinese stock market is the high number of state-owned enterprises (SOEs). For example, at the end of 2003, 74.57% of firms in the Chinese A-share market were SOEs. The objective of SOEs is not strictly profit maximization (e.g., Carpenter et al. 2021); we therefore also split all firms into SOE and non-SOE subsamples and redo our baseline analysis.

To conduct each test, we first sort all stocks into quintiles based on a firm characteristic such as book-to-market equity and then compute the average high-minus-low quintile raw return. Following HXZ (2020), we classify these anomaly variables into six categories: momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions. Not all of the documented anomalies in the U.S. market produce significant raw return spreads in China. When we use the Mainboard-VW procedure (Mainboard breakpoints with value-weighted returns in portfolio sorting) over the whole sample period, only 78 of the 469 (16.63%) anomaly variables have significant high-minus-low quintile returns with the single hypothesis testing (SHT hereafter) hurdle of $|t| \geq 1.96$, and 29 (6.18%) with the multiple hypothesis testing

(MHT hereafter) hurdle of $|t| \geq 2.78$, both of which are significant at the 5% level (Harvey et al. 2016). In the post-2007 subsample period, 61 of the 469 (13.01%) anomaly variables have significant high-minus-low quintile returns under the 5% SHT, but only 22 (4.69%) under the 5% MHT. The resulting low significance rate is consistent with the findings in the U.S. stock market documented by HXZ (2020), with the recent critiques of overfitting by McLean and Pontiff (2016), and with the failure to control for MHT identified in Harvey et al. (2016).

We also replicate our anomaly tests using three alternative sorting and weighting procedures, namely All-VW (all A-share breakpoints and value-weighted returns), Mainboard-EW (Mainboard breakpoints and equal-weighted returns), and All-EW (all A-share breakpoints with equal-weighted returns). We provide concrete evidence to validate the reliability of the Mainboard-VW procedure. We find that the conventional All-EW procedure is indeed problematic because it allocates excessive weight to microcaps, which have very limited investment capacity. In contrast, the Mainboard-VW procedure used in this paper is a more reliable and appropriate method for anomaly tests in the Chinese A-share market.

We use two methods to compare factor model performance. Over the whole sample period, the CH3-factor model, CH4-factor model (CH3 augmented by a turnover factor), and *q*-factor model perform best, explaining 53.85%, 47.44%, and 25.64%, respectively, of the anomaly variables with significant high-minus-low quintile returns. In the post-2007 subsample period, the *q*-factor model is the best performer and can explain 73.77% of anomaly variables with significant high-minus-low quintile returns. The unexplained variables are clustered in the anomalies associated with trading frictions.

Our study contributes to three streams of the literature. First, our study contributes to capital market research in general by providing up-to-date evidence from the Chinese stock market. In addition to HXZ (2020), many recent studies summarize and test large-scale anomalies in the U.S. market.[2] We add to the anomaly literature by providing large-scale evidence from the world's second-largest stock market. Second,

[2] For example, McLean and Pontiff (2016) summarize 97 anomaly variables and find that the predictability of many anomalies declines dramatically after they are published. Green et al. (2017) examine 94 firm characteristics and show that return predictability has fallen sharply since 2003. Linnainmaa and Roberts (2018) find that very few anomalies can be replicated before and after publication. Chordia et al. (2020) construct more than two million strategies based on firm-level accounting variables from Compustat and market variables from the CRSP. They find that over 90% of these strategies are insignificant.

our study contributes to the asset pricing literature, especially the stock anomaly literature on the Chinese stock market. We build a large portfolio database and provide numerous basic stylized facts. The literature using Chinese data commonly focuses on fewer anomalies.[3] We instead perform the largest anomaly test to date in an effort to provide a foundation for future asset-pricing studies in China. Third, our study contributes to the rapidly growing literature on the Chinese stock market. We consider several of its special features, such as the split-share structure reform, the implementation of new accounting standards, and SOEs versus non-SOEs, and try to understand their influence on our results. We also summarize the differences between the results from the Chinese and U.S. markets and explore potential explanations. Our findings can help provide a better understanding of the Chinese stock market.

2. Data and methodology

2.1 Development and special features of the Chinese stock market

The Chinese A-share market was established in 1990, and thus has a shorter history than the markets of developed countries. However, it has become increasingly important because of its rapid growth in market capitalization. Panel A of Table 1 presents an overview of stocks used in our sample. By the end of December 2018, the total market capitalization of the A-share market exceeded 32 trillion *yuan* (roughly US$4.8 trillion) and the number of listed firms had reached more than 3,300, compared with only 2.40 trillion *yuan* and 844 firms at the end of December 1999.[4] In terms of market capitalization and trading volume, the Chinese A-share market is now the world's second-largest stock market, after the U.S. market.[5] The Chinese stock market has received much attention from the global market in recent years after several major events, such as the inclusion of Chinese A-shares in the MSCI Emerging Markets Index (which

[3] For example, Hsu et al. (2018) examine 17 anomaly variables. Jiang et al. (2018) construct factors based on 75 firm characteristics using principal component analysis and partial least squares approaches. Qiao (2019) constructs 231 anomalies in the Chinese A-share market and finds that 41 anomalies (17.7%) have significant return spreads at the 5% level (with $|t| \geq 1.96$). However, Qiao (2019) only uses the CAPM to explain the significant anomalies and does not use other factor models to adjust return spreads. Leippold et al. (2021) use 94 stock-level characteristics and 11 macroeconomic variables to examine the predictive power of various machine-learning algorithms in the Chinese market.
[4] Firms in the financial industry and firms with abnormal trading status at the end of each year are dropped out of our sample and thus not included when we calculate the descriptive statistics.
[5] At the end of 2018, the total market capitalization of listed firms in the U.S. stock market was roughly US$30.44 trillion. Please refer to https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?locations=US&view=chart.

started in June 2018) and the launch of the Shanghai–Hong Kong Stock Connect Program (in November 2014) and Shenzhen–Hong Kong Stock Connect Program (in December 2016).[6]

Similar to the NYSE in the U.S. market, the Shanghai and Shenzhen Mainboards, on which large and mature firms are listed, are the major components of the Chinese A-share market. Chinese A-shares also cover the Small and Medium Enterprise (SME) board and the Growth Enterprise Market (GEM) board on the Shenzhen Stock Exchange. The SME board was established in 2004 to provide wider equity financing channels for small and growth firms.[7] The GEM board, also known as the ChiNext Board, is a NASDAQ-type exchange for high-growth, high-tech start-ups that was launched in 2010.[8] Panel A of Table 1 provides the summary statistics of the number of listed firms on the Shanghai Mainboard, Shenzhen Mainboard, SME board, and GEM board in our sample at the end of each year. The total number and market capitalization of A-shares has increased dramatically in these four boards over the past two decades.[9]

The Chinese stock market has undergone many reforms since its establishment in 1990. Two of these are of particular importance, especially for asset-pricing studies: (i) the completion of the split-share structure reform at the end of 2007 and (ii) the implementation of the new Accounting Standards for Business Enterprises (ASBE) as of January 1, 2007. Therefore, the post-2007 subsample represents a cleaner sample for asset-pricing tests in the Chinese stock market. The China Securities Regulatory Commission (CSRC), which is analogous to the Securities and Exchange Commission (SEC) in the U.S., initiated the split-share structure reform in April 2005 to eliminate the circulation differences between non-tradable and tradable shares. Before this reform, approximately two-thirds of shares in the A-share market were held directly by the state or other government entities and were non-tradable, creating a unique

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[6] By the end of January 2022, Chinese stocks accounted for about 32.08% of the MSCI Emerging Market Index (https://www.msci.com/documents/10199/c0db0a48-01f2-4ba9-ad01-226fd5678111).

[7] The SME board was merged into the Shenzhen Mainboard in February 2021.

[8] Although it is outside our sample period, the Shanghai Stock Exchange Science and Technology Innovation Board (the STAR Market) established on July 22, 2019 is a Chinese science- and technology-focused equities market.

[9] Based on our sample, the number of A-share listed firms increased nearly threefold between 1999 and 2018, from 844 at the end of 1999 to 3,357 at the end of 2018. The total market capitalization of all A-shares increased by 12.72 times, from 2.40 trillion *yuan* to 32.93 trillion *yuan*, during this period. The number of listed firms on the SME and GEM boards increased particularly rapidly. By the end of 2018, 874 firms were listed on the SME board and 734 firms on the GEM board, together accounting for 47.90% of all A-share listed firms.

phenomenon in the A-share market in which the same share could have different benefits and rights. The value of non-tradable shares is not connected to market price. Because of the differences in the pricing mechanisms between non-tradable and tradable shares, significant agency problems may arise when substantial shareholders cannot benefit from market price increases (Beltratti et al. 2012). As a result, market prices cannot reflect the intrinsic values of listed firms, and firm managers may not care about value maximization. By the end of 2007, the market values of the listed firms that had completed or begun the reform process had reached 98% of all listed firms' market values. This indicates that the split-share structure reform was essentially complete by this point. Accordingly, market prices better reflect the intrinsic value of listed firms in the post-2007 sample period.

Another significant change is the implementation of the long-awaited new ASBE in 2007. The Ministry of Finance (MOF) formally announced the issuance of the new ASBE on February 15, 2006. The standards, substantially in accordance with the International Financial Reporting Standards (IFRS), became mandatory for listed firms in the A-share market starting on January 1, 2007, and represent a milestone in China's accounting system. In the post-ASBE period, accrual-based earnings management decreased because of improved accounting quality (Ho et al. 2015).

2.2 Data and summary statistics

We retrieve data regarding stock returns and accounting information from the China Stock Market and Accounting Research (CSMAR) database, which follows the standards of international databases such as CRSP and Compustat.[10] We focus only on the Chinese A-share market available for domestic investors in *yuan* or RMB. We treat China's 3-month RMB deposit rate as a risk-free rate, which we obtain from the People's Bank of China website.[11] We obtain the annualized deposit rate and convert it into the monthly

[10] The CSMAR database has been developed to meet the needs for financial analysis and research in China and is the only Chinese database available on the Wharton Research Data Services website. We obtain transaction data from CSMAR's China Stock Market Trading Database, which includes stock returns and market returns with cash dividends reinvested, number of shares outstanding, and closing prices. Accounting data are from CSMAR's China Stock Market Financial Statements Database, which covers the annual and quarterly consolidated financial statements of listed firms.

[11] See http://www.pbc.gov.cn/zhengcehuobisi/125207/125213/125440/125838/125888/2968982/index.html. The risk-free rate in the CSMAR is the one-year fixed-term deposit rate or the one-year Treasury note issued by the Chinese government. We choose the 3-month deposit rate following previous studies of the Chinese capital market.

risk-free rate. Our sample covers all Chinese A-shares with available accounting and stock market information, including listed firms on the two Mainboards, the SME board, and the GEM board. Our A-share benchmark return is the market return from the CSMAR database, a circulation market cap-weighted return calculated using all available A-shares.

To ensure the quality of the data, we apply the following standard screening procedures used in previous studies. First, we exclude firms with negative book equity. Second, we exclude financial firms based on the CSRC industry classification. Third, we exclude firms marked as "ST" (special treatment) or "PT" (particular transfer) or firms that have any other abnormal trading status, as they could be distressed or illiquid because of additional restrictions on trading. Finally, we exclude penny stocks with a share price below 5 *yuan* after forming quintiles but before calculating quintile returns because of microstructure concerns and the lack of trading activity.

Our sample covers annual and quarterly financial statement data from 1999 to 2018 and stock return data from July 2000 to June 2019, a total of 228 months. We focus on the post-2000 period in our main body of analysis for three reasons. First, during the earlier period, the number of listed stocks is relatively small. When we form anomaly quintile portfolios, if the number of stocks in each portfolio is not sufficient, a major concern is that the sorted portfolios may not be well diversified. This would reduce the power of our tests. Second, the price limit rule in the Chinese stock market began on December 16, 1996, which helps rein in extreme stock returns. We choose the post-1997 period to ensure uniformity in the trading data. Third, it is important to note that although the Chinese A-share market opened for trading in December 1990, accounting information that is sufficiently reliable for use in analysis is only available from the late 1990s onward.[12] Therefore, we choose the post-2000 period to ensure uniformity in the accounting data.

[12] The MOF promulgated seven specific sets of standards in 1998, including the "Standards for Cash Flow Statements," "Standards for Post Balance Sheet Events," "Standards for Debt Restructuring," "Standards for Revenue," "Standards for Investments," "Standards for Construction Contracts," and "Standards for Changes in Accounting Policies and Accounting Estimates and Correction of Accounting Errors." These standards have been implemented since January 1, 1999, after which the regulation of accounting treatment and information disclosure began to gradually improve. Moreover, the MOF issued an indispensable additional regulation in 1999, requiring all listed companies to adopt the retrospective method in handling changes in accounting policies and the allowance method in handling losses resulting from non-performing accounts. It also required firms to set up four reserves in accordance with the new standards.

Our analysis starts with all listed firms' 1999 annual financial reports to reflect the implementation of the new accounting standards.

2.3 Testing portfolios

Since Fama and French (1993), most U.S. market studies have used NYSE breakpoints in forming value-weighted portfolios. HXZ (2020, p. 2027) elaborate that "NYSE breakpoints assign a fair number of small and big stocks to extreme deciles" and thus alleviate the effect of microcaps. These microcaps tend to exaggerate the magnitude of anomalies, particularly when combined with equal-weighted returns. As the two A-share Mainboards are NYSE-type, we use a similar procedure (i.e., A-share Mainboard breakpoints) to construct portfolios. Related research on the Chinese A-share market has rarely paid attention to this issue, probably because of the lack of microcaps in the early period. However, the past decade has witnessed a rapid increase of microcaps since the launch of the GEM board. By the end of 2018, the number of firms listed on the GEM board exceeded one-third of the Mainboard scale, as shown in Panel A of Table 1. The Mainboard rather than all A-share breakpoints should therefore be used when constructing portfolios to eliminate the effect of microcaps, especially in extreme groups.

We also follow HXZ (2020) in using value-weighted portfolio returns, as an equal-weighted average assigns excessively large portfolio weights to microcaps. Anomaly returns in microcaps are extremely difficult to exploit in practice because of short-sales restrictions, large transaction costs, and a lack of liquidity. We use circulation market equity (stock price times shares outstanding, from CSMAR) as stock weights at the beginning of portfolio formation. As the Chinese A-share market does not have as many listed firms as the U.S. market, and the dispersion in many anomaly variables is relatively low, we sort all stocks into quintiles instead of deciles and explore the difference in returns between the extreme quintiles.

We next construct testing portfolios with A-share Mainboard breakpoints and value-weighted returns based on the 469 anomaly variables.[13] For annually sorted testing quintiles, we sort all A-share stocks at

[13] Some anomaly variables from HXZ (2020) are not available in China, especially those in the intangibles and trading frictions categories (e.g., organizational capital, citations, capital leases, mortgages and other secured debt, convertible debt, pension plans, order backlogs, and broker-dealer data). Moreover, some variables in China have too many missing or zero values (e.g., segment files, dividends, payouts, stock repurchases, preferred stocks, and preferred dividends in arrears). To compensate for the loss of these variables, we add some new anomaly variables by including the holding horizons of 3 and 9 months.

the end of June of each year *t* into quintiles based on each anomaly variable at the fiscal year end in calendar year *t*-1 and calculate the quintile value-weighted returns from July of year *t* to June of year *t*+1.[14] For the monthly sorted testing portfolios associated with the latest earnings data, we use the earnings data from the CSMAR quarterly financial statements in the months immediately after each quarterly earnings announcement date. For monthly sorted testing portfolios using quarterly accounting variables other than earnings, we impose a 4-month lag between the fiscal quarter end and stock returns in subsequent months. We do so because quarterly items other than earnings data are usually not available on earnings announcement dates in China. Detailed variable definitions, portfolio constructions, and a list of the original reference sources can be found in Online Appendix A and Table A1. References for these original sources are also reported in the Online Appendix. For most of the sorting variables, we hold the portfolios for one year. For the variables that are constructed and rebalanced monthly, we construct portfolios with five holding periods (1, 3, 6, 9, and 12 months). This implementation is inspired by the momentum test in different holding periods from Chan et al. (1996). In the main test, we report our results using the Mainboard-VW procedure. We also summarize our results under three alternative procedures, All-VW, Mainboard-EW, and All-EW, for comparison.

