Anomalies in the China A-share market[1]

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Abstract

This paper sheds light on the similarities and differences with respect to the presence of anomalies in the China A-share market and other markets. To this end, we examine the existence of 32 anomalies in the China A-share market over the period 2000-2019. We find that value, risk, and trading anomalies carry over to China A-shares. Evidence for anomalies in the size, quality, and past return categories is substantially weaker, with the exception of a strong residual momentum and reversal effect. We document that most anomalies cannot be explained by industry composition, and are present among large, mid, and small capitalization stocks. We are the first to examine the existence of residual reversal, return seasonalities, and connected firm momentum for the China A-share market. We find strong out-of-sample evidence for the former two, but not the latter. Specific characteristics of the China A-share market, such as short-sale restrictions, the prevalence of state-owned enterprises, and the effect of stock market reforms, are examined in more detail. These features do not seem to be important drivers of our empirical findings.

JEL Classification Code: G10, G11, G12, G15, G23, G40

Keywords: Alpha, Anomalies, Asset management, China, Investing, Stock market

1. Introduction

The Chinese stock market is the second-largest in the world with a total market capitalization of USD 8.5 trillion at the end of 2019, compared to USD 37.4 trillion for the United States and USD 6.2 trillion for Japan.[2] Until recently, however, access to this market was limited due to restrictions imposed by the Chinese government. The A-shares market, the RMB-denominated domestic Chinese stock market, has been liberalized step by step. First through the Qualified Foreign Institutional Investor program that started in 2002, extended with the Renminbi Qualified Foreign Institutional Investor program in 2011, and later through the Shanghai-Hong Kong and Shenzhen-Hong Kong Stock Connect programs in 2014 and 2016, respectively. This gradual liberalization opened up new investment opportunities for foreign investors. Foreign A-share ownership is estimated to have increased from less than 1% in 2012 to 7.3% of the free float in 2019.[3] The regulatory and economic landscape have led to unique properties of the Chinese A-shares market. For example, the trading being dominated by retail investors, state owned enterprises, frequent stock suspension, lower data consistency due to evolving reporting standards, a large shell value for listed firms, and limited short sale possibilities; see also Lu and Fu (2014). Therefore, a better understanding of the drivers behind Chinese A-shares returns is crucial. Despite the rapidly growing body of literature, there is considerable heterogeneity in the choice of sample period, data source, in accounting for A-shares market characteristics, and even in factor definitions. As a result, there is no consensus on the existence and pervasiveness of asset pricing anomalies in the Chinese A-share market. We address this concern by choosing a well-motivated sample period, a reliable data provider, and applying a series of filters to improve data quality.

The early literature dealing with the cross-section of the Chinese stock market focused on out-of-sample evidence for the Fama and French (1993) three-factor model that includes in addition to the market factor also a size (stocks with low market capitalization outperform stocks with high market capitalization) and value factor (stocks with high book-to-market ratios outperform stocks with low book-to-market ratios); see Wang and Xu (2004), Eun and Huang (2007), and Wang and Di Iorio (2007). The disadvantage of most of these studies is that they include a rather small cross-section of stock returns and a short time-series, which increases the chance that a small number of observations influence the results.[4] These studies generally find that beta is not a priced factor, that there is a strong size effect, and that the value effect is weakly positive. More recent studies with a focus on the three-factor model, such as Huang, Yang, and Zhang (2013), Xu and Zhang (2014), Xie and Qu (2016), Liu, Stambaugh, and Yuan (2019) and Hu, Chen, Shao, and Wang, (2019) confirm that there is a size effect, and that the value effect based on the book-to-market ratio is less robust than a value effect based on the earnings-to-price ratio. Most recent studies also incorporate the profitability and investment factors of the five-factor model by Fama and French (2015). For example,

[2] Source: World Exchanges.

[3] Source: https://www.ubs.com/global/en/asset-management/insights/china/2019/stock-connect-china-a-shares-faqs-equity-investing.html

[4] To be specific, Wang and Xu (2004) use sample period 1996-2002, Eun and Huang (2007) use 1995-2004, and Wang and Di Iorio (2007) use 1994-2002.

Guo, Zhang, Zhang, and Zhang (2017), Lin (2017), and Huang (2019) find that the five-factor model is better able to price the cross-section of Chinese stock returns, but that this is mainly due to the profitability factor, and not the investment factor. Other articles expand the set of investigated anomalies beyond the Fama-French factors, such as Chen et al. (2010), Cheung, Hoguet, and Ng. (2015), Cakici, Chan, and Topyan (2017), Hsu, Viswanathan, Wang, and Wool (2018), Qiao (2019), and Fang and Olteanu-Veerman (2020). In addition to size and value investment signals, these typically also investigate momentum, mean-reversion, dividend yield, and volatility effects. There seems to be limited evidence for the existence of momentum and mean-reversion effects, but most studies find positive dividend and volatility effects. These studies use the China A-share market as an out-of-sample environment to test anomalies documented in other markets, a well-known procedure to guard against factor data mining (see Harvey, Liu, and Zhu 2016). Since the China A-share market has hardly been financially integrated with other markets, this is a particularly useful market for out-of-sample testing.

The contributions of this paper are threefold. First, we aim to fill the gap in the literature by examining the existence of anomalies using a rigorous anomaly replication framework. Our scope of anomalies consists of previously studied anomalies in the A-shares literature such as size, value, momentum, and low-risk. We analyze interactions of factors with firm size and industry composition, which have been proposed as (partial) explanations, but it is uncommon to examine these in this strand of literature. We also show that most anomaly returns are not driven by the short leg, which eliminates limits to arbitrage as an explanation for their existence. Second, we extend the set to recently documented anomalies for which this study is the first out-of-sample study on Chinese A-shares, such as the connected firm momentum effect due shared analyst spillovers of Ali and Hirshleifer (2020), return seasonalities from Keloharju, Linnainmaa, and Nyberg (2016, 2021), and residual reversal by Blitz, Huij, Lansdorp, and Verbeek (2013). Third, we examine whether anomaly strength is different for state-owned enterprises (SOEs) and whether it changed after the introduction of the Split-Share Structure Reform. Lin, Lu, Zhang, and Zheng (2020) review the potential sources of underperformance of SOEs compared to private firms. They list that SOEs (a) can be seen as public goods, potentially leading employees to shirk, (b) contribute to social stability policy, potentially providing excessive welfare, (c) have agency problems between controlling shareholders and minority shareholders, and (d) have to deal with information asymmetry because of a hierarchical governance structure. These differences with private companies may lead them to be valued on a different basis, leading to a different and time-varying share of SOEs in anomaly portfolios, which may affect their risk and return characteristics. Moreover, the China Securities Regulatory Commission's (CSRC) Split Share Structure Reform relaxed restrictions on SOEs and brought a large proportion of non-tradable shares to the market; see Liao, Liu, and Wang (2014). At about the same time, accounting standard reforms started to resemble more closely the International Financial Reporting Standards (IFRS), leading to more transparent, reliable, and comparable company data. The post-reform period is therefore more comparable to the situation in developed equity markets, while the pre-reform period may contain a business environment that is less informative for the future. These analyses allow us to rule out that these China-specific circumstances explain the existence of these anomalies.