2.4 Factor constructions and properties of factors

We follow Fama and French (1993), Carhart (1997), Fama and French (2015), and HXZ (2015) to construct eleven factors for the Chinese A-share market: market (MKT), size-1 (SMB-FF3), size-2 (SMB-FF5), size-3 (ME), value-1 (HML-FF3), value-2 (HML-FF5), investment-1 (CMA), investment-2 (I/A), profitability-1 (RMW), profitability-2 (ROE), and momentum (MOM).[15] All of the factors use the A-share Mainboard to decide breakpoints. We then calculate the value-weighted returns. We construct the monthly return of the market factor (MKT) as the value-weighted market return from CSMAR minus China's 3-month RMB deposit rate. Details of the factor construction process can be found in Section B of the Online

[14] Although A-share listed firms must release prior-year annual reports before the end of April, the CSRC allows them to delay until the end of June. We therefore rebalance the sorted portfolios annually at the end of June.

[15] These eleven factors have been used in four factor models: the Fama–French three-factor model (MKT, SMB-FF3, and HML-FF3); the Carhart four-factor model (MKT, SMB-FF3, HML-FF3, and MOM); the HXZ *q*-factor model (MKT, ME, I/A, and ROE); and the Fama–French five-factor model (MKT, SMB-FF5, HML-FF5, RMW, and CMA).

Appendix data manual. We also obtain the CH3 and CH4 factors from Professor Robert Stambaugh's website.[16] The CH3 factors consist of the market (MKT-CH), adjusted size (SMB-CH), and adjusted value (VMG) factors, where VMG (value minus growth) is based on earnings to price (EP). The CH4-factor model is the CH3-factor model augmented by a turnover factor, PMO (pessimistic minus optimistic), based on abnormal turnover.

We mainly use the HXZ *q*-factor model (MKT, ME, I/A, and ROE), the Fama–French five-factor model (MKT, SMB-FF5, HML-FF5, RMW, and CMA), the CH3-factor model (MKT-CH, SMB-CH3, and VMG), and the CH4-factor model (MKT-CH, SMB-CH4, VMG, and PMO) in the following factor model performance comparison section. We also report the summary statistics and correlation matrix of these factors in Table 1. Panels B and C report the means, standard deviations, and *t*-statistics of the monthly factor returns for the whole period (July 2000 to June 2019) and the post-2007 period (July 2008 to June 2019), respectively. In the whole sample, SMB-FF5 is the only significant factor among the five Fama–French factors, with a 0.68% average monthly return and significance at the 5% level based on the SHT. The mean return of the size factor (SMB-CH3) in the CH3 model is 0.73% per month, significant at the 5% SHT. However, the size factor (SMB-CH4) in the CH4 model is only marginally significant. The mean returns of the value factor (VMG) and the turnover factor (PMO) are 1.20% and 0.93% per month, respectively, and both are statistically significant at the 1% level based on the SHT. All of the factors in the *q*-factor model earn significant average monthly returns at the 5% SHT except for the market factor, which is the same as in the Fama–French five-factor model at 0.62%. The size factor ME demonstrates the largest *t*-statistic of 3.12 (with a mean return of 0.78%) among all factors in the *q*-factor model. The investment factor I/A and the profitability factor ROE have significantly positive mean returns of 0.29% and 0.54% per month, respectively. The post-2007 subsample results are similar to those in the whole period. We discuss the properties of factors in more detail in Online Appendix Section B.

Panels D and E of Table 1 report the factor correlation matrix over the whole and subsample periods,

[16] Please refer to http://finance.wharton.upenn.edu/~stambaug/.

respectively. For the whole period, among similar factors, the correlation between the HML-FF5 and VMG value factors is 0.40, which is the lowest, while the correlations between the ME, SMB-FF5, and SMB-CH3 (or SMB-CH4) size factors are the highest at 0.81–0.96. The correlation between the CMA and I/A investment factors is 0.87, and the correlation between the RMW and ROE profitability factors is 0.76. The results from the post-2007 period are similar to those in the whole period.

[Insert Table 1 here]

2.5 Factor model comparison

We use the seven prominent factor models to explain the anomaly variables with significant high-minus-low quintile raw return spreads. Following HMXZ (2021), we use two methods to compare factor model performance. In the first method, we use four measures to compare factor model performance, including the average magnitude of the high-minus-low quintile alphas ($\overline{|\alpha_{H-L}|}$), the number of high-minus-low alphas with $|t| \geq 1.96$ ($\#|t| \geq 1.96$), the mean absolute alpha across the anomaly quintiles in a given category ($\overline{|\alpha|}$), and the number of sets of quintiles within a given category for which the factor model is rejected by the GRS test at the 5% level ($\#p < 5\%$). For all four measures, a smaller number indicates better factor model performance.

In the second method, we construct combined anomaly variables across all those having significant high-minus-low quintile returns in a category and across each of the six categories. Specifically, we construct the composite score for each stock by equally weighting the stock's percentile rankings for all of the anomaly variables in a given category. Because different anomaly variables predict stock returns with different signs, we realign the anomaly variables to yield positive slopes before constructing the composite score. We use the quintiles formed on the composite scores as the testing portfolios in the factor regression and factor model comparison. We then use the high-minus-low quintile alpha, its *t*-statistic, the mean absolute alpha, and the GRS *p*-value to compare factor model performance.

3. Main results: Replication and digestion of anomalies

Our anomaly variables contain annual and monthly sorted variables. There are 104 unique annual and 73 unique monthly sorted variables with five holding periods, yielding a total of 469 anomaly variables. Of these, 45 are in the momentum panel, 68 in the value-versus-growth panel, 36 in the investment panel, 94 in the profitability panel, 83 in the intangibles panel, and 143 in the trading frictions panel. We sort all of the A-share stocks by these anomaly variables into quintiles and then calculate the value-weighted return spreads of the high-minus-low quintiles. We use the traditional 5% significance level based on SHT and MHT to define significant anomalies (i.e., $|t| \geq 1.96$ and $|t| \geq 2.78$, respectively).[17]

3.1 Rationale for using the Mainboard-VW procedure

We sort the quintile portfolios using the Mainboard-VW procedure to alleviate the impact of microcaps, which is analogous to the NYSE-VW procedure. In this section, we provide more concrete evidence for the reliability of the Mainboard-VW procedure. For comparison purposes, we also calculate our results using three alternative procedures: All-VW, Mainboard-EW, and All-EW.

Table 2 compares the differences in characteristics between microcaps, small stocks, and big stocks. We follow Fama and French (2008) and HXZ (2020) to allocate stocks into three size groups. Microcaps refer to those below the 20th percentile of mainboard size breakpoints, small stocks are those between the 20th and 50th percentiles, and big stocks include stocks above the median of mainboard size breakpoints. Panel A shows that the average number of microcaps in our whole sample is 449, accounting for 28.73% of the total number of stocks in the market (1,563). However, the total market cap and circulation market cap of the microcaps only account for 8.78% and 6.70%, respectively, of the aggregate market value of all A-shares. Big stocks account for 42.03% (657) of the total number but for 77.48% and 79.41% of the aggregate total market cap and circulation market cap, respectively. Microcaps earn an average value-weighted (equal-weighted) return of 1.40% (1.69%) per month, while for the big stocks, this is only 0.71% (0.91%). Microcaps have the largest cross-sectional standard deviation in monthly returns of 9.93%, followed by small stocks (9.71%) and big stocks (9.47%). In the other three panels of Table 2, we directly report the portfolio weights allocated to microcaps and the investment capacity of portfolios under four

[17] Assuming a stationary return distribution, a *t*-statistic of 1.96 (2.78) in China's 19-year sample is equivalent to 3.18 (4.51) in a 50-year sample in the U.S. market. Under this assumption, a *t*-statistic of 1.96 (2.78) in our post-2007 subsample (11 years) is equivalent to 4.18 (5.93) in a 50-year sample in the U.S. market. Therefore, using the standard cutoffs in a shorter Chinese sample is actually more stringent, because the equivalent cutoffs in the long U.S. sample would be much higher.

different procedures. In Panel B, we calculate the time-series average of weights on microcaps for the lowest and highest quintile portfolios of each anomaly and report the average across all anomalies in a given category. The All-EW procedure allocates a large number of portfolio weights to microcaps, whereas the Mainboard-VW procedure assigns a fair number of portfolio weights to microcaps. For instance, in the "All" columns, the lowest quintile allocates on average 26.86% to microcaps with the All-EW procedure, but the corresponding figure for the Mainboard-VW procedure is only 8.20%.

We then follow HXZ (2020, Section 2.3.2) to calculate the investment capacity of portfolios. The investment capacity for a value-weighted portfolio is the aggregate circulation market equity of all of its stocks; for an equal-weighted portfolio, the investment capacity is the number of stocks in that portfolio multiplied by the minimum stock circulation market equity in that portfolio. For the lowest and highest quintile portfolios of each anomaly, we compute the investment capacity as a fraction of the aggregate A-shares circulation market cap at each month, take its time-series average, and then report the average across all of the anomalies in a given category in Panel C. In Panel D, we calculate the investment capacity in trillions of *yuan* for the lowest and highest quintile portfolios of each anomaly at the end of 2018 and report the average across all anomalies in a given category.

The investment capacity is much larger under the VW than the EW procedure in terms of percentage or RMB amount. For example, in the "All-High" columns in Panel C, the investment capacity of the highest quintile is on average 21.27% of the aggregate circulation market cap of all A-shares under the Mainboard-VW procedure but only 1.90% using the All-EW procedure. At the end of 2018, the investment capacity of the highest quintile is 4.44 trillion *yuan* according to the Mainboard-VW procedure, while it is only 0.22 trillion *yuan* under the All-EW procedure, as shown in the "All-High" columns in Panel D.

Overall, we show that the conventional All-EW procedure is indeed problematic because it allocates excessive weight to microcaps and the investment capacity under this procedure is accordingly very limited. In contrast, the Mainboard-VW procedure used in this paper is more reliable and appropriate.

[Insert Table 2 here]

3.2 Summary of anomaly replication results under four different sorting procedures

We report in Table 3 the significance rates of the high-minus-low quintile return spreads, CAPM alphas, and FF3-factor alphas for each category of anomaly variables under the four different sorting procedures. We find that using the conventional All-EW procedure to form anomalies may be misleading. Over the whole sample period, overweighting microcaps with the EW procedure can substantially increase the significance rates in all three panels.[18] For example, Panel A shows that in "All categories," 16.63% of anomaly variables have significant high-minus-low return spreads under the 5% SHT using the Mainboard-VW procedure, whereas this number more than doubles under the All-EW procedure, to 47.55%. Even under the 5% MHT with $|t| \geq 2.78$, the All-EW procedure produces 30.28% of significant high-minus-low return spreads.

[Insert Table 3 here]

3.3 Detailed replication results for individual anomalies using the Mainboard-VW procedure

Table 4 reports the anomaly variables with significant high-minus-low quintile raw returns under the Mainboard-VW procedure across the whole sample period (Panel A) and the post-2007 subsample period (Panel B) when applying the 5% SHT. We report the average of the high-minus-low quintile returns (denoted as m) for each significant anomaly variable.[19] In total, 78 out of 469 anomaly variables are significant in the whole period, and 61 in the post-2007 period. We now discuss the detailed results in each of the six categories. Because the results in the post-2007 period are similar to those across the whole period, we discuss them in brief and only mention notable differences between the two periods.

3.3.1 Momentum

Seven of the 45 momentum anomalies are significant (#1 to #7) in the whole period (Panel A). The high-minus-low quintiles formed based on the standardized unexpected earnings (Sue) variable over holding horizons of 1 month, 3 months, 6 months, and 9 months earn on average 1.17%, 0.82%, 0.54% and 0.47% per month, respectively. The high-minus-low cumulative abnormal returns around earnings

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[18] Online Appendix Figure A1 presents the significance rates of the high-minus-low return spread, CAPM alpha, and FF3-factor alpha for each category using all four different procedures for the post-2007 subsample period. The results are robust and similar.
[19] To save space, the corresponding t-statistics (denoted as t_m) are not reported in Table 5. Instead, superscripts ^{a} and ^{b} indicate that the absolute t-statistics are above the thresholds of 1.96 (but below 2.78) and 2.78 for each anomaly variable, respectively. Details of the corresponding t-statistics for each anomaly variable are reported in Online Appendix Tables A3 and A4.

announcements (Abr) quintile over the 9-month holding horizon earns an average return of 0.32% per month. The high-minus-low quintiles on six-month residual momentum over the 3-month and 6-month holding horizons earn average returns of 0.56% and 0.44% per month. The significant anomalies in this category arise mainly from earnings surprise and return-related variables. Seven of the 45 momentum anomalies are significant (#1 to #7) in the post-2007 period (Panel B): Sue1, Sue3, Sue6, Sue9, Sue12, Abr6, and Abr9. Note that the high-minus-low quintiles on Sue1 and Sue3 earn average returns of 0.93% and 0.75%, respectively, with *t*-statistics above 3.

3.3.2 Value-versus-growth

Six out of the 68 value-versus-growth anomalies are significant (#8 to #13) in the whole period (Panel A)**.** The high-minus-low quintile on quarterly earnings-to-price over the 1-month holding horizon (Ep^q1) yields on average 0.84% per month. The high-minus-low net debt-to-price (Ndp) quintile over the 1-month holding horizon earns an average returns of 0.68% per month. The high-minus-low quintiles on quarterly net debt-to-price over the 3- , 6-, 9-, and 12-month holding horizons (Ndp^q3, Ndp^q6, Ndp^q9, and Ndp^q12) earn average returns of 0.74%, 0.68%, 0.71%, and 0.72% per month, respectively. This evidence suggests that the significant anomalies in this category come mainly from net debt-to-price, with only one from earnings-to-price and none from long-term return reversal. Only one of the 68 value-versus-growth anomalies is significant (#8) in the post-2007 period (Panel B), which is the five-year sales growth rank (Sr), with an average return of -0.66% per month.

3.3.3 Investment

Only one of the 36 investment anomalies is significant (#14) in the whole period (Panel A)**.** The high-minus-low quintile return on net operating assets (Noa) is -0.51% per month. However, nine of the 36 investment anomalies are significant (#9 to #17) in the post-2007 period (Panel B). The high-minus-low quintile formed based on composite equity issuance (Cei) earns an average monthly return of -0.68%. The high-minus-low net operating assets (Noa) quintile earns a return of on average -0.67% per month. The magnitudes of average returns of the high-minus-low quintiles on changes in PP&E and inventory to assets (dPia), change in long-term net operating assets (dLno), change in net non-current operating assets (dNco), and change in non-current operating assets (dNca) exceed 0.6% per month. The high-minus-low quintile return on investment-to-assets (I/A) is -0.58% per month, which is similar to the return reported in HXZ (2020) from the U.S. market (-0.46% per month).[20] The high-minus-low quintiles on change in net financial assets (dFin) and change in financial liabilities (dFnl) also generate significant return spreads.