Our findings are as follows. First, we find robust empirical evidence for the presence of anomalies within the value, risk, and trading categories. Evidence for anomalies in the size, quality and past return categories is substantially weaker, with the exception of a strong residual momentum and reversal effect. The anomalies are typically present among stocks with large, mid, and small market capitalization, but most of the time somewhat stronger for the latter. Our results indicate that within industry effects are the driving forces behind most anomalies. We are the first to present robust out-of-sample evidence for return seasonalities and residual reversal effects, while the evidence for connected firm momentum is weaker. For value-weighted anomaly portfolios, a little more than half of the performance can be attributed to the short leg, suggesting that limits to arbitrage are only a partial explanation for the existence of most anomalies. When we split our sample into SOEs and non-SOEs, we find that anomalies are not confined to either of the two, even though both subsamples have markedly different characteristics. Finally, our results indicate that after market reforms and liberalizations, the excess returns of anomalies are somewhat lower, but have not completely vanished.

The remainder of this paper is organized as follows. We provide a brief overview of the data in Section 2. Section 3 describes how we construct investment strategies. Section 4 contains the raw returns of the anomalies. In Section 5, we examine interactions of anomalies with size and industry effects. In Section 6, we analyze whether anomaly returns are driven by three China-specific characteristics: short-sales constraints, the presence of SOEs, and a structural break related to market reform. Finally, Section 7 concludes.

2. Data

The data used in this paper is obtained from the China Stock Market & Accounting Research (CSMAR) database. CSMAR is one of the most comprehensive databases covering Chinese financial markets and is widely used in the literature. From this database, we retrieve a broad range of data such as daily stock trading data and quarterly financial statement data between January 1, 1990 and 31 December, 2019 for all RMB-denominated stocks listed on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). This includes Main Board stocks, which are mature stocks similar to those on the New York Stock Exchange (NYSE), as well as SSE Star Market and SZSE ChiNext stocks, which resonate more closely to Nasdaq stocks. Given that the A-shares market first opened for trading in 1990 with the re-establishment of the SSE and the opening of the SZSE in 1991, this forms the longest-available sample period.[5]

[5] Trading on the SSE actually dates back to the 1860s. However, trading halted due the Second World War and the SSE closed down in 1949. Price data from 1870 to 1940 has been reconstructed and is available at: https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/historical-financial-research-data/shanghai-stock-exchange-project

Although data before 2000 is collected, we define our main sample period from January 2000 through December 2019.[6] The primary reason for this start date is to ensure a sufficiently broad cross-section of stocks. Table 1 shows that there were less than 1,000 listed firms before 2000. The period up until 1996 is also characterized by extreme returns and volatility with annual market returns ranging between -30 and 150 percent, and market volatility peaking at 134 percent in 1994. Throughout this paper, the market index is represented by an internally calculated value-weighted market portfolio. This market portfolio consists of all available (investable) A-shares from CSMAR.[7] The one-year RMB lump-sum deposit rate is used as a proxy for the Chinese risk-free rate, as is common in this literature.

< INSERT TABLE 1 HERE >

Another motivation for the sample start date is data availability and quality. Cash flow statements are only disclosed starting from the financial reporting year 1997 and regulations invoking uniform accounting standards across firms were only enacted in 1999. The former implies that cash flows are only available for use in portfolio formation from 1998 onward. We also employ variables such as three-year volatility, residual momentum, and return seasonalities which require multiple years of historical data. Moreover, a connected-firm momentum signal is calculated which relies on analyst coverage data from the Institutional Brokers Estimate System (IBES) database, as used by De Groot, Swinkels, and Zhou (2021).[8] Sufficient analyst coverage data is only available around 2000.[9] As such, starting our analysis in 2000 ensures that we have a balanced panel of anomalies.

For similar reasons, the equivalent choice of starting date is also made by a number of studies in the literature (e.g., Liu, Stambaugh, and Yuan 2019, Qiao, 2019). However, some of the literature chooses earlier start dates. For example, Wang and Xu (2004) opt for 1996 since this coincides with the implementation of price stabilization. This measure imposes a minimum holding period constraint of one day and a daily price change limit of ten percent to curb market volatility and reduce price manipulation.[10] Despite the very limited cross-section available for portfolio construction, Wu (2011) and Xu and Zhang (2014) begin their analysis as far back as 1990 and 1992 to increase the sample length as much as possible. Some papers do not study the entire A-share universe but rather focus on the constituents of the MSCI China A-shares Onshore Index, which starts in 2001. Although there is a clear preference for CSMAR and WIND, some authors use less well-known databases such as the Great China Database (Naughton,

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[6] Our analysis begins in 2000 but we make use of data from 1990 to 1999 for the computation of our accounting and trading variables.

[7] Although an equivalent market index is directly available from CSMAR, our analysis suggests that this index is subject to a look-ahead bias with respect to trade suspensions.

[8] Analyst coverage data from IBES is the only non-CSMAR data used in this paper.

[9] At the beginning of our sample, the number of firms with shared analyst data is 50, which increases to 100 in 2005, 500 in 2010, and 1000 in 2016. Stocks with shared analyst data have outperformed the average stock of the universe with 0.3% per month, suggesting that there is some selection effect for this variable.

[10] Darby, Zhang, and Zhang (2021) examine the interaction between institutional trading and regulatory price limits.

Truong, and Veeraraghavan 2008) or the PACAP-CCER China Database (Chen, Kim, Yao, and Yu 2010). The heterogeneity further extends into data filters and investment universes, which influences overall findings and raises concern regarding the robustness of the literature. We address this concern by choosing a well-motivated sample period, a reliable data provider, and applying a series of filters to improve data quality. The filters exclude stocks with unreliable data or abnormal behavior from our portfolios. Following Liu, Stambaugh, and Yuan (2019), we (i) require stocks to have been listed for at least six months, (ii) have been suspended for less than five trading days in the past month, and (iii) have been suspended for less than 120 trading days in the past year.[11] The latter two restrictions are particularly important as they reduce the impact of frequent and/or prolonged trading suspensions on our findings; see also Tian (2019) on the effect of suspensions on anomalies. To ensure practical feasibility, we also exclude stocks that are suspended on portfolio construction or rebalancing days. Following Hsu et al. (2018) and Lin (2019), we exclude stocks with a 'special treatment' or 'particular transfer' status. These stocks are subject to trading restrictions and additional controls such as a maximum daily price change of five percent. Lastly, due to the constrained and costly initial public offering (IPO) process in China, Liu, Stambaugh, and Yuan (2019) shows that small stocks have a substantial shell value as potential reverse merger candidates. They show that the market value and return variation of the smallest 30% of stocks is largely driven by their shell component rather than fundamentals. To avoid shell-contamination we follow their recommendation and eliminate microcaps, the bottom 30% of stocks ranked by market value, from our sample.

Due to evolving accounting standards in China, quarterly financial statements are only available from 2002 onward. Prior to this, we use semi-annual reports.[12] To match accounting data extracted from these reports with returns data, we make use of statement release dates. In case no release data is available, we discard all interim reports but retain the annual reports.[13] For the latter, we assume a statement release date of May 1st because all listed firms are required to disclose their annual report before the end of April. This way we ensure that no forward-looking information is used in portfolio construction.

[11] Trading suspensions can be mandatory (initiated by the regulator) or voluntary (initiated by the company) and aimed to calm down investors with a stabilized share price. He, Gan, Wang, and Chong (2019) find that suspensions are associated with negative abnormal returns, higher trading volume, and higher volatility in the post-suspension period, hence not achieving their desired goal. Figure A1 in Appendix A plots the percentage of suspended stocks over time. It can be seen that in 2006 and 2015 no less than 20 percent of the number of stocks are suspended.

[12] It is necessary to adjust the magnitude of the flow variables. In the immediate period following 2002, which is the period when statements become quarterly, the period over which the flow variables are calculated will differ between firms. For instance, the latest-available accounting statement from one firm in 2002 may be its previous-year annual report, while another firm may have already released a quarterly statement. One way to address this is to scale all semi-annual data by two and annual data by four. As frequently done in practice, we instead use trailing twelve-month (TTM) values since this eliminates seasonality.

[13] All interim income statement and cash flow statement data, i.e., all flow variables, from CSMAR corresponds to cumulative year-to-date (YTD) values. For example, the quarter three revenue in a particular year corresponds to the sum of the revenue over the first three quarters of that year. This induces a seasonality in the accounting data and invalidates cross-sectional comparison. More specifically, using this data will result in cross-sectionally comparing values calculated over different period lengths with each other. In the most extreme case, one would compare the fourth quarter revenue of a firm, which is the annual revenue, with the first quarter revenue of another firm. To correct for this, we take the first-difference of any subsequent values within an accounting year. This correction ensures that the period over which flow variables are calculated matches exactly with the period of the financial statement.

The final matter concerns state-owned enterprises (SOEs). Along the same line as Liao, Liu, and Wang (2014), four criteria are used to classify firms as SOE or non-SOE.[14] These criteria boil down to determining if the Chinese state is the ultimate controlling party of the company. This data is available in CSMAR at an annual frequency as of 31 December 2003. Since China's secondary privatization wave was sparked by the Split-Share Structure Reform in 2005, we backfill the data from 2003 as relatively few companies changed ownership status prior to this. In case this yearly updated ownership data is unavailable, we resort to using the 'static' company ownership field provided by CSMAR. This data is predominantly used to fill missing ownership data for the handful of companies delisted before 2003, as well as for a score of companies listed in 2019 for which controlling shareholder data is not yet available.

< INSERT FIGURE 1 HERE >

Figure 1 illustrates that the two samples differ with respect to their industry composition.[15] Although manufacturing companies dominate both subsamples, there is a tilt towards utilities, transportation, construction, and mining for SOEs. Conversely, information technology and wholesale and retail are more prevalent among non-SOEs. We also observe a structural change around 2007. This does not only coincide with the listing of extremely large Chinese companies such as the Industrial and Commercial Bank of China (ICBC), but also with the Split-Share Structure Reform.

< INSERT TABLE 2 HERE >

Table 2 reports summary statistics for SOEs and non-SOEs. The average SOE is twice as large in terms of market capitalization and approximately five times larger as measured by book value, earnings, and sales. Naturally, this translates into the average SOE being priced more conservatively with respect to BM, EP, and SP. However, as indicated by the median values, the averages may not accurately characterize SOEs because these are inflated by a few outliers. As of December 2019, nine of the ten largest listed companies in China are SOEs and these companies have an average market value of CNY 900 billion. This is two orders of magnitude larger than the median size of CNY

[14] The four criteria are: (i) the state is the majority shareholder of the company, (ii) the state holds and controls over 30% of the voting rights, (iii) the state's voting rights grant it the authority to elect over 50% of the board of directors, and (iv) the state can exert significant influence on decisions made in shareholder meetings.

[15] For this illustration, we use the CSRC 2001 Industry Classification which comprises 13 sector groups: 'Agriculture, forestry, livestock farming, fishery', 'Mining', 'Manufacturing', 'Electric power, gas and water production and supply', 'Construction', 'Transport and storage', 'Information technology, 'Wholesale and retail trade', 'Finance and insurance', 'Real estate', 'Social service', 'Communication and cultural industry', and 'Comprehensive'. We merge 'Information technology' and 'Communication and cultural industry' into one combined sector group and also merge 'Finance and insurance' and 'Real estate', giving rise to 11 sector groups. Later, when we examine industry-adjusted anomaly returns, we use the full industry classifications and switch to the more granular, 2012 industry classification.

4 billion. Comparing median values, SOEs are only larger by a narrow margin. However, SOEs do remain more value-like. On the other hand, SOEs tend to invest less, are less profitable, are suspended less, and are somewhat less volatile. The differences in industry structure shown in Figure 1 may offer an additional explanation why SOEs score higher on value metrics. Transportation and utilities companies tend to be relatively stable companies with a high value of tangible assets, while information technology companies are often growth firms with comparatively more intangible assets.

3. Portfolio construction and anomaly definitions

Following common convention in the literature, we form a long-short portfolio at the end of each month for each anomaly by sorting stocks into deciles based on the latest value of the corresponding accounting or stock characteristic. We then form a long-short portfolio using the top and bottom deciles, where we define the long leg such that it is expected to have a higher average return than the short leg. For example, because small firms have higher expected returns than large firms, we choose the decile with the smallest stocks as the long leg of the portfolio and the decile with largest stocks as the short leg.