3.3.4 Profitability

Eight of the 94 profitability anomalies are significant (#15 to #22) in the whole period (Panel A)**.** Of the eight significant variables in this category, the high-minus-low quintiles on the four-quarter changes in ROE (dRoe) and in ROA (dRoa) variables both earn on average around 1.10% at the 1-month holding horizon and have the largest *t*-statistics in this category, and earn 0.68% and 0.65%, respectively, at the 3-month holding horizon with *t*-statistics around 3. The high-minus-low quintiles on quarterly asset turnover over the 1-, 3- , 6-, and 9-month holding horizons (Ato^q1, Ato^q3, Ato^q6, and Ato^q9) earn average returns of 0.56%, 0.63%, 0.44%, and 0.42% per month, respectively. The quarterly Roe variable is a benchmark characteristic in the *q*-factor model. The high-minus-low quintiles on quarterly Roe over the 1- and 3-month horizons (Roe^q1 and Roe^q3) yield 0.49% and 0.37% per month, although both are insignificant. In contrast, the Roe factor in the *q*-factor model has a similar average return of 0.54% per month, which is significant at the 5% level under SHT (*t*-stat = 2.36), suggesting that it is important to sort profitability jointly with investment (see Section 4.4.3 for detail). The significant anomalies in this category are mainly attributed to changes in ROA, changes in ROE, and quarterly asset turnover. Six of the 94 profitability anomalies are significant (#18 to #23) in the post-2007 period (Panel B). Among these six anomaly variables, two (dRoe1 and dRoa1) are also significant at the 5% MHT. The high-minus-low quintile on quarterly Roe over the 1-month horizon (Roe^q1) earns an average return spread of 0.48% per month, although this is insignificant (*t*-stat = 1.16).

3.3.5 Intangibles

[20] Many studies find that total asset growth (i.e., I/A in our paper) and some investment variables predict returns negatively in the U.S. and other markets, but not in China (Cooper et al. 2008; Titman et al. 2013; Hsu et al. 2018; Liu et al. 2019; Qiao 2019; Wen 2019). The major difference arises from differences in (i) the sample period, (ii) the data source, (iii) the stocks included in the sample, and (iv) the data filtering and sorting procedures. We find that I/A can be a significant variable in the post-2007 period.

Ten of the 83 intangibles anomalies are significant (#23 to #32) in the whole sample (Panel A). The high-minus-low quintile on quarterly R&D-to-market over 1-month holding period (Rdm^{q}1) earns an average return of 0.83%, which is the most significant variable in this category. The high-minus-low quintiles formed on quarterly R&D-to-market (Rdm^q) over the other four holding horizons (3, 6, 9, and 12 months) also earn significant returns of 0.73%, 0.59%, 0.60%, and 0.61% per month, respectively. The high-minus low advertising expense-to-market (Adm) quintile earns on average 0.66% per month. The high-minus-low quintiles formed on quarterly asset liquidity (Ala^q) earn average returns of 0.49% and 0.45% per month, respectively, at the 6- and 9-month holding horizons. The lagged returns of past 12 month (R_a^1) and from the years 2 to 5 variable ($R_n^{[2,5]}$) have significant return spreads of 0.57% and -0.60%, respectively. Seven of the 83 intangibles anomalies are significant (#24 to #30) in the post-2007 subsample (Panel B). The Ala^q anomaly is the most robust variable in this category, with all five holding horizons (1, 3, 6, 9, and 12 months) significant. The high-minus-low quintile on quarterly tangibility (Tan^{q}12) and cash-to-asset (Cta12) over the 12-month holding horizon also earn significant returns of 0.63% and 0.71%, respectively. The significant anomalies are mainly concentrated on quarterly asset liquidity.

3.3.6 Trading frictions

Forty-six of the 143 trading frictions anomalies are significant (#33 to #78) in the whole sample (Panel A). This category has the highest significance rate (32.17%) and number of significant anomaly variables (46), of which 20 are significant at the 5% MHT. This suggests that trading frictions are very important in the Chinese stock market. Trading volume (Rtv), share price (Pps), effective bid-ask spread (Esba), and quoted bid-ask spread (Qsba) are the most significant anomaly variables in this category. The return spreads on high-minus-low quintiles sorted on Rtv, Pps, Esba, and Qsba are robust across all five holding horizons (1, 3, 6, 9, and 12 months).

Next, we find that eight of the volatility variables have significant return spreads, including idiosyncratic volatility estimated from the CAPM (Ivc), the FF3-factor (Ivff3), the FF5-factor (Ivff5), the *q*-factor (Ivq), the CH3-factor (Ivch3), the CH4-factor (Ivch4) models, and systematic volatility risk (Svr) over the 1-month holding horizon, and Ivff3 over the 3-month holding horizon. Eleven of the skewness variables earn significant returns, including total skewness (Ts), idiosyncratic skewness estimated from the CAPM (Isc), the FF3-factor (Isff3), the *q*-factor (Isq), the CH3-factor (Isch3), and the CH4-factor (Isch4) models over the 1-month holding horizon, and Ts, Isc, Isq, Isch3, and Isch4 over the 3-month holding horizon. The high-minus-low quintiles on Dimson beta (β^D) and coefficient of variation for share turnover (Cvt) over the 1-month holding horizon have significant return spreads of 0.79% and -0.59% per month, respectively. The high-minus-low quintiles on maximum daily return (Mdr) earns on average -0.82% per month at the 1-month holding horizon, and -0.65% at the 3-month holding horizon.[21] The short-term reversal (Srev) anomaly earns an average return of -0.84% per month.

Finally, the liquidity-related variables also generate significant return spreads. The high-minus-low quintiles sorted on RMB trading volume (Rtv) earn average returns of -1.30%, -1.00%, -0.93%, -0.96%, and -1.00% at 1-, 3-, 6-, 9-, and 12-month holding horizons, respectively.[22] The high-minus-low quintiles on share price (Pps) generate significant return spreads across all five holding horizons, earning on average -1.58%, -1.21%, -1.12%, -1.12%, and -1.06% at 1-, 3-, 6-, 9-, and 12-month holding horizons, respectively. The high-minus-low quintiles on the effective bid-ask spread (Esba) and quoted bid-ask spread (Qsba) both have significant return spreads across all five holding horizons. These liquidity-related variables are the most significant anomaly variables in the trading-frictions category, in terms of both magnitude and significance. The high-minus-low volume-synchronized probability of informed trading (Vpin) quintiles over the 3- and 6-month holding horizons also have significant return spreads.

Thirty-one of the 143 trading frictions anomalies are significant (#31 to #61) in the post-2007 subsample (Panel B). The number of significant anomaly variables in this category decreases by 32.61% in this subsample period compared to the whole sample period, from 46 to 31. Among these 31 anomaly variables that are significant at the 5% SHT, 16 are also significant at the 5% MHT. This category has the largest magnitudes of return spreads and is the most significant of all of the categories for the post-2007

[21] Many studies find that lottery-like stocks significantly underperform non-lottery-like stocks in the U.S. market (e.g., Bali et al. 2011; An et al. 2020). In the Chinese market, only the high-minus-low quintile on the maximum daily return (Mdr) over the 1-month holding horizon is significant, while Mdr over the 3-, 6-, 9-, and 12-month holding horizons is insignificant.

[22] While the RMB trading volume anomaly variable is highly significant, the share turnover variable is not. In contrast, Liu et al. (2019) find that their sentiment factor based on abnormal turnover, PMO, earns an annual return of 12%.

period. The high-minus-low absolute return-to-volume (Ami) quintile earns on average 1.33%, 1.28%, 1.26%, 1.24%, and 1.20% at 1-, 3-, 6-, 9-, and 12-month holding horizons, respectively. The RMB trading volume (Rtv), share price (Pps), effective bid-ask spread (Esba), and quoted bid-ask spread (Qsba) variables are the most significant and robust anomalies in this category.

[Insert Table 4 here]

3.4 Results of the factor model comparison

Table 5 shows the overall performance of different factor models in explaining the anomaly variables with significant high-minus-low raw return spreads under the Mainboard-VW procedure at the 5% SHT: 78 anomaly variables over the whole sample and 61 for post-2007 periods. Based on these significant variables, we compare the performance of the seven asset pricing models studied in this paper using the four measures outlined in the discussion of the first method in Section 2.5.

Over the whole period (Panel A of Table 5), the CH3, CH4, and *q*-factor models perform best. The CH3 model shows the smallest number of significant high-minus-low alphas (#$|t| \geq 1.96$) at 36, suggesting that it can explain 53.85% (1 – 36/78) of the anomaly variables with significant return spreads. In contrast, the *q*-factor model has the smallest mean absolute alpha across the anomaly quintiles ($\overline{|\alpha|}$) at 0.30% per month. Both models have the smallest number (53) of sets of anomaly quintile portfolios rejected by the GRS test at the 5% level (#p < 5%). The *q*-factor model can explain 25.64% (1 – 58/78) of anomaly variables with significant return spreads.

In the post-2007 period, the *q*-factor model has the smallest numbers and magnitudes across all four performance measures (i.e., $\overline{|\alpha_{H-L}|}$, #$|t| \geq 1.96$, $\overline{|\alpha|}$, and #p < 5%), suggesting that the *q*-factor model delivers the best performance for this time period. Across the 61 significant anomaly variables in this time period, the *q*-factor model can explain 73.77% (1 – 16/61) of anomaly variables with significant return spreads. The average magnitude of the high-minus-low alphas ($\overline{|\alpha_{H-L}|}$) is 0.56% per month and the mean absolute *q*-factor alpha ($\overline{|\alpha|}$) is 0.24% per month. However, the *q*-factor model is still rejected by the GRS test at the 5% level in 18 sets of quintile portfolios (#p < 5%). Compared to the other factor models, the *q*-

factor model performs better in capturing anomalies in the post-2007 period than across the whole period. This result is consistent with our expectations, in that this subsample period features more reliable accounting statements and more closely aligned interests between managers/controlling shareholders and other shareholders. For these reasons, this time period is more suitable for applying the q-factor model to explain cross-sectional stock returns.[23] In the post-2007 period, 16 significant anomaly variables cannot be explained by the q-factor model under the 5% SHT. All of them belong to the trading frictions category. The evidence suggests that the biggest challenge to the q-factor model in the Chinese market is its limited power to explain trading frictions-related anomalies. This is not a surprise given that the current q-factor model does not have a trading frictions component built into it.[24]

[Insert Table 5 here]

We also use an alternative method (i.e., testing the quintiles formed on composite scores) following HMXZ (2021) to compare the performance of different factor models based on the combined anomaly variables discussed in relation to the second method outlined in Section 2.5. Online Appendix Table A2 reports the results based on the combined anomaly variables in each category over the whole and the post-2007 periods. For each model and each set of quintiles, we report the high-minus-low alpha (α_{H-L}) and its t-statistic (t_{H-L}), the mean absolute alpha ($\overline{|\alpha|}$), and the GRS p-value (p_{GRS}). The factor model comparison results are similar to those documented in Table 5.

Table 6 reports the performance of different factor models in explaining significant anomalies under the Mainboard-VW procedure across the whole period and the post-2007 period. We use three measures for factor model comparison: the high-minus-low quintile alpha (α), mean absolute alpha ($\overline{|\alpha|}$) across the quintile portfolios, and p-value of the GRS test under the 5% SHT. To save space, we only report the performance of four factor models (FF5, q-factor, CH3, and CH4) in Table 6. We present the performance

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[23] The q-theory behind the q-factor model assumes that firms make investment decisions based on the rule of firm value maximization. However, before the split-share structure reform, controlling shareholders holding large blocks of non-tradable shares might not have cared particularly about firm value maximization because they could not derive much benefit from share price appreciation. As a result, managers of firms holding a large amount of non-tradable shares were more likely to cater to their controlling shareholders' preferences and thus might have been less likely to make decisions in line with q-theory.

[24] If trading frictions affect firms' cost of capital, this can also be captured by the q-theory model. However, we need a model that carefully considers trading frictions, which is outside the scope of this study. We leave this to be considered in future research.

of the other factor models in Online Appendix Tables A3 and A4 and the corresponding factor loadings and *t*-statistics in Online Appendix Tables A5 and A6.

For the momentum category, Sue1 and Sue3 have the most significant and largest high-minus-low quintile alphas (α) in terms of magnitude under the FF5-factor model in both sample periods and under the *q*-factor model over the whole period. In the value-versus-growth category, over the whole period, Ndp is the relatively most robust anomaly based on the α measure and can only be explained by the FF5-factor model. In the investment category, Noa has significant αs under the FF5-factor model in both sample periods, while it is insignificant under the *q*-factor, CH3- and CH4-factor models. In the profitability category, dRoe1 has significant αs under all four factor models over the whole period, but it can be explained by the *q*-factor, CH3- and CH4-factor models in the post-2007 period. In the intangibles category, the Adm and Rdm^{q}1 anomalies have significant FF5-factor alpha (α_{FF5}) and *q*-factor alpha (α_q) over the whole sample period. The trading frictions category has the largest number of significant αs, and the magnitudes are also much larger. For example, over the whole sample period, the share price (Pps) anomaly generates significant *q*-factor alpha (α_q) ranging from -1.52% to -2.15% across all five holding horizons. The quoted bid-ask spread anomalies Qsba1 generates significant CH3 alpha (α_{CH3}) and CH4 alpha (α_{CH4}) both at 2.11%, and Qsba3 generates significant *q*-factor alpha of 2.02%. In the post-2007 period, Pps1, Esba, and Qsba anomalies still generate significant *q*-factor alphas (α_q), with an absolute magnitude close to or over 2%. The CH4 alphas that Qsba anomalies generate exceed 2% for all five holding horizons.

Over the whole sample, the mean absolute alphas ($\overline{|\alpha|}$) of significant anomalies under these four factor models range from 0.08% to 1.06% per month. In the post-2007 subsample, among the 16 significant anomalies that cannot be explained by the *q*-factor model based on the high-minus-low alpha (α_q), the mean absolute alpha across the quintile portfolios ($\overline{|\alpha_q|}$) ranges from 0.19% to 0.76%. In contrast, among 44, 27, and 28 significant anomalies based on α under the FF5-factor, CH3-factor, and CH4-factor models, the mean absolute alphas range from 0.12% to 0.90%.

[Insert Table 6 here]

3.5 Robustness checks

We conduct a battery of tests to check the robustness of our baseline results. We give an overview of the anomaly testing results using six different portfolio construction procedures in Online Appendix Table A7. We then provide the results from the non-microcaps subsample in Online Appendix Table A8 using the Mainboard-VW to avoid the influence of microcaps on our results. In terms of average stock size, the Shanghai Mainboard is roughly 1.21 times the size of the Shenzhen Mainboard at the end of 2018 based on data shown in Panel A of Table 1. To reduce the effect of this difference, we use only the Shanghai Mainboard breakpoints for portfolio sorting, and we report the results in Online Appendix Table A9. We also use three alternative sorting procedures in the anomaly tests: All-VW, Mainboard-EW, and All-EW. We give the full details of the results in Online Appendix Tables A10–A12. Our results remain robust under all of the above tests. In addition, untabulated results (available upon request) for samples including earlier years are similar and robust (i.e., the post-1993 sample and the post-1997 sample).