To determine the weights of the stocks within the portfolio legs, we employ equal-weights and value-weights. The significance of considering value-weights is underscored by Hou, Xue, and Zhang (2020) who argue that this weighting scheme results in more reliable inference since equal-weights overweight microcaps, inflating the magnitude of anomalies. Although we already exclude microcaps from our sample, implying that the microcap bias should be largely mitigated, value-weights represent more realistic portfolios to investors and also impose a stricter testing hurdle. On the other hand, value-weights may be dominated by a few mega-cap stocks in our sample, which might also be undesirable, and equal-weights do not suffer from this.

We acknowledge that shorting stocks may not be feasible in practice due to short-sale constraints in China. However, employing this procedure is the norm for the asset pricing literature including those studying A-shares. Moreover, long-only investors who are benchmarked against an index are short (relative to the index) in the stock they do not invest in. To address the concern that factor returns are primarily driven by the short side, we decompose factor portfolios into their separate long and short legs.

We use the overlapping holding period approach by Jegadeesh and Titman (1993) to increase the power of our tests and to eliminate seasonal effects. In each month, there exist K subportfolios, where each subportfolio is formed in the previous K-1 months. To compute portfolio returns for month t, we average over the returns of the K subportfolios. This boils down to rebalancing 1/K of the portfolio each month. For K = 1, this is equivalent to simple monthly portfolio rebalancing.

< INSERT TABLE 3 HERE >

Our set of firm characteristics that we examine is based on prior literature in the China A-share market, such as Hsu et al. (2018) and Liu, Stambaugh, and Yuan (2019). We supplement these series with variables that have been used in other studies that focus on the China A-share market, and extend with a few characteristics that are promising based on research on developed markets, but have not yet been investigated for China A-shares. Table 3 reports an overview of all the characteristics alongside their expected sign. The definition of the characteristics is based on previous literature. Exact variable definitions and operational details are provided in Appendix B. We closely adhere to either the variable definition in the original study, or if applicable, adjustments made by the A-shares literature to account for differences in accounting standards or characteristics of the Chinese stock market. Notable examples of the latter are SIZE and MAX. Chinese firms can issue B-shares and H-shares in addition to A-shares. SIZE is based on the total number of A-shares outstanding instead of the total of all three share classes outstanding. Hu et al. (2019) argue that since only A-shares are accessible to general domestic investors, the A-shares market value is the most representative measure of firm size to A-shares investors. For MAX, we explicitly delete 'zero return' observations on days that a stock is suspended, which otherwise could be the highest return during a negative month. This adjustment is not necessary for the U.S., since trade suspensions are much less prevalent there. A second correction is needed because maximum daily price limits of 10% artificially deflate the maximum or minimum return. Following Nartea, Kong, and Wu (2017), we aggregate the daily returns after a stock hits the price limit to compute a proxy for the true daily return. For example, if a stock hits the upper limit of 10% and has a return of 5% on the trading next day, MAX is calculated as 15%. This adjustment ensures that our sorting procedure can differentiate between stocks that did or did not hit the price barrier.

4. Anomaly returns

Table 4 presents average long-short portfolio returns of 32 anomalies over our twenty-year sample period.[16] T-statistics are calculated using Newey and West (1987) standard errors.

< INSERT TABLE 4 HERE >

As expected, the equal-weighted returns are in most cases greater in magnitude and statistical significance relative to the value-weighted returns. Statistical significance at the 5% level for value-weighted returns implies significance

[16] In the main text we discuss long-short portfolios based on the top decile minus the bottom decile. For the interested reader we have also included the average returns of each of the decile portfolios for each of the firm characteristics. These can be found in Table C3 in Appendix C. A clear monotonic pattern is observed for anomalies with significantly positive long-short returns, while the pattern is rather flat and inconsistent for insignificant anomalies such as ACC or BETA. This shows the existence of a strong empirical relation between anomalies and returns that is not limited to the tails of the returns distribution.

for equal-weighted returns, while the reverse does not hold. Holding period length has an overall negative effect on anomaly pervasiveness with average returns and the corresponding t-statistics decaying as the holding period increases. This is a commonly reported result in the literature. Nevertheless, this effect is not uniform across anomalies. Anomalies in the value, quality, and risk category are most persistent. This is unsurprising since these anomalies tend to be slow signals which remain relatively unchanged from one month to the next. Anomalies such as momentum and seasonalities are faster signals, as they rely on the continuation of a (short-term) trend or re-occurrence of a historical pattern, causing outperformance to decay more quickly.

4.1 Size

It is a priori not clear whether we should find an unconditional size effect. Van Dijk (2011) reviews the literature on the size effect and finds that the empirical evidence has been weak after the size effect was established by Banz (1981). Moreover, Hanauer and Lauterbach (2019) find no size effect for their sample of 21 emerging markets. Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018), Hou and Van Dijk (2019), and Blitz and Hanauer (2021) report that the weak size effect in developed markets is for a large part attributable to low profitability of smaller firms. After controlling for profitability and market beta, these authors do find a size effect.

In our sample, the unconditional size anomaly yields a moderate but insignificant average return, with a 0.59% excess return per month, with a t-statistic of 1.36 for the equally weighted portfolio construction and a one month holding period. This is about half of the 1.09% that Liu, Stambaugh, and Yuan (2019) report for the China A-share market over their sample period 2000 to 2016.[17] When we restrict our sample to end in 2016, we find the same significant result as them. The last three years of our sample have seen substantially negative returns for the size factor. A disadvantage of a relatively short sample period is that adding only a few years can materially affect the overall results and statistical inference. Note that, following Liu, Stambaugh, and Yuan (2019), we excluded the smallest 30% of stocks from our sample to avoid contamination with the shell-value premium among micro caps. This reduces the spread between the largest and smallest companies in our investment universe. Without this filter, the average size return is 1.56% with a t-value of 2.67.

4.2 Value

The value premium is present for all value measures, at least for equally weighted portfolios. For example, the classic BM ratio yields 1.12% excess return per month with a t-statistic of 3.02. For longer holding periods, the returns decrease somewhat, as do the t-values. For the BM ratio with a 12-month holding period, the excess return drops to 0.79% per month, with a t-statistic of 1.77. The EP and SP ratio result in similar returns and t-values. The DP ratio is somewhat weaker with 0.76% per month for a one-month and 0.66% per month for a twelve-month holding period.

[17] The size effect for the China A-share market has also been documented for earlier samples with a relatively small cross-section of stocks. Among others, Wang and Xu (2004), Eun and Huang (2007), Cakici, Chan, and Topyan (2017), Hsu et al. (2018) and Hu et al. (2019) document significantly positive size effects in their samples.

The CP and OCP ratios are similar to the DP ratio. For the value-weighted portfolios, average returns tend to be close to the equally weighted portfolios, but because of less diversification the t-statistics are somewhat lower. Note that we exclude negative values of BM, EP, CP, and OCP, as is common in the literature. In unreported results we find that results are weaker when negative values are included. This holds especially for cash flows, which are negative 54% of the time, and less so for operational cash flows (22% negative), earnings (8% negative), and book values (0% negative).This suggests that investors are more optimistic about firms with negative earnings or cash flows than those with low positive earnings or cash flows, as the latter outperform the former. Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994) argue that current earnings and cash flows predict returns because they can be interpreted in terms of expected growth rates. Since negative values cannot be interpreted as such, they are not relevant predictors of future returns.

4.3 Quality

We find mixed results for the group of quality factors. The factors linked to profitability, ROE, GP, and OP have a return exceeding 0.50% per month for the equally weighted portfolio, and have t-statistics close to or above two. These results are similar for ROE in Qiao (2019). For GP and OP, the frequency of updating seems to matter a lot for the results. Hsu et al. (2018) and Qiao (2019) show that GP and OP have about zero excess returns with an annual update, but Qiao (2019) finds about one percent excess return per month when using quarterly data. We use trailing twelve month values and update quarterly. Therefore, it is consistent that our returns are in between both these numbers. The investment variables INV ASSET and INV BOOK have the wrong sign and are in a few cases even statistically significant. Accruals (ACC and TOTAL ACC) and NOA are also weak anomalies in our sample. This is consistent with Hsu et al. (2018) and Qiao (2019), who also do not find that these quality variables are associated with positive excess returns. Li, Niu, Zhang, and Largay III (2011) report weak evidence for the accruals anomaly in China. Guo et al. (2017) also finds that profitability factors are stronger than investment factors in the China A-shares market, but Huang (2019) finds that both are not statistically significantly different from zero. Using a broad sample of 21 emerging markets, Hanauer and Lauterbach (2019) also find that GP and OP are the strongest quality variables.

4.4 Risk

Chinese economist Wu Jinglian coined the 'Casino Theory' in 2001, suggesting that widespread speculation and market manipulation result in China's equity markets to bear resemblance to a casino, limiting their ability to efficiently allocate capital.[18] The low volatility anomaly by Ang, Hodrick, Xing, and Zhang (2006) and Blitz and Van Vliet (2007) exploits that risk and return are not necessarily positively related. Although Blitz, Falkenstein, and Van Vliet (2014) offer several explanations for the existence of the low volatility effect, the explanation that low risk stocks are undervalued due to investors' preference for risky stocks with lottery-like payoffs predicts a strong effect in China. In accordance with this, there is widespread evidence that various measures of risk including maximum

[18] Source: https://www.economist.com/finance-and-economics/2001/03/01/sauna-sleaze

daily returns in the recent past (MAX), an indicator for investor preference for lottery-like stocks, predict future returns; see Bali, Cakici, and Whitelaw (2011) and for evidence for China Cheema, Nartea, and Man (2020). Yao, Wang, Cui, and Fang (2019) also find evidence of gambling behavior by retail investors in the Chinese stock market.

The results in Table 4 are excess returns of the long portfolio consisting of low-risk stocks and a short portfolio consisting of high-risk stocks, without applying leverage to account for the difference in riskiness of both legs. Low risk portfolios tend to have a substantially higher return than high risk portfolios, which are statistically significant in all cases except for the sorts on beta. The sort on three year volatility leads to a 0.90% per month excess return with a t-statistic of 2.99 for a one-month holding period, which only marginally decreases to 0.85% (t-statistic 2.87) for a 12-month holding period. These results are in line with Blitz and Van Vliet (2007) for developed markets, Blitz, Pang, and Van Vliet (2013) for emerging markets, and Blitz, Hanauer, and Van Vliet (2021) for China A-shares. Note that even a zero excess return could already point to an anomaly relative to the CAPM if the low-risk portfolio has a substantially lower beta than the high-risk portfolio. To deal with this challenge, Frazzini and Pedersen (2014) create a 'betting against beta' factor in which the low and high risk portfolios are leveraged to have a beta of one. However, since applying leverage requires additional assumptions, we refrain from this in our analyses. The alphas relative to the CAPM for each of the five risk variables VOL 1M, VOL 3Y, BETA, IVOL, and MAX are 1.27 (t-stat 4.27), 1.10 (t-stat 3.92), 0.58 (t-stat 2.02), 1.21 (t-stat 3.85), and 1.32 (t-stat 5.69), respectively. For a full table with CAPM alphas instead of excess returns, see Table C1 in Appendix C.

4.5 Past returns

We find no significant price momentum effect. The 12-1 month momentum strategy generates a 0.33% per month return (t-statistic 0.92) for the equally weighted portfolio and a 0.35% (t-statistic 0.79) for the value-weighted portfolio. The weak return on momentum strategies is consistent with the existing literature; Chen et al. (2010), Cheung, Hoguet, and Ng (2015), Cakici, Chan, and Topyan (2017), Hsu et al. (2018), Qiao (2019), Chui, Subrahmanyam, and Titman (2020), and Fang and Olteanu-Veerman (2020) find no momentum effect for the China A-shares market.[19] The lack of momentum is generally attributed to high turnover in Chinese markets shortening the period over which cycles of overreaction and subsequent correction occurs. This could be related to more frequent reversals of the market factor (see Gao, Guo, and Xiong 2021), which also negatively affect the performance of momentum in Japan; see Hanauer (2014) and Cheema and Nartea (2017). One way to correct for market dynamics is to implement the residual momentum strategy of Blitz, Huij, and Martens (2011). Indeed, this strategy generates a statistically significant 0.66% per month (t-statistic 3.36) excess return for the equally weighted and 0.59% per month (t-statistic 2.11) excess return for the value-weighted strategy. This confirms the results of Lin (2019) for the China A-share market.

[19] An exception is Naughton, Truong, and Veeraraghavan (2008) who find a significant momentum effect for Chinese A-shares over the period 1995-2005. Chui, Subrahmanyam, and Titman (2020) do find momentum in Chinese B-shares, which they relate to higher institutional ownership, due to currency conversion restrictions by domestic retail investors.