For factor model comparison, we also construct the combined anomaly variables across all of the variables with significant high-minus-low CAPM alphas and FF3-factor alphas. The untabulated results are similar and robust to those reported in Online Appendix Table A2. Over the whole period, the CH3- and CH4-factor models demonstrate better performance. In contrast, the *q*-factor model performs the best over the post-2007 period. In the above main tests, we directly retrieve the CH3 and CH4 factors constructed by Liu et al. (2019) for model comparison. Liu et al. (2019) use data from WIND to construct their CH3 and CH4 factors, while our data come from CSMAR. For a robustness check, we also strictly follow Liu et al. (2019) and use their data filters and sorting procedures to construct the CH3 and CH4 factors using the CSMAR data. We find that the model comparison results reported in Table 5 are robust to our constructed CH3 and CH4 factors; we present the results in Online Appendix Table A13.

4. Discussion of results specific to China

4.1 Low replication rates in the Chinese versus U.S. markets

Details of the insignificant (corresponding to the SHT hurdle of $|t| \geq 1.96$) anomaly variables in the whole and post-2007 periods, including the insignificant high-minus-low return spreads and the corresponding t-statistics, are available upon request. We provide a pure out-of-sample replication test for anomaly variables similar to those studied by HXZ (2020) using Chinese A-shares data. The low significance rate of anomalies when we use the Chinese data may be attributed to several issues. First, there are fundamental differences between the two stock markets, such that we should not expect anomalies discovered in the U.S. market to be significant in the Chinese market. Second, the Chinese data span a much shorter sample period, 19 years in this paper versus more than 50 years in recent U.S. studies. This shorter sample makes it more difficult to clear the hurdle of the $|t| = 1.96$ cutoff. Hence, the lower significance rate may simply reflect the lack of statistical power when using the shorter Chinese sample period. Third, the U.S. anomalies have been weakening over time (e.g., Green et al. 2017). As a result, we must acknowledge that the low significance rate across the 19 years of our Chinese sample may not necessarily contradict the long-sample U.S. evidence. Nevertheless, the large-scale anomaly test set out in this paper is still of great importance to research in the Chinese A-share market.

4.2 Replication of the results of HXZ over the recent 19-year period

HXZ (2020) provide testing portfolio data for 187 anomalies on their website.[25] We replicate the tests using their data over the sample periods adopted in our study. Online Appendix Table A14 shows that only 45 out of 187 (24.06%) anomalies remain significant ($|t| \geq 1.96$) based on the high-minus-low decile return spreads in the most recent period from July 2000 to June 2019, among which only 9 (4.81%) are significant at $|t| \geq 2.78$ under MHT. In the post-2007 period (July 2008 to June 2019), only 30 out of 187 (16.04%) anomalies remain significant ($|t| \geq 1.96$), of which only 9 (4.81%) are significant at $|t| \geq 2.78$. The significance rate at the 5% SHT is higher in the U.S. than in China across the whole 2000–2019 period (24.06% versus 16.63%). In contrast, the significance rate in the U.S. declines substantially in the post-2007 period, becoming very similar to that found in China (16.04% versus 13.01%).

4.3 SOE vs non-SOE results

4.3.1 Anomaly results in the SOE and non-SOE subsamples

[25] Please refer to http://global-q.org/testingportfolios.html.

Because the objective of SOEs in China is not strictly profit maximization, we split our sample into SOEs and non-SOEs and redo all of the anomaly tests and factor model comparison tests in these two subsamples. We obtain the ownership property (i.e., SOE or non-SOE) of each firm from the China Listed Firm's Equity of Nature Research Database in CSMAR. These ownership property data have been available since December 2003. Therefore, we can only study anomaly replication and digestion for the period after 2003 in this section. Table 7 summarizes the number of anomaly variables with significant return spreads and alphas from the seven factor models in the SOE and non-SOE subsamples over our two time periods (July 2004–June 2019 and July 2008–June 2019). We also report the number of SOE and non-SOE firms year by year in Online Appendix Table A15, which indicates that the ownership property of a firm may vary from year to year because the controlling shareholders or ultimate controllers may change over time. Panel A of Table 7 reports the anomaly test results in the SOE subsample. Under the 5% SHT, 44 (9.38%) of the 469 anomaly variables demonstrate significant high-minus-low return spreads across both the whole and post-2007 periods. Panel B of Table 7 reports the anomaly test results for the non-SOEs subsample. Under the 5% SHT, 90 (19.19%) and 107 (22.81%) of the 469 anomaly variables reveal significant high-minus-low return spreads across the whole and post-2007 periods, respectively. These results suggest that there is a much greater number of significant anomaly variables in the non-SOE subsample than in the SOE subsample, especially in the post-2007 period.

[Insert Table 7 here]

Carefully investigating the underlying reasons for these results is beyond the scope of this study. We therefore only propose three potential explanations and leave more detailed explorations for future research. First, from the perspective of time series, the post-2007 period provides a cleaner sample for asset-pricing tests in the Chinese stock market, as we argued in Section 2.1. In the post-2007 period, after the completion of the split-share structure reform, market prices can better reflect the intrinsic value of listed firms (Liao et al. 2014). In addition, the quality of firms' accounting information seems to have improved after the implementation of the new Accounting Standards (Ho et al. 2015). We may capture more variations between firms in the anomaly tests over the post-2007 period. Second, the non-SOE subsample tends to be more diverse and show more variations in portfolio sorting.[26] Lastly, the accounting information for SOE firms might be less reliable (Fan and Wong 2002; Chen et al. 2008), which means that accounting-related measures in the SOE firms may not be able to capture real cross-sectional variations in portfolio sorting.[27] As a result, we may find more significant anomalies in the non-SOE subsample. In this cleaner non-SOE post-2007 subsample period, the significance rate of anomaly variables is 22.81%, which is similar to the U.S. evidence over the same time period at 16.04% (Panel B of Table A14).

4.3.2 Factor model performance in the SOE and non-SOE subsamples

Online Appendix Table A16 presents the overall performance of different factor models in explaining the anomaly variables that have significant high-minus-low return spreads in the SOE and non-SOE subsamples across the whole sample period (Panels A and B) and the post-2007 subsample period (Panels C and D). In the SOE subsample, the CH3- and *q*-factor models relatively outperform for the whole period, and the *q*-factor model is the best performer for the post-2007 period. Among four performance measures ($\overline{|\alpha_{H-L}|}$, $\#|t| \geq 1.96$, $\#p < 5\%$, and $\overline{|\alpha|}$), the *q*-factor model derives the smallest value for three of them and is the second best in one measure ($\overline{|\alpha|}$) for the whole sample. For the post-2007 subsample, the *q*-factor model is the best performer across all four measures. In the non-SOE subsample, the *q*-factor, CH3-factor, and CH4-factor models are the best performers in the whole sample, whereas the CH4- and *q*-factor models demonstrate the best performance in the post-2007 subsample.

4.4 Further discussion of the differences in anomaly results between China and the U.S.

4.4.1 Further discussion of the results in the momentum category

In the momentum category, we find that the major difference between our results from China and previous U.S. results is that both price momentum and earnings momentum work in the U.S., while it is the earnings momentum (Sue and Abr) that works in China, with only the six-month residual momentum with the

[26] In our sample, the number of SOE firms are relatively stable from 824 in 2003 to 994 in 2018. The number of non-SOE firms exceeds SOE firms since 2010, and becomes twice higher than SOE firms with 2,363 in 2018.

[27] For example, Fan and Wong (2002) find that controlling owners of firms with highly concentrated ownership tend to report accounting information for self-interested purposes, which may cause reported earnings to lose credibility. They also find that higher ownership concentration is related to lower informativeness of reported earnings. Chen et al. (2008) find that local governments may provide subsidies to help local listed SOEs in earnings management to meet regulatory requirements.

3-month ($\epsilon^6 3$) and 6-month ($\epsilon^6 6$) horizons of the price momentum category significant (consistent with the findings of Chui et al. (2010)).[28] Our results seem to be inconsistent with the findings in the U.S. market reported by Chordia and Shivakumar (2006) that earnings momentum drives price momentum. There are four potential reasons why price momentum and earnings momentum behave differently in China. First, the Chinese market has historically been dominated by speculation-oriented retail investors (Liu et al. 2019; Carpenter et al. 2021), who focus on short-term profit instead of long-term gain. By the end of 2019, retail investors held 20.59% of the market cap in the Shanghai Stock Exchange, compared with 15.74% for institutional investors.[29] Second, because insider trading has historically been prevalent in China, retail investors hesitate to hold on to winner stocks for too long. Because the momentum strategy is based on past 6- or 12-month returns, it is very unlikely to generate return continuation when retail investors rush to realize their gains. Third, the reason that earnings momentum works in China, especially for the short holding horizon of one month, is that retail investors are chasing short-term gains from firms that have just announced good earnings. Finally, the fact that price momentum barely work might be consistent with a lack of disposition-induced price momentum, as predicted by the model of Grinblatt and Han (2006), in that retail investors in China trade too much and too often and focus too much on short-term profit, and short-selling is practically prohibited.[30] As a result, retail investors in China might be less subject to disposition-induced price momentum (Chui et al. 2022).[31]

4.4.2 Further discussion of the results in the value-versus-growth category

We find a very low significance rate in this anomaly category in China. Only six and one variables

[28] Price momentum is the combined effect of earnings momentum and trading frictions in the Chinese stock market. However, most of the frictions variables negatively predict stock returns, in opposition to earnings momentum variables. When there is positive news, trading volume increases, leading to negative stock returns in the future. When there is negative news, trading volume may not increase because of short-sale constraints in China. This asymmetric effect may affect the performance of price momentum.

[29] Moreover, retail investors account for 99.76% (99.74%) of total stock accounts in the Shanghai (Shenzhen) Stock Exchange. Please refer to p. 565 of the Shanghai Stock Exchange Statistics Annual Report of 2020 (http://www.sse.com.cn/aboutus/publication/yearly/documents/c/tjnj_2020.pdf).

[30] This is evidenced by the Shanghai-mainboard stock turnover ratio of more than 157% in 2019 (the Shanghai Stock Exchange Statistics Annual Report of 2020). Kong et al. (2015) find that price momentum is not associated with the disposition effect in the Chinese market, as predicted by Grinblatt and Han (2006), based on the framework of mental accounting and prospect theory.

[31] We find that Sue variables are quite significant over different holding horizons in China, which is different from Chui et al. (2022) probably due to some differences in calculation details. For example, we construct the Sue variables following Foster, Olsen, and Shevlin (1984) and HXZ (2020), use the mainboard breakpoints, and divide stocks into five quintiles.

have significant high-minus-low return spreads in the whole and post-2007 periods, respectively. However, in both periods, book-to-market, book-to-June-end market equity, and quarterly book-to-market variables do not have a significant high-minus-low return spread. We speculate that the potential reason for the low significance rate compared with the U.S. sample might be that we include SOEs in our sample. As we have argued above, the managers of SOEs may behave differently from their non-SOE counterparts with respect to value maximization, which may contaminate our results. We therefore argue that the non-SOE subsample over the post-2007 period is a cleaner sample for asset pricing tests. To confirm this hypothesis, Online Appendix Table A17 shows that in the non-SOE subsample over the post-2007 period, the number of variables with significant high-minus-low return spreads in this category increases to 14, which is more consistent with the evidence from the U.S. market in HXZ (2020).

4.4.3 Further discussion of the results in the investment and profitability categories

Under the Mainboard-VW procedure, only 1 and 9 of 36 (2.78% and 25.00%) variables have significant high-minus-low return spreads in the investment category across the whole and post-2007 periods, respectively, compared with 73.7% in HXZ (2020). In addition, only 8 and 6 of 94 (8.51% and 6.38%) variables have significant high-minus-low return spreads in the profitability category across the whole and post-2007 periods, respectively, compared with 44.3% in HXZ (2020). Because more profitable firms tend to invest more and these two characteristics predict returns with opposite signs, they can offset each other in a one-way unconditional sorting. The high correlation between investment and profitability may be the reason for the low significance rate in these two categories in China.

In the untabulated results (available upon request), we show that return on equity (Roe) and return on assets (Roa) are significantly correlated with investment-to-assets (I/A), both annually and quarterly. Constructing profitability-neutral investment variables and investment-neutral profitability variables in precisely the same manner as the HML factor (2×3 sorts) in Fama and French (1993) may be a potential way to mitigate the influence of the high correlation between investment and profitability in China for future research. For example, the untabulated results (available upon request) show that the two-way double sorting indeed increases the significance rate in the profitability category. The number of variables with significant return spreads increases from 8 to 15 in the profitability category over the whole period, and the corresponding number increases from 6 to 15 in the post-2007 period.

4.4.4 Further discussion of the results in the intangibles category

Under the Mainboard-VW procedure, Panel B of Table 4 shows that 7 intangibles-related variables have significant high-minus-low return spreads under the 5% SHT after 2007, including two variables that also have significant high-minus-low return spreads for the whole period (Panel A of Table 4).

Five quarterly asset liquidity anomalies (Ala^q) are the most significant intangibles-related anomalies for the post-2007 period. The average high-minus-low quintile return spreads on the return in month *t*-12 (R_a^1) and the past 4-year return from months *t*-60 to *t*-13 ($R_n^{[2,5]}$) are also significant across the whole sample period. None of the seasonality variables in the intangibles category has significant return spreads over the post-2007 period in China. In contrast, seasonality anomalies are very strong and robust in the U.S. market and cannot be explained by existing asset pricing models. A possible reason for this difference may be that the earnings report frequencies and schedules are quite different between the two markets. All firms in China have their fiscal year end in December, while firms in the U.S. have different fiscal year ends. Moreover, there is no capital gain/loss tax in China. As a result, investors in China do not have a tax-loss selling incentive.[32] We argue that the institutional difference between the two markets may be why seasonality anomalies do not work in China, especially over the post-2007 period.

4.4.5 Further discussion of the results in the trading frictions category

In HXZ (2020), only four of the 106 (3.8%) trading frictions–related anomaly variables have significant high-minus-low return spreads. In contrast, we find that across both time periods in China, the trading frictions category is the most important and significant, with many anomaly variables demonstrating significant return spreads. In China, 46 of the 143 (32.17%) trading frictions variables have significant high-minus-low return spreads in the whole period, and 31 (21.68%) in the post-2007 period under the 5%

[32] Previous studies find little evidence supporting the tax-loss selling hypothesis for emerging markets (Claessens et al. 1995; Fountas and Segredakis 2002). Li et al. (2018) extend Heston and Sadka (2008, 2010) to examine return seasonality anomalies in an international setting that covers 21 advanced and 21 emerging markets. They find that return seasonality is only significant in advanced markets and does not work in emerging markets. However, they do not explore the reason behind this phenomenon.

SHT. These results suggest that trading frictions play a more important role in the Chinese than the U.S. market.[33] For the trading frictions variables with significant return spreads, the average magnitude of the quintile spreads is very high, at 0.96% per month in the full period, increasing to 1.55% for the post-2007 period. We suspect that the average returns of certain frictions anomalies may be amplified by a volatility effect ("Jensen's effect") in China. The significance of the high-minus-low quintile return spread is based on the arithmetic mean, which is the compounded average plus a volatility effect. When volatility is high, the arithmetic mean is inflated. Return volatility is much higher in the Chinese stock market than in the U.S. market. For example, in the post-2007 period, the Chinese market factor has a monthly volatility of 7.84%, compared with only 4.47% for the U.S. market factor. To reduce the volatility effect, we also calculate the compounded (geometric) average return for each variable. The untabulated results (available upon request) show that the value-versus-growth and trading frictions categories have the highest average volatility in the full period, the trading frictions category is the highest for the post-2007 period, and the magnitude of the geometric mean returns is smaller than that of the arithmetic mean returns.