The past returns category also offers opportunities to investigate anomalies that have not been investigated earlier for the Chinese A-share market. The first of these new signals is connected-firm momentum (CF MOM) that was tested first by Ali and Hirshleifer (2020) for US and developed international markets. The momentum signal is not based on a firm's own momentum, but on a portfolio of stocks linked to the company through common analyst coverage. The CF MOM strategy generates a positive return of 0.46% per month (t-stat 1.54) and 0.61% per month (t-stat 1.72) for equal- and value-weighted, respectively. Although these returns have the expected sign and magnitude, they are not statistically significant. Given the lack of power stemming from our relatively short sample period, our results are inconclusive whether the findings of Ali and Hirshleifer (2020) can be extended to the domestic Chinese equity market.

We also investigate the short-term price reversal effect by Lehmann (1990) and Jegadeesh (1990). This anomaly has shown to be significant in the US and Europe even after accounting for trading costs; see De Groot, Huij, and Zhou (2012). Positive short-term reversal effects in the Chinese A-share market have already been documented by Cakici, Chan, and Topyan (2017), Hsu et al. (2018), Qiao (2019), and Liu, Stambaugh, and Yuan (2019). We confirm these results with a return of 1.42% per month (t-stat 4.35) and 0.80% per month (t-stat 1.88) for the equally and value-weighted portfolios, respectively. In addition, we test the residual reversal strategy described in Blitz, Huij, Lansdorp, and Verbeek (2013). In similar fashion as the residual momentum strategy, the residual reversal strategy hedges out exposures to the market, size, and value factors. As far as we know, this factor has not been examined for the Chinese A-share market. The added value of residual reversal over conventional short-term reversal is absent in our sample, possibly because conventional reversal already has a relatively high excess returns. Even though our sample period is rather short, we can test whether long-term reversal strategies of De Bondt and Thaler (1985), i.e., sorting stocks on their five years minus the last year past return from low to high, are profitable in the Chinese A-share market too. We find strong long-term reversal effects, with 0.71% per month (t-statistic 2.18) and 0.81% per month (t-statistic 1.92) for equally and value-weighted portfolios, respectively. This confirms the results reported in Hsu et al. (2018) and Qiao (2019).

A domain that has been left unexplored in the literature on Chinese A-shares is return seasonalities at the individual stock level; see Heston and Sadka (2008, 2010). Keloharju, Linnainmaa, and Nyberg (2016) show that expected stock returns vary per month and previous shocks persists for up to twenty years. A return seasonality strategy that selects stocks based on their historical same-calendar-month returns earns significantly positive returns, while a seasonal reversal strategy selecting stocks based on other-calendar-month returns earns significantly negative returns. In a follow-up study, Keloharju, Linnainmaa, and Nyberg (2021) document that return seasonalities and seasonal reversals do not subsume each other and arise from temporary mispricing rather than momentum or long-term reversals. A key insight they develop is that both anomalies carry independent information such that a factor sorted on both seasonalities and seasonal reversals has increased predictability over the standalone characteristics. As far as we know, we are the first to test these seasonal anomalies in the Chinese A-share market. We find out-of-sample evidence for this anomaly, with excess returns of 0.42% (t-statistic 2.79), 0.81% (t-statistic 3.28), and 0.89% (t-statistic 4.16) for seasonal, seasonal reversal, and the combination of both, respectively. Note that the quick disappearance of excess returns for the monthly seasonal for longer holding periods is logical, as the signal for this month's seasonal should not have predictive power longer than one month by definition.

4.6 Trading

Following the literature, we also examine whether trading activity cause excess returns. More specifically, we investigate share turnover over the past year, abnormal trading volume over the past month, and a stock's illiquidity as defined by Amihud (2002). Each of these three measures generates positive excess returns, and for the equally weighted portfolios statistically significant excess returns, 0.88% (t-statistic 3.26), 1.72% (t-statistic 5.50), and 1.24% (t-statistic 3.35). For the value-weighted portfolios only abnormal turnover is statistically significant, as in Zhang, Chen, and Yeh (2021). This anomaly proxies for investor sentiment and is especially effective in China because the A-shares market is dominated by retail traders who may be sentiment-driven traders according to Chen, Kim, Nofsinger, and Rui (2007) and Liu, Stambaugh, and Yuan (2019). Note that the excess returns reported here do not include transactions costs, which are important for investment strategies with short holding periods. We will turn to this in the next subsection.

4.7 Break-even transaction costs

Table 4 contains excess returns that have not been adjusted for trading costs. It is not obvious how to take into account trading costs, as good estimates at the individual stock level are not available over our sample period. Therefore, we compute the turnover for each of the strategies and calculate the break-even transaction costs for each anomaly for each holding period. High break-even transaction costs suggest that investors may easily exploit the anomalies, and therefore that our findings are also practically relevant. We calculate anomaly turnover as the sum of the two-way turnover of the long and short legs, i.e., the top and bottom deciles. As such, a complete portfolio change takes into account that 100% of the long portfolio needs to be sold, and 100% new stocks need to be bought, and 100% of the short portfolio needs to be bought, and 100% new stocks need to be shorted, which would result in a maximum turnover of 400%. The results can be found in Table 5.

As a concrete example, consider the BM value characteristic. For a one-month holding period, this anomaly has an average monthly equally weighted return of 1.12% and a monthly turnover of 76.67%. To calculate the turnover, we take the sum of the average monthly two-way turnover of the top and bottom BM portfolios, which are 33.20% and 43.48%, respectively. The break-even transaction cost corresponds to the percentage cost per trade for which an investor breaks even. Given a 1.12% average return, the break-even cost is 1.47% (which equals 1.12% divided by 76.67%).

< INSERT TABLE 5 HERE >

Table 5 shows that those anomalies with economically and statistically significant returns have large break-even transaction costs, even for shorter holding periods. This is because anomalies such as value and low-volatility do not require much turnover, as they tend to be slow-moving characteristics.[20] For example, BM has a 76.77% turnover with a 1-month holding period, leading to 1.47% break-even transactions costs. For a 12-month holding period, turnover reduces to only 17.92%, and since the average return is still 0.79% per month, break-even trading costs are as high as 4.44%. Of course, there are also anomalies that are affected more by transaction costs. For example, the short-term volatility effect has a turnover of 265.43%, short-term reversal and residual reversal 355.26% and 361.93%, seasonal 366.76%, and abnormal turnover 254.16%. This translates into break-even costs as low as 0.12% for SEAS.

Even the anomalies for which the average returns do not decay much for longer holding periods, such as the short-term volatility effect and the abnormal turnover anomaly, have relatively high break-even transaction costs. This is because the drop in turnover is much higher than the drop in return. However, the short-term reversal anomalies and the seasonal effect are much more sensitive to transaction costs. Gao, Zhao, and Wang (2020) report that for their sample of Chinese A-shares over the period 2009 to 2017, the quoted and effective spreads fluctuate between 0.11% and 0.37% per trade. This is considerably below most reported break-even transaction costs, although we acknowledge that trading costs in the first eight years of our sample could be somewhat higher. Note, however, that techniques that mitigate trading costs as in Novy-Marx and Velikov (2019) have not been taken into account yet. This break-even transaction cost analysis confirms that for most anomalies evaluated in Table 4, adjusting for transaction costs is unlikely to affect the reported positive excess returns, indicating that investors can exploit these in practice.

5. The influence of size and industry effects

In the previous section, assets are sorted on the anomaly characteristic, disregarding any exogenous influences. To ensure that our findings are not driven by small-capitalization or industry effects, we perform size- and industry-neutral sorts. These sorts alleviate size or industry bias by splitting up the investment universe into size deciles or China-specific industry classification, the CSRC sector groups.[21] Within each of these groups, anomaly deciles are formed based on the sorting variable. Stocks within each anomaly decile are pooled together, after which the returns are equal- or value-weighted. This ensures that the composition of the portfolio is equally distributed over size deciles or industries.

[20] See, for example, Van Vliet (2018) for turnover of low-volatility strategies.
[21] The sector classification changes during our sample period. From the start of our sample until Sept 2012, we use the old CSRC classification with 13 sectors, and from October 2012 the new, more granular, CSRC 2012 classification with 19 sectors.

Fama and French (2012) find that factor premiums tend to be the largest among smaller stocks, also in a sample of international stocks. The importance of forming size-neutral sorts is stressed by Liu, Stambaugh, and Yuan (2019), who argue that the size premium in China could obscure anomaly premiums. For some factor premiums, such as value, the within industry effect is strong, but the across industry effect weak; see Doeswijk and Van Vliet (2011). For example, mining companies tend to have high BM ratios and technology companies often have a low BM ratio. As a result, sorting based on BM may inadvertently lead to an industry tilt towards mining companies in the value portfolio and a tilt towards technology companies in the growth portfolio. As far as we know, industry-neutral factor premiums have not been investigated before in the China A-shares market.

< INSERT TABLE 6 HERE >

Table 6 reveals that most anomaly premiums are unfazed by size effects.[22] Similar to Liu, Stambaugh, and Yuan (2019), profitability effects become more pronounced after neutralizing size effects. For the other anomalies, the influence of size effects is even smaller. Table C4 in Appendix C contains the anomaly returns for each size decile. It shows that anomalies that exist in the full sample, are also present in groups of small, middle, and large capitalization stocks. However, they tend to be quantitatively larger for smaller stocks.

Industry-neutral returns are also closely in line with those in Table 4. Value, volatility, and turnover effects remain mostly unchanged. The t-statistics mostly increase, because neutralizing industry exposure decreases the volatility of the long-short strategies. Strong industry-adjusted low-risk effects are consistent with Asness, Frazzini, and Pedersen (2014). Momentum effects are slightly lower, which may be due to the industry momentum effect that is extensively documented in the literature; see Moskowitz and Grinblatt (1999). Short-term reversals are somewhat stronger when adjusted for industry effects, which is consistent with Hameed and Mian (2015). Another notable difference is CF MOM, for which the average monthly return is now close to zero. Return seasonalities remain strong after correcting for industry effects. The influence of holding period on size-neutral and industry-neutral returns reflects the same pattern seen for the unconditional sorts: Returns decay as holding period increases. As there is little reason for these pattern to change in subsequent analyses, which covers different sample periods and methods, going forward we condense our results by only reporting results for a one-month holding period.

Summarizing, size-neutral and industry-neutral anomaly portfolios paint a very similar picture as the not neutralized versions that we showed in the previous section.

[22] Table 6 contains equally-weighted portfolios; for value-weighted portfolios see Table C2 in Appendix C.

6. Chinese market characteristics

Our sample filters and variable definitions already account for a number of characteristics of the Chinese A-shares market such as trade suspensions, shell-value contamination among microcaps, and daily price limits. This section extends our analysis to additional Chinese market characteristics and studies how these influence our previous conclusions. First, we examine the impact of short-sale constrains on Chinese factor premiums. This is extremely relevant from a practical point-of-view, since shorting restrictions challenge the case for factor investing in China. Second, we explore to what extent government ownership affects factor dynamics by considering cross-sectional differences between SOEs and non-SOEs. Lastly, we study anomaly returns after the Split-Share Structure Reform in 2007.

6.1 Short-sale constraints

Forming long-short portfolios is one of the fundamental cornerstones of factor investing. Accordingly, much of the literature on factors and asset pricing anomalies centers on the efficacy of these portfolios. Despite short-sale constraints in China, the A-shares literature also remains fixated on zero-investment factor portfolios. However, short selling has only been possible in China since 2010; see Lu, Ren, en Zhao (2018). The list containing stocks that can be shorted has grown over time, from 90 in March 2010 to 500 in January 2013 and 900 in September 2014. The stocks that can be shorted are typically large capitalization stocks. This means that since 2013 more than 70% of total market capitalization is eligible for shorting. However, during large part of the sample period studied in the literature, the plain implementation of long-short strategies was infeasible. In addition, lending fees for Chinese A-shares are high, typically 3%-5% above the prime rate on bank loans (adding up to a total rebate rate of 8-11%) according to Lu, Ren, and Zhao (2018). They account for shorting restrictions by adding shorting costs and limiting the scope of the short legs to shortable stocks. This leads them to conclude that even the size factor, which is short the liquid large capitalization stocks, cannot be exploited profitably by investors in real life. This is one of the explanations why there seems to be a persistent valuation difference between shares of the same companies listed in Hong Kong and Shanghai; see Carpenter, Whitelaw, and Zou (2019) and Ding and Feng (2019).[23] Shleifer and Vishny (1997) argue that asset pricing anomalies may persist because market inefficiencies inhibit arbitrageurs from eliminating mispricing. This would imply that the anomalous returns from long-short portfolios are driven by the short side, as mispricing requiring short sales is in general more difficult to arbitrage. This begs the question whether the factor profits that we reported in the previous sections are driven by the negative performances of the short legs, or that investors that buy the long legs are able to outperform the market index.

[23] Whether the Hong Kong-Shanghai Stock Connect has increased or decreased the A-H premium is still a topic of debate. Fan and Wang (2017) and Pan and Chi (2019) find that premiums become smaller, while Hui and Chan (2018) find that the premium has increased.