5. Conclusion

We examine the significance rate of 469 stock anomaly variables using the largest dataset of Chinese A-shares to date. This large-scale anomaly test is of great significance for academics and practitioners. Under the Mainboard-VW procedure, we find that even at the 5% significance level under SHT, 391 (83.37%) of the 469 anomaly variables do not generate significant high-minus-low quintile raw return spreads in the Chinese A-share market. Further controlling for risk increases the failure rate slightly to 395 (84.22%) based on CAPM alphas and 408 (86.99%) based on Fama–French 3-factor alphas. This low significance rate is consistent with the findings of HXZ (2020) in the U.S. stock market. We empirically show that the conventional All-EW procedure for the anomaly test is indeed problematic in the Chinese A-

[33] Exploring the reasons behind this difference is very important. One possible reason is that the Chinese stock market is dominated by speculation-oriented retail investors (Liu et al. 2019; Carpenter et al. 2021). The excessive trading by retail investors may have a large effect on trading frictions anomalies. Another potential direction is to explore whether the more significant trading frictions anomalies in China than in the U.S. are related to short-sales restrictions in China. However, our preliminary results indicate that the frictions-based anomalies in China are more driven by their long legs than short legs. We leave more detailed explorations for future research.

share market, which assigns too much weight to microcaps and has a very limited investment capacity. The All-EW procedure is thus misleading when calculating anomalies. In contrast, the Mainboard-VW procedure is more reliable and appropriate for the anomaly test.

The Chinese stock market differs from the U.S. stock market during our sample period. We therefore also consider the special features of the Chinese market. From its inception up to 2007, the Chinese A-share market underwent many important reforms, in particular the split-share structure reform and the implementation of new accounting standards conforming to the IFRS. We therefore argue that the post-2007 period provides a more suitable setting for researchers to conduct empirical asset-pricing tests. We provide fresh evidence that of the 469 anomaly variables, 61 (21) produce high-minus-low return spreads under SHT (MHT) at the 5% significance level in the post-2007 period.

We use two methods to compare the performance of seven prominent factor models. We document that the CH3-factor, CH4-factor, and *q*-factor models demonstrate the best performance over the whole sample period. The *q*-factor model is the best performer in the post-2007 period. Specifically, at the 5% significance level under SHT, the *q*-factor model can explain 25.64% of the anomaly variables with significant high-minus-low return spreads over the whole period, whereas its explanatory power increases dramatically to 73.77% in the post-2007 period. This confirms our argument that future empirical asset-pricing studies in China should pay more attention to the post-2007 period. Trading frictions represent one of the most important anomaly categories in the Chinese market. However, the *q*-factor model has limited explanatory power for this category of anomalies.[34]

We regard the non-SOE subsample in the post-2007 period as a cleaner sample, given that non-SOEs give more weight to profit maximization and the post-2007 period provides a better market environment. In this cleaner sample, 22.81% of anomaly variables gain significant high-minus-low return spreads, which

[34] A modified *q*-factor model combining the trading frictions feature may demonstrate great potential to understand the Chinese stock market. Alternatively, one may want to use the HXZ *q*-factor model augmented with one of the factors from the trading frictions category to form an augmented *q*-factor model with five factors, as Liu et al. (2019) use to augment their CH3-factor model with a turnover factor to form their CH4-factor model.

is similar to the U.S. evidence during the same period at 16.04%. The *q*-factor and CH4-factor models perform best in this cleaner sample.

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Table 1. Descriptive statistics of the A-share market and factor characteristics in different sample periods

Panel A reports the annual number of listed firms in our sample, including the Shanghai (SH) Mainboard, Shenzhen (SZ) Mainboard, Small and Medium Enterprise (SME) board, and Growth Enterprise Market (GEM) board between 1999 and 2018 inclusively. Firms in the financial industry and firms that have abnormal trading status at the end of each year are dropped out of the sample and thus not included in this table. We also report total market capitalization (TMV, in trillion *yuan*) and circulation market capitalization (CMV, in trillion *yuan*) at the end of each year, in each board on the Chinese A-share market. Panels B and Panel C report the average return (Mean, in %), *t*-statistic, and standard deviation (Std Dev, in %) of each factor for the whole sample period from July 2000 to June 2019 (228 months) and for the post-2007 subsample period from July 2008 to June 2019 (132 months), respectively. Panels D and Panel E report the correlation matrix for these factors in the two sample periods. The constructions and definitions of the factors are detailed discussed in Section B of the Online Appendix data manual. [a], [b] and [c] represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Overview of the stocks in our sample

Year	#A-shares	#SH Mainboard	#SZ Mainboard	#SME	#GEM	A-shares TMV	A-shares CMV	SH TMV	SH CMV	SZ TMV	SZ CMV	SME TMV	SME CMV	GEM TMV	GEM CMV
1999	844	434	410	0	0	2.40	0.73	1.32	0.39	1.08	0.34	0	0	0	0
2000	968	516	452	0	0	4.42	1.44	2.48	0.77	1.94	0.67	0	0	0	0
2001	1,041	587	454	0	0	3.97	1.24	2.54	0.72	1.43	0.51	0	0	0	0
2002	1,080	648	432	0	0	3.43	1.07	2.30	0.65	1.13	0.42	0	0	0	0
2003	1,105	695	410	0	0	3.75	1.10	2.68	0.71	1.07	0.40	0	0	0	0
2004	1,190	743	409	38	0	3.34	1.00	2.37	0.65	0.93	0.35	0.04	0.01	0	0
2005	1,019	621	348	50	0	2.34	0.68	1.67	0.44	0.62	0.22	0.05	0.02	0	0
2006	1,104	679	342	83	0	5.03	1.83	3.63	1.17	1.24	0.60	0.16	0.06	0	0
2007	1,242	704	358	180	0	22.24	6.91	17.48	4.53	3.83	2.03	0.93	0.34	0	0
2008	1,363	729	383	251	0	8.30	3.27	6.23	2.13	1.49	0.89	0.58	0.24	0	0
2009	1,456	731	385	305	35	17.43	10.04	12.14	6.85	3.57	2.49	1.57	0.68	0.16	0.03
2010	1,775	740	379	505	151	19.58	13.89	11.84	9.41	3.66	2.79	3.35	1.49	0.72	0.20
2011	2,054	775	384	618	277	15.43	11.68	9.42	7.95	2.67	2.16	2.61	1.33	0.73	0.25
2012	2,252	840	394	669	349	16.36	12.75	9.94	8.57	2.84	2.34	2.72	1.51	0.86	0.33
2013	2,264	848	426	654	336	17.87	14.28	9.84	8.61	3.05	2.48	3.52	2.40	1.46	0.79
2014	2,324	873	415	659	377	26.23	21.27	15.21	13.24	4.51	3.63	4.52	3.20	1.99	1.20
2015	2,499	937	404	698	460	40.77	30.66	19.79	16.30	6.40	5.15	9.36	6.22	5.21	2.99
2016	2,748	1,043	404	759	542	39.03	29.08	19.30	15.63	5.95	4.84	8.89	5.79	4.89	2.82
2017	3,156	1,241	397	841	677	42.85	32.47	21.86	17.68	6.61	5.56	9.62	6.46	4.76	2.78
2018	3,357	1,320	429	874	734	32.93	25.89	17.69	14.81	4.74	4.00	6.55	4.69	3.95	2.38

Panel B: Factor return spreads for the whole sample period (July 2000 to June 2019)

	MKT	ME	I/A	ROE	SMB-FF5	HML-FF5	RMW	CMA	MKT-CH	SMB-CH3	SMB-CH4	VMG	PMO
Mean (in %)	0.62	0.78	0.29	0.54	0.68	0.42	-0.14	0.05	0.46	0.73	0.54	1.20	0.93
t-stat	1.15	3.12	2.10	2.36	2.42	1.79	-0.61	0.35	0.89	2.50	1.76	4.82	3.98
Std Dev (in %)	8.18	3.78	2.08	3.47	4.21	3.53	3.51	2.33	7.78	4.41	4.59	3.77	3.51

Panel C: Factor return spreads for the post-2007 subsample period (July 2008 to June 2019)

	MKT	ME	I/A	ROE	SMB-FF5	HML-FF5	RMW	CMA	MKT-CH	SMB-CH3	SMB-CH4	VMG	PMO
Mean (in %)	0.58	1.06	0.38	0.62	0.93	0.11	-0.18	0.17	0.36	0.98	0.80	0.91	0.88
t-stat	0.85	2.99	2.38	2.52	2.43	0.36	-0.71	0.98	0.55	2.56	2.04	2.85	2.71
Std Dev (in %)	7.84	4.09	1.82	2.84	4.42	3.60	2.93	1.99	7.54	4.39	4.52	3.65	3.73

Panel D: Correlation matrix for the whole sample period (July 2000 to June 2019)

	MKT	ME	I/A	ROE	SMB-FF5	HML-FF5	RMW	CMA	MKT-CH	SMB-CH3	SMB-CH4	VMG	PMO
MKT	1.00												

ME	0.11	1.00											
I/A	0.00	0.05	1.00										
ROE	-0.35[c]	-0.41[c]	-0.16[b]	1.00									
SMB-FF5	0.14[b]	0.96[c]	0.15[b]	-0.56[c]	1.00								
HML-FF5	0.04	-0.56[c]	0.04	0.11[a]	-0.54[c]	1.00							
RMW	-0.42[c]	-0.48[c]	-0.37[c]	0.76[c]	-0.57[c]	0.21[c]	1.00						
CMA	0.05	0.14[b]	0.87[c]	-0.43[c]	0.28[c]	0.01	-0.56[c]	1.00					
MKT-CH	0.99[c]	0.07	-0.06	-0.31[c]	0.09	0.07	-0.36[c]	-0.01	1.00				
SMB-CH3	0.25[c]	0.81[c]	0.24[c]	-0.51[c]	0.85[c]	-0.47[c]	-0.61[c]	0.34[c]	0.16[b]	1.00			
SMB-CH4	0.26[c]	0.81[c]	0.24[c]	-0.55[c]	0.87[c]	-0.48[c]	-0.63[c]	0.35[c]	0.17[c]	0.99[c]	1.00		
VMG	-0.35[c]	-0.58[c]	-0.10	0.72[c]	-0.65[c]	0.40[c]	0.71[c]	-0.31[c]	-0.30[c]	-0.64[c]	-0.69[c]	1.00	
PMO	-0.26[c]	0.10	-0.05	0.04	0.09	-0.27[c]	0.10	-0.11[a]	-0.26[c]	0.08	0.08	0.03	1.00
Panel E: Correlation matrix for the post-2007 subsample period (July 2008 to June 2019)													
	MKT	ME	I/A	ROE	SMB-FF5	HML-FF5	RMW	CMA	MKT-CH	SMB-CH3	SMB-CH4	VMG	PMO
MKT	1.00												
ME	0.11	1.00											
I/A	-0.17[a]	-0.15[a]	1.00										
ROE	-0.42[c]	-0.38[c]	-0.02	1.00									
SMB-FF5	0.15[a]	0.98[c]	-0.10	-0.49[c]	1.00								
HML-FF5	0.00	-0.76[c]	0.28[c]	0.14	-0.73[c]	1.00							
RMW	-0.42[c]	-0.50[c]	-0.19[b]	0.71[c]	-0.55[c]	0.22[b]	1.00						
CMA	-0.04	-0.07	0.90[c]	-0.29[c]	0.00	0.27[c]	-0.37[c]	1.00					
MKT-CH	1.00[c]	0.09	-0.19[b]	-0.42[c]	0.13	0.00	-0.40[c]	-0.05	1.00				
SMB-CH3	0.25[c]	0.91[c]	-0.07	-0.37[c]	0.90[c]	-0.68[c]	-0.55[c]	-0.03	0.21[b]	1.00			
SMB-CH4	0.27[c]	0.91[c]	-0.06	-0.42[c]	0.91[c]	-0.68[c]	-0.57[c]	-0.01	0.23[c]	0.99[c]	1.00		
VMG	-0.38[c]	-0.62[c]	0.20[b]	0.71[c]	-0.68[c]	0.54[c]	0.67[c]	-0.01	-0.38[c]	-0.60[c]	-0.66[c]	1.00	
PMO	-0.31[c]	0.21[b]	-0.04	-0.03	0.19[b]	-0.28[c]	-0.07	-0.05	-0.32[c]	0.20[b]	0.19[b]	-0.12	1.00

Table 2. The average monthly values, portfolio weights allocated to microcaps and investment capacity for the whole sample period (July 2000 to June 2019, 228 months)
Panel A presents value-weighted and equal-weighted averages and standard deviations (Std Dev) of monthly raw returns for all the A-shares (Market), microcaps (Micro), small, big, and all-but-micro stocks in our sample. The breakpoints are the 20th and 50th percentiles of mainboard market cap. Panel A also reports the number of stocks averaged across each month and the average percentage of total market capitalization and circulation market capitalization in each size group. Panels B-D report the portfolio weights allocated to microcap stocks. "Mom," "VvG," "Inv," "Prof," "Intan," and "Fric," denote the six categories of anomaly variables, momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions, respectively, and "All" includes all six categories. All stocks are sorted into quintiles in each category. "Low" denotes the lowest quintile and "High" the highest quintile. "Mainboard-VW" denotes Mainboard breakpoints and value-weighted returns, "Mainboard-EW" is Mainboard breakpoints and equal-weighted returns, "All-VW" is all A-share breakpoints and value-weighted returns, and "All-EW" is all A-share breakpoints and equal-weighted returns. Panel B computes the time-series average of weights allocated to microcap stocks in the lowest and highest quintile portfolios in each anomaly variable and shows the cross-sectional average across all the anomaly variables in a given category. In Panel C, we calculate the investment capacity for the lowest or highest quintile portfolio in each anomaly variable as a fraction of aggregate all A-shares circulation market cap in each month, compute the time-series average, and then report the cross-sectional average across all the anomaly variables in a given category. Panel D instead calculates and reports the investment capacity in trillions of *yuan* at the end of December 2018. All of the symbols and variable definitions are described in Online Appendix A and Table A1.

Panel A: Average monthly values

	Number of firms	% of total market cap	% of circulation market cap	Average of VW returns	Std Dev of VW returns	Average of EW returns	Std Dev of EW returns	Cross-sectional Std Dev of returns
Market	1,563	100.00%	100.00%	0.80%	8.63%	1.28%	9.84%	9.88%
Micro	449	8.78%	6.70%	1.40%	10.40%	1.69%	10.73%	9.93%
Small	457	13.74%	13.89%	1.13%	10.02%	1.34%	10.30%	9.71%
Big	657	77.48%	79.41%	0.71%	8.44%	0.91%	9.26%	9.47%
All-but-micro	1,114	91.22%	93.30%	0.76%	8.57%	1.09%	9.63%	9.67%

Panel B: Portfolio weights allocated to microcaps (in %)

	All-Low	Mom-Low	VvG-Low	Inv-Low	Prof-Low	Intan-Low	Fric-Low	All-High	Mom-High	VvG-High	Inv-High	Prof-High	Intan-High	Fric-High
Mainboard-VW	8.20	6.87	6.87	8.40	11.94	7.60	6.15	6.80	6.25	5.56	5.39	4.37	6.95	11.98
Mainboard-EW	26.44	24.86	24.26	26.46	32.56	25.25	23.56	25.04	24.49	25.78	21.49	20.72	25.27	32.94
All-VW	8.47	6.99	6.92	8.25	12.02	8.49	6.36	7.05	6.25	5.93	5.48	4.28	7.49	12.30
All-EW	26.86	25.02	24.38	26.36	32.76	26.41	23.97	25.34	24.53	26.23	21.55	20.60	25.96	33.33

Panel C: Investment capacity as a fraction of the aggregate market capitalization (in %)

	All-Low	Mom-Low	VvG-Low	Inv-Low	Prof-Low	Intan-Low	Fric-Low	All-High	Mom-High	VvG-High	Inv-High	Prof-High	Intan-High	Fric-High
Mainboard-VW	17.30	17.63	18.00	13.51	12.78	17.44	25.33	21.27	21.78	19.41	19.91	29.91	18.87	18.14
Mainboard-EW	1.78	1.77	2.00	1.52	1.50	1.70	2.34	1.94	2.01	1.43	1.95	2.25	1.73	2.26
All-VW	17.38	16.85	17.45	14.14	13.16	16.96	26.06	20.87	21.89	20.35	18.30	29.87	18.28	17.69
All-EW	1.76	1.70	1.97	1.54	1.53	1.60	2.35	1.90	2.00	1.48	1.86	2.23	1.69	2.21

Panel D: Investment capacity at the end of December 2018 (in trillion *yuan*)

	All-Low	Mom-Low	VvG-Low	Inv-Low	Prof-Low	Intan-Low	Fric-Low	All-High	Mom-High	VvG-High	Inv-High	Prof-High	Intan-High	Fric-High
Mainboard-VW	3.46	3.59	4.17	2.57	2.20	3.24	5.51	4.44	5.11	3.53	3.72	6.87	4.06	3.60
Mainboard-EW	0.19	0.20	0.23	0.16	0.16	0.18	0.22	0.22	0.21	0.13	0.20	0.22	0.22	0.29
All-VW	3.65	3.16	3.82	3.10	2.23	3.48	6.04	4.45	5.44	4.16	3.16	7.21	4.01	3.39
All-EW	0.19	0.19	0.21	0.17	0.16	0.19	0.23	0.22	0.22	0.16	0.18	0.24	0.22	0.27

Table 3. Significance rates for each category under four different portfolio construction procedures for the whole period (July 2000 to June 2019, 228 months)

This table reports the significant rates of raw return spreads (Panel A), CAPM alphas (Panel B), and Fama-French 3-factor alphas (Panel C) for each category under four different portfolio construction procedures. The alphas summarized in Panels B and C are the significant CAPM and Fama-French 3-factor alphas of those anomalies with significant raw return spreads. "Mainboard-VW" and "Mainboard-EW" denote Mainboard breakpoints with value- and equal-weighted returns; "All-VW" and "All-EW" denote all A-share breakpoints with value- and equal-weighted returns, respectively, in portfolio sorts. We apply the absolute *t*-statistics cutoff of 1.96 from single hypothesis testing at the 5% significance level and 2.78 from multiple hypothesis testing at the 5% level. For each category, the numbers report the fractions of significant anomalies with *t*-statistics above the cutoffs. Note that there are 45, 68, 36, 94, 83, and 143 anomalies in the momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions categories, respectively. The total number of anomalies is 469 in "All categories".

Panel A: Significant rates of raw return spreads for each category under four different portfolio construction procedures														
	Momentum		Value-versus-growth		Investment		Profitability		Intangibles		Trading frictions		All categories	
	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$
Mainboard-VW	15.56%	4.44%	8.82%	0.00%	2.78%	0.00%	8.51%	5.32%	12.05%	2.41%	32.17%	13.99%	16.63%	6.18%
All-VW	15.56%	4.44%	5.88%	0.00%	11.11%	2.78%	6.38%	4.26%	12.05%	1.20%	33.57%	13.29%	16.84%	5.76%
Mainboard-EW	17.78%	4.44%	67.65%	52.94%	61.11%	22.22%	39.36%	20.21%	18.07%	13.25%	64.34%	44.06%	46.91%	29.64%
All-EW	17.78%	4.44%	69.12%	54.41%	61.11%	30.56%	37.23%	19.15%	19.28%	13.25%	66.43%	44.06%	47.55%	30.28%
Panel B: Significant rates of CAPM alphas for each category under four different portfolio construction procedures														
	Momentum		Value-versus-growth		Investment		Profitability		Intangibles		Trading frictions		All categories	
	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$
Mainboard-VW	15.56%	4.44%	5.88%	0.00%	2.78%	0.00%	8.51%	5.32%	10.84%	2.41%	31.47%	12.59%	15.78%	5.76%
All-VW	15.56%	4.44%	2.94%	0.00%	11.11%	2.78%	6.38%	4.26%	10.84%	1.20%	32.17%	11.89%	15.78%	5.33%
Mainboard-EW	15.56%	4.44%	66.18%	44.12%	61.11%	22.22%	36.17%	12.77%	18.07%	10.84%	64.34%	44.06%	45.84%	26.44%
All-EW	15.56%	4.44%	69.12%	47.06%	58.33%	30.56%	34.04%	12.77%	18.07%	10.84%	66.43%	43.36%	46.27%	27.29%
Panel C: Significant rates of Fama-French 3-factor alphas for each category under four different portfolio construction procedures														
	Momentum		Value-versus-growth		Investment		Profitability		Intangibles		Trading frictions		All categories	
	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$	$\|t\| \geq 1.96$	$\|t\| \geq 2.78$
Mainboard-VW	15.56%	4.44%	1.47%	0.00%	2.78%	0.00%	8.51%	5.32%	6.02%	1.20%	27.27%	9.79%	13.01%	4.69%
All-VW	15.56%	4.44%	1.47%	0.00%	2.78%	2.78%	6.38%	4.26%	6.02%	1.20%	27.27%	10.49%	12.58%	4.90%
Mainboard-EW	17.78%	4.44%	48.53%	29.41%	11.11%	2.78%	7.45%	4.26%	8.43%	8.43%	61.54%	39.86%	31.34%	19.40%
All-EW	17.78%	4.44%	48.53%	27.94%	11.11%	5.56%	6.38%	4.26%	12.05%	8.43%	62.94%	38.46%	32.20%	18.98%

Table 4. Raw return spreads for each significant anomaly

This table reports the high-minus-low quintile return spreads for significant anomalies that are based on the benchmark of raw returns for the whole sample period (in panel A) and the post-2007 subsample period (in panel B). For each high-minus-low quintile, *m* is the average raw return spread (in %). ^{a} and ^{b} indicate absolute *t*-statistics exceeding the thresholds of 1.96 (but below 2.78) and 2.78, respectively. Columns 1–7 in Panel A and columns 1–7 in Panel B report the results related to the momentum category; columns 8–13 in Panel A and columns 8 in Panel B report the results related to the value-versus-growth category; columns 14 in Panel A and columns 9–17 in Panel B report the results related to the investment category; columns 15–22 in Panel A and columns 18–23 in Panel B report the results for the profitability category; columns 23–32 in Panel A and columns 24–30 in Panel B report the results for the intangibles category; and columns 33–78 in panel A and columns 31–61 in Panel B report the results for the trading frictions category. Note that there are 45, 68, 36, 94, 83, and 143 anomalies in the momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions categories, respectively.

Panel A: Raw return spreads for each significant anomaly across the whole sample period (July 2000 to June 2019, 228 months)

	Momentum (7)							Value-versus-growth (6)						Investment (1)	Profitability (8)					
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Sue1	Sue3	Sue6	Sue9	Abr9	ϵ^{6}3	ϵ^{6}6	Ep^{q}1	Ndp	Ndp^{q}3	Ndp^{q}6	Ndp^{q}9	Ndp^{q}12	Noa	dRoe1	dRoe3	dRoa1	dRoa3	Ato^{q}1	Ato^{q}3
m	1.17^{b}	0.82^{b}	0.54^{a}	0.47^{a}	0.32^{a}	0.56^{a}	0.44^{a}	0.84^{a}	0.68^{a}	0.74^{a}	0.68^{a}	0.71^{a}	0.72^{a}	-0.51^{a}	1.16^{b}	0.68^{b}	1.08^{b}	0.65^{b}	0.56^{a}	0.63^{b}

	Profitability (8)		Intangibles (10)										Trading frictions (46)							
#	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
	Ato^{q}6	Ato^{q}9	Adm	Rdm^{q}1	Rdm^{q}3	Rdm^{q}6	Rdm^{q}9	Rdm^{q}12	Ala^{q}6	Ala^{q}9	R^{1}_{a}	$R^{[2,5]}_{n}$	Ivc1	Ivff31	Ivff33	Ivff51	Ivq1	Ivch31	Ivch41	Svr1
m	0.44^{a}	0.42^{a}	0.66^{b}	0.83^{b}	0.73^{a}	0.59^{a}	0.60^{a}	0.61^{a}	0.49^{a}	0.45^{a}	0.57^{a}	-0.60^{a}	-0.77^{a}	-0.93^{b}	-0.62^{a}	-0.72^{a}	-0.89^{a}	-0.87^{a}	-0.86^{a}	-0.51^{a}

	Trading frictions (46)																			
#	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	β^{D}1	Cvt1	Rtv1	Rtv3	Rtv6	Rtv9	Rtv12	Pps1	Pps3	Pps6	Pps9	Pps12	Mdr1	Mdr3	Ts1	Ts3	Isc1	Isc3	Isff31	Isq1
m	0.79^{a}	-0.59^{a}	-1.30^{b}	-1.00^{a}	-0.93^{a}	-0.96^{a}	-1.00^{b}	-1.58^{b}	-1.21^{b}	-1.12^{b}	-1.12^{b}	-1.06^{b}	-0.82^{a}	-0.65^{a}	-0.64^{b}	-0.35^{a}	-0.51^{a}	-0.38^{a}	-0.34^{a}	-0.40^{a}

	Trading frictions (46)																	
#	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78
	Isq3	Isch31	Isch33	Isch41	Isch43	Srev	Esba1	Esba3	Esba6	Esba9	Esba12	Qsba1	Qsba3	Qsba6	Qsba9	Qsba12	Vpin3	Vpin6
m	-0.25^{a}	-0.39^{a}	-0.34^{b}	-0.41^{a}	-0.31^{a}	-0.84^{a}	1.70^{b}	1.65^{b}	1.58^{b}	1.48^{b}	1.41^{b}	2.07^{b}	1.99^{b}	1.85^{b}	1.65^{b}	1.59^{b}	-0.91^{a}	-0.74^{a}

Panel B: Raw return spreads for each significant anomaly across the post-2007 subsample period (July 2008 to June 2019, 132 months)

	Momentum (7)							Value-versus-growth (1)	Investment (9)									Profitability (6)		
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Sue1	Sue3	Sue6	Sue9	Sue12	Abr6	Abr9	Sr	I/A	dPia	Noa	dLno	Cei	dNco	dNca	dFin	dFnl	dRoe1	dRoe3	dRoe6
m	0.93^{b}	0.75^{b}	0.62^{b}	0.49^{a}	0.39^{a}	0.40^{a}	0.33^{a}	-0.66^{a}	-0.58^{a}	-0.63^{b}	-0.67^{a}	-0.63^{a}	-0.68^{a}	-0.64^{a}	-0.66^{a}	0.46^{a}	-0.38^{a}	1.02^{b}	0.68^{a}	0.54^{a}

	Profitability (6)			Intangibles (7)							Trading frictions(31)									
#	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
	dRoa1	dRoa3	dRoa6	Tan^{q}12	Cta12	Ala^{q}1	Ala^{q}3	Ala^{q}6	Ala^{q}9	Ala^{q}12	Me	Ivch31	Svr1	β^{D}1	β^{PS}3	β^{PS}6	Rtv1	Rtv3	Rtv6	Rtv9
m	0.96^{b}	0.67^{a}	0.52^{a}	0.63^{a}	0.71^{a}	0.83^{a}	0.86^{a}	0.81^{a}	0.76^{a}	0.76^{a}	-1.31^{a}	-0.94^{a}	-0.62^{a}	1.04^{a}	-0.49^{a}	-0.44^{a}	-1.91^{b}	-1.71^{b}	-1.60^{b}	-1.55^{b}

	Trading frictions (31)																			
#	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	Rtv12	Pps1	Pps3	Pps6	Ami1	Ami3	Ami6	Ami9	Ami12	Ts1	Srev	Esba1	Esba3	Esba6	Esba9	Esba12	Qsba1	Qsba3	Qsba6	Qsba9
m	-1.50^{b}	-1.37^{b}	-1.15^{a}	-0.97^{a}	1.33^{a}	1.28^{a}	1.26^{a}	1.24^{a}	1.20^{a}	-0.63^{a}	-1.11^{a}	2.41^{b}	2.39^{b}	2.22^{b}	2.06^{b}	1.91^{b}	2.84^{b}	2.68^{b}	2.45^{b}	2.23^{b}

	Trading frictions (31)
#	61
	Qsba12
m	2.07^{b}

Table 5. Overall performance of different factor models in explaining significant anomalies

This table reports the overall performance of different factor models in explaining the significant anomaly variables based on high-minus-low quintile return spreads. For each factor model and each anomaly category, $\overline{|\alpha_{H-L}|}$ is the average magnitude of the high-minus-low quintile alphas, $\#|t| \geq 1.96$ is the number of high-minus-low quintile alphas with $|t| \geq 1.96$ (i.e., single hypothesis testing at the 5% significance level); $\overline{|\alpha|}$ is the mean absolute alpha across all anomaly quintiles in a given category, and $\#p < 5\%$ is the number of sets of quintiles within a given category, with which the factor model is rejected by the GRS test at the 5% level. There are 45, 68, 36, 94, 83, and 143 anomalies in the momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions categories, respectively. The total number of anomalies is 469 in "All" category. We report the results for the CAPM, FF3-factor, FF5-factor, *q*-factor, Liu-Stambaugh-Yuan CH3-factor and CH4-factor, and Carhart 4-factor (Car4) models. Panel A reports the results over the whole sample period (July 2000 to June 2019, 228 months), and Panel B reports the results in the post-2007 subsample period (July 2008 to June 2019, 132 months).

Panel A: The whole sample period (2000/07–2019/06), Mainboard-VW

	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$
	All (78)				Momentum (7)				Value-versus-Growth (6)				Investment (1)			
CAPM	0.85	74	0.39	65	0.63	7	0.32	4	0.72	4	0.32	5	0.53	1	0.34	1
FF3	0.70	61	0.33	67	0.73	7	0.27	6	0.44	1	0.21	1	0.70	1	0.24	1
FF5	0.71	66	0.32	62	0.69	7	0.26	6	0.37	1	0.22	1	0.80	1	0.28	1
q	0.83	58	0.30	53	0.38	3	0.18	0	1.26	6	0.38	6	0.29	0	0.18	0
CH3	0.64	36	0.39	53	0.37	2	0.36	1	0.59	3	0.34	4	0.20	0	0.37	1
CH4	0.67	41	0.43	58	0.38	2	0.37	2	0.73	5	0.43	6	0.16	0	0.44	1
Car4	0.72	67	0.30	61	0.59	7	0.22	5	0.50	2	0.23	2	0.74	1	0.26	1
					Profitability (8)				Intangibles (10)				Frictions (46)			
CAPM					0.75	8	0.36	8	0.60	9	0.33	8	0.97	45	0.44	39
FF3					0.85	8	0.33	8	0.44	5	0.27	9	0.77	39	0.37	42
FF5					0.78	8	0.32	8	0.41	5	0.25	5	0.80	44	0.36	41
q					0.36	3	0.19	3	0.77	7	0.26	8	0.95	39	0.34	36
CH3					0.21	1	0.39	7	0.46	0	0.34	8	0.80	30	0.42	32
CH4					0.20	1	0.42	7	0.45	3	0.37	9	0.85	30	0.45	33
Car4					0.65	8	0.27	8	0.42	6	0.21	5	0.85	43	0.34	40

Panel B: The post-2007 subsample period (2008/07–2019/06), Mainboard-VW

	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$	$\overline{\vert\alpha_{H-L}\vert}$	$\#\vert t\vert\geq1.96$	$\overline{\vert\alpha\vert}$	$\#p<5\%$
	All (61)				Momentum (7)				Value-versus-Growth (1)				Investment (9)			
CAPM	1.10	58	0.43	40	0.59	7	0.24	4	0.63	1	0.30	0	0.60	8	0.31	3
FF3	0.76	44	0.29	44	0.80	7	0.24	7	0.11	0	0.17	0	0.42	3	0.25	2
FF5	0.69	44	0.30	45	0.83	7	0.25	7	0.13	0	0.23	0	0.38	4	0.27	3
q	0.56	16	0.24	18	0.14	0	0.13	0	0.03	0	0.09	0	0.15	0	0.13	0
CH3	0.73	27	0.37	26	0.19	0	0.23	0	0.47	0	0.27	0	0.28	0	0.27	1
CH4	0.80	28	0.36	26	0.24	1	0.21	1	0.57	0	0.28	0	0.30	0	0.25	0
Car4	0.75	43	0.29	49	0.78	7	0.23	7	0.09	0	0.17	0	0.41	2	0.24	2
					Profitability (6)				Intangibles (7)				Frictions (31)			

CAPM	0.75	6	0.35	5	0.73	7	0.27	0	1.52	29	0.57	28
FF3	0.81	6	0.31	4	0.71	7	0.21	5	0.87	21	0.34	26
FF5	0.90	6	0.34	5	0.73	7	0.23	6	0.71	20	0.33	24
q	0.23	0	0.11	0	0.06	0	0.12	0	0.97	16	0.36	18
CH3	0.16	0	0.27	1	0.49	0	0.27	0	1.15	27	0.47	24
CH4	0.23	0	0.26	1	0.39	0	0.25	0	1.27	27	0.48	24
Car4	0.77	6	0.30	6	0.68	7	0.20	7	0.87	21	0.33	27

Table 6. Explaining each of the significant anomalies with different factor models

This table reports the performance of different factor models in explaining each of the anomalies with significant raw return spreads for the whole sample period (Panel A) and the post-2007 subsample period (Panel B). For each high-minus-low quintile, α_{FF5}, α_q, α_{CH3}, and α_{CH4} are the FF5-factor alpha, *q*-factor alpha, CH3-factor alpha, and CH4-factor alpha (in %), respectively. ^{a} and ^{b} indicate absolute *t*-statistics exceeding the thresholds of 1.96 (but below 2.78) and 2.78, respectively. $\overline{|\alpha_{FF5}|}$, $\overline{|\alpha_q|}$, $\overline{|\alpha_{CH3}|}$, and $\overline{|\alpha_{CH4}|}$ are the mean absolute alphas (in %) from the corresponding factor models across the quintile portfolios for a given anomaly. p_{FF5}, p_q, p_{CH3}, and p_{CH4} are the *p*-values of the GRS test on the null that all alphas across the quintiles are jointly zero in the corresponding factor models. We have 45, 68, 36, 94, 83, and 143 anomalies in the momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions categories, respectively. Columns 1–7 in panel A and columns 1–7 in panel B report the results related to the momentum category; columns 8–13 in panel A and columns 8 in panel B report the results related to the value-versus-growth category; columns 14 in panel A and columns 9–17 in panel B report the results related to the investment category; columns 15–22 in panel A and columns 18–23 in panel B report the results for the profitability category; columns 23–32 in panel A and columns 24–30 in panel B report the results for the intangibles category; and columns 33–78 in panel A and columns 31–61 in panel B report the results for the trading frictions category. All of the symbols, variable definitions, and portfolio constructions are described in Online Appendix A and Table A1.

Panel A: Explaining significant anomalies with different factor models for the whole sample period (July 2000 to June 2019, 228 months)

	Momentum (7)							Value-versus-growth (6)						Investment (1)	Profitability (8)					
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Sue1	Sue3	Sue6	Sue9	Abr9	$\epsilon^6 3$	$\epsilon^6 6$	Ep^{q}1	Ndp	Ndp^{q}3	Ndp^{q}6	Ndp^{q}9	Ndp^{q}12	Noa	dRoe1	dRoe3	dRoa1	dRoa3	Ato^{q}1	Ato^{q}3
α_{FF5}	1.11^b	0.86^b	0.65^b	0.57^b	0.53^b	0.58^a	0.52^a	0.91^b	0.29	0.29	0.22	0.24	0.25	-0.80^b	1.18^b	0.81^b	1.08^b	0.76^b	0.61^b	0.73^b
α_q	0.78^b	0.39	0.15	0.16	0.30^a	0.48^a	0.39	1.01^b	1.11^b	1.42^b	1.36^b	1.34^b	1.31^b	-0.29	0.68^a	0.12	0.62^a	0.10	0.27	0.46^a
α_{CH3}	0.47	0.18	0.03	0.06	0.22	0.91^b	0.69^b	-0.25	0.71^a	0.61	0.65	0.68^a	0.66^a	-0.20	0.60^a	0.14	0.44	0.03	0.05	0.21
α_{CH4}	0.50	0.20	0.05	0.03	0.19	0.93^b	0.77^b	-0.28	0.88^a	0.76^a	0.82^a	0.81^a	0.81^a	-0.16	0.66^a	0.21	0.49	0.07	-0.03	0.13
$\overline{\lvert\alpha_{FF5}\rvert}$	0.38	0.32	0.29	0.28	0.19	0.21	0.19	0.40	0.19	0.20	0.18	0.18	0.19	0.28	0.40	0.30	0.43	0.35	0.26	0.27
$\overline{\lvert\alpha_q\rvert}$	0.21	0.19	0.17	0.25	0.08	0.18	0.16	0.28	0.37	0.41	0.42	0.41	0.41	0.18	0.23	0.18	0.29	0.22	0.12	0.15
$\overline{\lvert\alpha_{CH3}\rvert}$	0.45	0.47	0.44	0.43	0.18	0.30	0.23	0.38	0.36	0.33	0.32	0.33	0.35	0.37	0.39	0.39	0.42	0.43	0.38	0.36
$\overline{\lvert\alpha_{CH4}\rvert}$	0.48	0.51	0.47	0.47	0.15	0.29	0.22	0.42	0.50	0.41	0.39	0.42	0.44	0.44	0.42	0.43	0.46	0.47	0.41	0.40
p_{FF5}	0.00	0.00	0.00	0.00	0.00	0.02	0.16	0.00	0.19	0.10	0.29	0.35	0.27	0.00	0.00	0.00	0.00	0.00	0.01	0.00
p_q	0.07	0.38	0.66	0.33	0.11	0.13	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.06	0.33	0.01	0.11	0.41	0.07
p_{CH3}	0.06	0.11	0.20	0.18	0.52	0.01	0.06	0.11	0.06	0.02	0.05	0.05	0.05	0.03	0.04	0.04	0.01	0.02	0.09	0.04
p_{CH4}	0.06	0.09	0.10	0.08	0.50	0.01	0.03	0.04	0.00	0.00	0.01	0.01	0.01	0.02	0.04	0.07	0.01	0.04	0.02	0.02

	Profitability (8)		Intangibles (10)										Trading frictions (46)							
#	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
	Ato^{q}6	Ato^{q}9	Adm	Rdm^{q}1	Rdm^{q}3	Rdm^{q}6	Rdm^{q}9	Rdm^{q}12	Ala^{q}6	Ala^{q}9	R_a^1	$R_n^{[2,5]}$	Ivc1	Ivff31	Ivff33	Ivff51	Ivq1	Ivch31	Ivch41	Svr1
α_{FF5}	0.52^b	0.50^b	0.57^b	0.45^a	0.32	0.17	0.18	0.20	0.58^b	0.56^b	0.66^a	-0.37	-1.03^b	-1.25^b	-0.85^b	-1.08^b	-1.18^b	-1.15^b	-1.17^b	-0.56^a
α_q	0.29	0.32	0.66^b	1.32^b	1.23^b	1.11^b	1.10^b	1.06^b	0.08	0.03	0.36	-0.76^a	-1.07^b	-1.34^b	-1.22^b	-1.12^b	-1.29^b	-1.22^b	-1.24^b	-0.47
α_{CH3}	0.10	0.13	0.48	0.53	0.52	0.50	0.55	0.55	0.34	0.33	0.33	-0.51	-0.18	-0.48	-0.27	-0.27	-0.39	-0.31	-0.34	-0.21
α_{CH4}	0.00	0.01	0.38	0.56	0.58	0.57	0.61^a	0.62^a	0.11	0.13	0.23	-0.75^a	0.05	-0.28	-0.17	-0.07	-0.22	-0.14	-0.14	-0.41
$\overline{\lvert\alpha_{FF5}\rvert}$	0.27	0.26	0.25	0.25	0.25	0.26	0.25	0.26	0.25	0.24	0.25	0.25	0.37	0.42	0.27	0.33	0.39	0.40	0.39	0.29
$\overline{\lvert\alpha_q\rvert}$	0.16	0.15	0.22	0.38	0.34	0.30	0.29	0.29	0.13	0.15	0.24	0.29	0.34	0.35	0.32	0.34	0.34	0.38	0.37	0.17
$\overline{\lvert\alpha_{CH3}\rvert}$	0.37	0.36	0.33	0.36	0.35	0.34	0.35	0.36	0.37	0.36	0.22	0.39	0.18	0.25	0.18	0.20	0.22	0.22	0.21	0.24
$\overline{\lvert\alpha_{CH4}\rvert}$	0.41	0.40	0.39	0.38	0.37	0.36	0.37	0.38	0.40	0.40	0.18	0.45	0.22	0.22	0.17	0.22	0.22	0.21	0.21	0.25
p_{FF5}	0.00	0.00	0.03	0.01	0.02	0.08	0.12	0.07	0.00	0.00	0.07	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

p_q	0.03	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.56	0.63	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10
p_{CH3}	0.03	0.03	0.03	0.01	0.01	0.01	0.01	0.00	0.03	0.02	0.43	0.05	0.49	0.05	0.06	0.46	0.13	0.18	0.27	0.32
p_{CH4}	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.40	0.01	0.67	0.13	0.16	0.62	0.24	0.43	0.40	0.08

	Trading frictions (46)																			
#	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	β^D1	Cvt1	Rtv1	Rtv3	Rtv6	Rtv9	Rtv12	Pps1	Pps3	Pps6	Pps9	Pps12	Mdr1	Mdr3	Ts1	Ts3	Isc1	Isc3	Isff31	Isq1
α_{FF5}	0.34	-0.62[a]	-0.76[b]	-0.50[b]	-0.39[a]	-0.40[b]	-0.38[b]	-1.04[b]	-0.61[a]	-0.57[a]	-0.56[b]	-0.54[b]	-1.23[b]	-0.93[b]	-0.48[a]	-0.16	-0.52[a]	-0.37[a]	-0.47[b]	-0.52[b]
α_q	0.58	-0.52[a]	-0.51[b]	-0.15	-0.08	-0.10	-0.16	-2.15[b]	-1.75[b]	-1.69[b]	-1.65[b]	-1.52[b]	-0.99[b]	-0.89[b]	-0.48[a]	-0.27[a]	-0.54[a]	-0.29[a]	-0.52[b]	-0.59[b]
α_{CH3}	0.63	-0.62[a]	-0.86[b]	-0.64[a]	-0.63[a]	-0.67[b]	-0.70[b]	-1.51[b]	-1.18[a]	-1.24[b]	-1.25[b]	-1.14[b]	-0.40	-0.25	-0.57[a]	-0.21	-0.78[b]	-0.46[a]	-0.40[a]	-0.55[b]
α_{CH4}	1.00[b]	-0.53	-0.74[b]	-0.62[a]	-0.68[a]	-0.77[b]	-0.81[b]	-1.82[b]	-1.54[b]	-1.53[b]	-1.53[b]	-1.41[b]	0.04	-0.01	-0.44	-0.21	-0.71[b]	-0.40[a]	-0.31	-0.53[a]
$\overline{\lvert\alpha_{FF5}\rvert}$	0.26	0.24	0.42	0.37	0.34	0.33	0.32	0.40	0.38	0.35	0.29	0.28	0.42	0.31	0.20	0.10	0.21	0.15	0.15	0.16
$\overline{\lvert\alpha_q\rvert}$	0.19	0.19	0.26	0.19	0.17	0.16	0.17	0.55	0.52	0.53	0.50	0.46	0.33	0.27	0.14	0.13	0.17	0.15	0.19	0.19
$\overline{\lvert\alpha_{CH3}\rvert}$	0.35	0.26	0.56	0.53	0.51	0.50	0.50	0.39	0.39	0.39	0.39	0.38	0.26	0.20	0.28	0.20	0.31	0.22	0.20	0.25
$\overline{\lvert\alpha_{CH4}\rvert}$	0.43	0.25	0.56	0.56	0.56	0.56	0.57	0.48	0.46	0.43	0.43	0.42	0.21	0.20	0.26	0.20	0.31	0.21	0.21	0.26
p_{FF5}	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.32	0.08	0.01	0.12	0.02
p_q	0.03	0.05	0.00	0.18	0.36	0.30	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.03	0.03	0.06	0.01	0.01
p_{CH3}	0.06	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.02	0.11	0.01	0.02	0.07	0.00
p_{CH4}	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.07	0.20	0.02	0.02	0.01	0.00

	Trading frictions (46)																	
#	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78
	Isq3	Isch31	Isch33	Isch41	Isch43	Srev	Esba1	Esba3	Esba6	Esba9	Esba12	Qsba1	Qsba3	Qsba6	Qsba9	Qsba12	Vpin3	Vpin6
α_{FF5}	-0.23[a]	-0.62[b]	-0.44[b]	-0.60[b]	-0.39[b]	-0.68[a]	1.29[b]	1.22[b]	1.13[b]	1.01[b]	0.95[b]	1.69[b]	1.50[b]	1.38[b]	1.16[b]	1.11[b]	-1.08[b]	-0.84[b]
α_q	-0.31[a]	-0.51[b]	-0.49[b]	-0.64[b]	-0.49[b]	-0.68	1.50[b]	1.27[b]	1.15[b]	1.05[b]	0.95[b]	1.83[b]	1.67[b]	1.52[b]	1.31[b]	1.21[b]	-1.46[b]	-1.33[b]
α_{CH3}	-0.22	-0.58[b]	-0.43[b]	-0.61[b]	-0.36[a]	-0.38	1.90[b]	1.63[b]	1.44[b]	1.31[b]	1.18[b]	2.11[b]	1.85[b]	1.67[b]	1.44[b]	1.31[b]	-0.78	-0.62
α_{CH4}	-0.21	-0.59[b]	-0.44[b]	-0.59[b]	-0.38[b]	-0.07	1.89[b]	1.77[b]	1.68[b]	1.60[b]	1.50[b]	2.11[b]	2.02[b]	1.95[b]	1.77[b]	1.66[b]	-0.85[a]	-0.84[a]
$\overline{\lvert\alpha_{FF5}\rvert}$	0.11	0.20	0.15	0.18	0.17	0.27	0.70	0.63	0.59	0.55	0.52	0.78	0.67	0.62	0.57	0.55	0.44	0.39
$\overline{\lvert\alpha_q\rvert}$	0.11	0.15	0.14	0.22	0.16	0.22	0.70	0.57	0.50	0.44	0.41	0.77	0.65	0.56	0.49	0.45	0.53	0.47
$\overline{\lvert\alpha_{CH3}\rvert}$	0.19	0.25	0.21	0.23	0.21	0.26	0.95	0.86	0.78	0.73	0.70	1.02	0.90	0.82	0.76	0.73	0.52	0.49
$\overline{\lvert\alpha_{CH4}\rvert}$	0.20	0.28	0.22	0.24	0.21	0.27	0.99	0.92	0.85	0.81	0.79	1.06	0.96	0.89	0.84	0.82	0.53	0.51
p_{FF5}	0.03	0.01	0.00	0.01	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p_q	0.06	0.03	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p_{CH3}	0.02	0.08	0.01	0.02	0.05	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
p_{CH4}	0.02	0.05	0.01	0.01	0.03	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01

Panel B: Explaining significant anomalies with different factor models for the post-2007 subsample period (July 2008 to June 2019, 132 months)

	Momentum (7)							Value-versus-growth (1)	Investment (9)									Profitability (6)		
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Sue1	Sue3	Sue6	Sue9	Sue12	Abr6	Abr9	Sr	I/A	dPia	Noa	dLno	Cei	dNco	dNca	dFin	dFnl	dRoe1	dRoe3	dRoe6
α_{FF5}	1.21[b]	1.04[b]	0.92[b]	0.75[b]	0.64[b]	0.69[b]	0.57[b]	-0.13	-0.06	-0.40[a]	-0.86[b]	-0.22	-0.46	-0.43	-0.48[a]	0.34[a]	-0.19	1.20[b]	0.86[b]	0.69[a]

α_{q}	0.15	-0.03	0.09	0.10	0.08	0.25	0.25	0.03	-0.11	-0.13	-0.35	-0.37	0.09	0.06	0.03	-0.04	0.14	0.04	-0.27	-0.26
α_{CH3}	0.27	0.09	0.13	0.10	0.05	0.35	0.30	-0.47	-0.43	-0.45	-0.37	-0.41	-0.08	-0.21	-0.25	0.20	-0.11	0.45	0.11	0.01
α_{CH4}	0.29	0.14	0.21	0.15	0.08	0.41	0.42[a]	-0.57	-0.53	-0.38	-0.28	-0.41	-0.06	-0.27	-0.31	0.30	-0.18	0.53	0.22	0.13
$\overline{\|\alpha_{FF5}\|}$	0.33	0.29	0.26	0.24	0.22	0.23	0.20	0.23	0.22	0.28	0.30	0.28	0.30	0.30	0.31	0.23	0.23	0.40	0.33	0.27
$\overline{\|\alpha_{q}\|}$	0.10	0.08	0.07	0.09	0.09	0.24	0.23	0.09	0.11	0.05	0.14	0.15	0.24	0.13	0.11	0.15	0.12	0.09	0.11	0.09
$\overline{\|\alpha_{CH3}\|}$	0.26	0.27	0.27	0.26	0.25	0.17	0.14	0.27	0.33	0.32	0.28	0.27	0.09	0.31	0.32	0.27	0.27	0.25	0.25	0.26
$\overline{\|\alpha_{CH4}\|}$	0.24	0.25	0.25	0.23	0.22	0.12	0.12	0.28	0.31	0.29	0.25	0.24	0.06	0.29	0.30	0.25	0.26	0.29	0.23	0.23
p_{FF5}	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.51	0.29	0.04	0.03	0.46	0.24	0.04	0.08	0.05	0.15	0.00	0.00	0.01
p_{q}	0.67	0.75	0.92	0.75	0.61	0.28	0.16	0.94	0.84	0.94	0.64	0.60	0.78	0.64	0.81	0.61	0.78	0.65	0.65	0.67
p_{CH3}	0.35	0.33	0.27	0.16	0.15	0.23	0.29	0.52	0.11	0.14	0.10	0.28	0.89	0.12	0.15	0.04	0.15	0.19	0.18	0.09
p_{CH4}	0.49	0.45	0.07	0.04	0.05	0.27	0.21	0.47	0.09	0.21	0.20	0.41	0.92	0.23	0.18	0.08	0.27	0.15	0.20	0.11

	Profitability (6)			Intangibles (7)							Trading frictions (31)									
#	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
	dRoa1	dRoa3	dRoa6	Tan^{q}12	Cta12	Ala^{q}1	Ala^{q}3	Ala^{q}6	Ala^{q}9	Ala^{q}12	Me	Ivch31	Svr1	β^{D}1	β^{PS}3	β^{PS}6	Rtv1	Rtv3	Rtv6	Rtv9
α_{FF5}	1.13[b]	0.85[b]	0.68[a]	0.53[a]	0.74[b]	0.83[b]	0.84[b]	0.77[b]	0.71[b]	0.72[b]	0.02	-1.49[b]	-0.40	0.47	-0.50[a]	-0.46[a]	-0.88[b]	-0.66[b]	-0.54[b]	-0.46[a]
α_{q}	-0.10	-0.37	-0.35	-0.08	-0.15	-0.02	0.07	0.07	0.02	0.05	0.13	-1.55[b]	-0.50	0.73	-0.39	-0.35	-0.55[a]	-0.37	-0.25	-0.19
α_{CH3}	0.29	-0.01	-0.11	0.54	0.47	0.42	0.51	0.52	0.47	0.48	-0.72[b]	-0.53	-0.33	0.50	-0.54[a]	-0.50[a]	-1.11[b]	-0.93[b]	-0.83[b]	-0.79[b]
α_{CH4}	0.41	0.10	0.00	0.46	0.34	0.33	0.41	0.43	0.39	0.40	-0.80[b]	-0.08	-0.54	0.96[a]	-0.56[a]	-0.54[a]	-0.92[b]	-0.86[b]	-0.84[b]	-0.85[b]
$\overline{\|\alpha_{FF5}\|}$	0.39	0.32	0.29	0.18	0.22	0.24	0.26	0.25	0.24	0.24	0.14	0.48	0.21	0.30	0.18	0.17	0.38	0.35	0.32	0.30
$\overline{\|\alpha_{q}\|}$	0.13	0.13	0.11	0.06	0.08	0.24	0.15	0.11	0.11	0.11	0.20	0.50	0.30	0.27	0.20	0.21	0.19	0.13	0.10	0.10
$\overline{\|\alpha_{CH3}\|}$	0.31	0.28	0.28	0.27	0.27	0.27	0.27	0.28	0.28	0.28	0.42	0.27	0.21	0.31	0.18	0.16	0.56	0.53	0.51	0.49
$\overline{\|\alpha_{CH4}\|}$	0.30	0.26	0.26	0.25	0.24	0.25	0.24	0.24	0.25	0.25	0.43	0.16	0.25	0.39	0.15	0.13	0.49	0.51	0.51	0.50
p_{FF5}	0.00	0.04	0.07	0.06	0.02	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.09	0.02	0.22	0.31	0.00	0.00	0.00	0.00
p_{q}	0.26	0.40	0.52	1.00	0.90	0.07	0.46	0.70	0.72	0.53	0.05	0.00	0.05	0.06	0.31	0.37	0.04	0.16	0.34	0.32
p_{CH3}	0.03	0.08	0.09	0.08	0.12	0.06	0.14	0.12	0.11	0.08	0.00	0.14	0.34	0.15	0.17	0.25	0.00	0.00	0.00	0.00
p_{CH4}	0.04	0.13	0.18	0.16	0.31	0.15	0.19	0.18	0.20	0.16	0.00	0.25	0.15	0.08	0.21	0.30	0.00	0.00	0.00	0.00

	Trading frictions (31)																			
#	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	Rtv12	Pps1	Pps3	Pps6	Ami1	Ami3	Ami6	Ami9	Ami12	Ts1	Srev	Esba1	Esba3	Esba6	Esba9	Esba12	Qsba1	Qsba3	Qsba6	Qsba9
α_{FF5}	-0.41[a]	-0.73[a]	-0.50	-0.35	0.17	0.10	0.07	0.05	0.02	-0.36	-0.95[a]	1.40[b]	1.29[b]	1.11[b]	0.96[b]	0.84[a]	1.83[b]	1.58[b]	1.33[b]	1.13[b]
α_{q}	-0.14	-2.04[b]	-1.83[b]	-1.70[b]	-0.14	-0.22	-0.25	-0.28	-0.31	-0.30	-0.92[a]	1.96[b]	1.82[b]	1.54[b]	1.32[b]	1.13[b]	2.30[b]	2.10[b]	1.79[b]	1.53[b]
α_{CH3}	-0.77[b]	-1.41[a]	-1.25[a]	-1.25[a]	0.78[a]	0.67[a]	0.66[a]	0.65[a]	0.63[a]	-0.65[a]	-0.45	2.33[b]	2.15[b]	1.85[b]	1.64[b]	1.44[b]	2.57[b]	2.35[b]	2.04[b]	1.79[b]
α_{CH4}	-0.86[b]	-1.59[b]	-1.42[a]	-1.33[a]	0.76[a]	0.70[a]	0.73[a]	0.74[a]	0.73[a]	-0.44	-0.21	2.47[b]	2.43[b]	2.22[b]	2.05[b]	1.87[b]	2.66[b]	2.62[b]	2.41[b]	2.20[b]
$\overline{\|\alpha_{FF5}\|}$	0.29	0.39	0.38	0.35	0.17	0.14	0.14	0.13	0.12	0.15	0.34	0.51	0.47	0.45	0.42	0.39	0.62	0.55	0.49	0.46
$\overline{\|\alpha_{q}\|}$	0.11	0.56	0.53	0.51	0.26	0.26	0.27	0.29	0.30	0.21	0.28	0.64	0.54	0.49	0.45	0.40	0.76	0.62	0.52	0.47
$\overline{\|\alpha_{CH3}\|}$	0.47	0.35	0.36	0.38	0.34	0.33	0.31	0.30	0.30	0.24	0.28	0.83	0.78	0.69	0.64	0.59	0.88	0.80	0.72	0.66
$\overline{\|\alpha_{CH4}\|}$	0.48	0.35	0.36	0.37	0.34	0.34	0.33	0.32	0.31	0.20	0.19	0.86	0.84	0.77	0.70	0.64	0.90	0.86	0.80	0.72
p_{FF5}	0.00	0.00	0.00	0.00	0.05	0.10	0.05	0.04	0.05	0.47	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p_{q}	0.20	0.00	0.00	0.00	0.25	0.38	0.25	0.20	0.14	0.31	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p_{CH3}	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.00	0.06	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p_{CH4}	0.00	0.00	0.00	0.00	0.02	0.05	0.02	0.01	0.01	0.22	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Trading frictions
#	61
	Qsba12
α_{FF5}	1.00[a]
α_q	1.31[b]
α_{CH3}	1.58[b]
α_{CH4}	2.00[b]
$\overline{\|\alpha_{FF5}\|}$	0.43
$\overline{\|\alpha_q\|}$	0.42
$\overline{\|\alpha_{CH3}\|}$	0.61
$\overline{\|\alpha_{CH4}\|}$	0.66
p_{FF5}	0.00
p_q	0.00
p_{CH3}	0.00
p_{CH4}	0.00

Table 7. Number of significant anomaly variables and overall performance of different factor models: Mainboard-VW for SOEs versus non-SOEs subsamples

This table reports the number of significant anomaly variables and overall performance of factor models under the Mainboard-VW procedure (Mainboard breakpoints and value-weighted returns in portfolio sorts) for SOEs versus non-SOEs subsamples. Since the ownership property data in the CSMAR database is only available since December 31, 2003, our test in this table only covers the post-2003 period. We report the results in two sample periods: (i) the whole sample period (July 2004 to June 2019) and (ii) the post-2007 subsample period (July 2008 to June 2019). The first column reports the total number in the corresponding category. For each period, we report the number of anomaly variables with significant raw return spreads, CAPM alphas, FF3-factor alphas, FF5-factor alphas, q-factor alphas, CH3-factor alphas, CH4-factor alphas, and Carhart 4-factor alphas in each column. Panels A and B report the results for the SOEs subsample of traditional single hypothesis testing (SHT) at the 5% significance level with absolute t-statistic above 1.96, and of multiple hypothesis testing (MHT) at the 5% significance level with absolute t-statistic above 2.78, respectively. Panel C and Panel D report the results of SHT and MHT for the non-SOEs subsample, respectively.

	Total	The whole sample period: 2004/07–2019/06								The post-2007 subsample period: 2008/07–2019/06							
		Raw	α_{CAPM}	α_{FF3}	α_{FF5}	α_q	α_{CH3}	α_{CH4}	α_{CAR4}	Raw	α_{CAPM}	α_{FF3}	α_{FF5}	α_q	α_{CH3}	α_{CH4}	α_{CAR4}
Panel A: SOEs subsample (SHT: $\|t\| \geq 1.96$)																	
Momentum	45	5	5	5	5	1	0	0	5	5	5	5	5	0	0	0	5
Value-versus-growth	68	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0
Investment	36	2	1	1	1	0	0	1	1	5	5	2	2	0	0	0	2
Profitability	94	4	4	4	4	2	0	0	3	4	4	4	4	0	0	0	4
Intangibles	83	5	3	5	5	0	0	0	5	7	6	6	6	0	0	0	6
Trading frictions	143	27	26	18	21	20	19	22	25	23	20	14	12	14	16	20	15
Total	469	44	40	33	36	24	20	24	39	44	40	31	29	14	16	20	32
Panel B: SOEs subsample (MHT: $\|t\| \geq 2.78$)																	
Momentum	45	3	2	3	3	0	0	0	3	2	2	2	2	0	0	0	2
Value-versus-growth	68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Investment	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Profitability	94	2	2	2	2	0	0	0	2	2	2	2	2	0	0	0	2
Intangibles	83	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Trading frictions	143	14	14	12	12	13	13	14	14	15	14	11	11	11	11	10	11
Total	469	19	18	17	17	13	13	14	19	19	18	15	15	11	11	10	15
Panel C: Non-SOEs subsample (SHT: $\|t\| \geq 1.96$)																	
Momentum	45	3	3	3	3	0	3	2	3	5	5	5	5	0	3	2	5
Value-versus-growth	68	27	17	10	9	27	5	10	19	14	12	6	4	10	6	8	8
Investment	36	2	1	1	1	0	0	0	1	11	8	3	4	0	4	4	3
Profitability	94	13	7	6	6	5	8	8	6	4	4	4	4	1	3	2	4
Intangibles	83	9	9	8	8	8	8	8	9	9	9	8	8	6	7	6	8
Trading frictions	143	36	36	29	29	33	25	24	36	64	64	50	49	52	48	35	53
Total	469	90	73	57	56	73	49	52	74	107	102	76	74	69	71	57	81
Panel D: Non-SOEs subsample (MHT: $\|t\| \geq 2.78$)																	
Momentum	45	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	1
Value-versus-growth	68	10	5	5	5	6	2	5	5	5	5	0	0	0	5	5	0
Investment	36	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0
Profitability	94	0	0	0	0	0	0	0	0	2	2	2	2	0	1	1	2
Intangibles	83	6	6	5	6	6	6	6	6	6	6	6	6	6	3	2	6
Trading frictions	143	27	25	15	17	23	16	18	19	32	30	22	17	23	20	18	22
Total	469	43	36	25	28	35	24	29	30	48	45	31	26	29	29	26	31