To evaluate the influence of short-sale constraints on our findings, we split factors into their long and short legs, by subtracting the index return from the long leg, and subtracting the short leg from the same index return. This way, adding the long and short legs would lead to the factor returns that we presented before. The long legs can be interpreted as outperformance series relative to the index. It is however, not a priori clear what the best index is to perform this analysis. We can choose the market-capitalization index, which is the benchmark for most asset managers. However, evaluating an equally weighted portfolio of long or short stocks against a value-weighted index may be obscured by a size effect in the equally-weighted anomaly portfolios, and therefore attribute large part of the outperformance to the long leg. Note that the equally-weighted market portfolio has returned about 0.7% per month more than the value-weighted market portfolio, and that this 0.7% is close to the excess returns of the anomaly portfolios. For the same reason, using an equally-weighted index may attribute large part of the outperformance to the short leg. In Table 7 we show the decomposition of each of these possible choices.

< INSERT TABLE 7 HERE >

Table 7 breaks down factor premiums into their long and short legs. On the left-hand side, we have equally weighted anomaly portfolios and a value-weighted index. In the middle, we have value-weighted portfolios and a value-weighted index. These two situations are most relevant for active asset managers as they are often measured against a value-weighted index, and are more likely to give large stocks a higher weight than tiny stocks. On the right-hand side, we have equally-weighted anomaly portfolios and an equally-weighted index. This type of index may not be that relevant in the real world. Moreover, it includes the size effect in the benchmark. However, for equally weighted portfolios it might be relevant, as the long side may otherwise benefit from the size effect.

Table 7 shows that it depends critically on the benchmark index whether it is the long or short side that on average has a higher excess return. It also shows that the outperformance of the long and short sides is different across anomalies. The left panel shows for example that the long leg of BM has an excess return of 0.72% per month (t-statistic 2.75) and the short leg an excess return of 0.41% (t-statistic 1.42). And for most value anomalies we see a similar pattern. For the ABN TURN anomaly it is the other way around: the long leg has a 0.62% (t-statistic 2.30) excess return and the short leg an excess return that is almost double: 1.10% (t-statistic 3.57). Interestingly, the excess returns from CF MOM are also fully attributed to the long leg. An equally weighted average over all anomalies (including the non-significant ones) suggests that the magnitude of the outperformance of the long legs is 71% of the total excess return. The middle panel shows that the long legs are somewhat less important when they are value-weighted. On average 48% of the excess returns comes from the long legs. Notable here is the risk category. The low-risk portfolios seem to perform on par with the index, but the high-risk stocks underperform the index substantially. So, low-risk anomalies seem to consist of two parts; a low-risk portfolio that has the same return but lower risk than the index, and a high-risk portfolio that substantially underperforms the index while also having higher risk. We also see that the short-run predictors such as REV 1M and ABN TURN are mostly driven by the short side. Finally, the right panel clearly shows that when an equally-weighted index is used, more performance is attributed to the short side because of the size effect. Except for the group with Risk and the group with Trading characteristics, the anomaly performance is reasonably equally spread over the long and short side. Across all anomalies, about 35% is from the long side.

Altogether, long-only investors may use these insights to obtain excess returns relative to their benchmark index. Because of the somewhat higher returns for the short leg when anomalies and the index are both value-weighted, we conclude that the performance of anomalies can only partially be attributed to limits to arbitrage.

6.2 State-owned enterprises

Another unique property of the Chinese A-shares market that has been left relatively unexplored is the widespread government ownership of listed firms. Table 1 shows that prior to 2010, over half of all listed firms in China were SOEs. A firm is classified as an SOE if the Chinese state is the ultimate controlling party of the company. While this number has since fallen to about one third, this remains high compared to developed markets.

SOEs tend to have different objectives, governance structures, and have easier access to capital than non-SOEs; see Lin, Lu, Zhang, and Zheng (2020). Liao, Liu, and Wang (2014) study the privatization effect in China by comparing the fundamental performance (e.g., revenue, profitability, employment) and stock performance of SOEs before and after the Split-Share Structure Reform. They report significant increases in both types of performance after privatization. This supports the hypothesis that SOEs are subject to agency problems, which give rise to a conflict of interest between government agents and public investors. These agency problems may induce governance problems, which is subsequently reflected in a firm's performance.

< INSERT TABLE 8 HERE >

This section fills this gap in the literature by exploring to what extent returns on our cross-section of anomalies differ between SOEs and non-SOEs. Table 8 reports average long-short returns for non-SOEs and SOEs.[24] Results are reported for a one-month holding period. Strikingly, differences between the two panels are rather small. On average, the magnitude of excess returns is 0.76% per month for non-SOEs and 0.79% for SOEs. This indicates that anomalies are generally equally prevalent among SOEs and non-SOEs.

There are a few exceptions. CP, NOA, SEAS and SEAS DIFF are only significant for SOEs, but not for non-SOEs. A possible explanation for these differences is that we also include the financial industry in our sample. Financials are

[24] Table 8 contains the equally weighted returns, but in Table C5 in Appendix C we also show the value-weighted returns. Table C6 in Appendix C contains the size-neutral equally and value-weighted returns.

a relatively large part of SOEs and since they have different accounting practices than companies in other industries they are often filtered out of the sample in anomaly studies in the U.S. such as Fama and French (1992). However, we verified that our empirical results are not driven by the choice to include or exclude stocks from the financial industry from our sample. In addition, we also checked for differences in total cash flows (CF) and operating cash flows (OCF) for SOEs and non-SOEs. Even though the anomaly based on CF is only half the size of OCF, it is statistically significant for SOEs, while OCF gives consistently positive results for both SOEs and non-SOEs. Figure A2 in Appendix A shows that while the median operating cash flow is larger for SOEs than for non-SOEs, the total cash flows are substantially lower and almost the same, possibly caused by additional financing activities of SOEs. Since the OCF excludes these activities and focuses more on the operational business, analysts are more likely to focus on OCF when it comes to company valuation. This could explain why for SOEs CP is strong, while it is not for non-SOEs. The other way around, i.e., factors that are significant for non-SOEs but not for SOEs, is not present in our data. This suggests that stock prices for non-SOEs are slightly more efficient than those of SOEs.

Contrary to expectations, anomaly returns in SOEs are found to not be materially different from those in non-SOEs. Whereas the typical SOE is more value-like and less profitable than the typical private investor-owned firm, this nor differences in industry composition translate into distinctly different factor dynamics between the two types of firms. As such, there does not seem to be much need for investors to treat SOEs differently than non-SOEs when it comes to factor investing. A possible reason for the lack of empirical attention for the difference between SOEs and non-SOEs could be our 'non-finding'. We know that results that align with the null hypothesis are less likely to be published in the academic literature.

6.3 Split-share subsample

Finally, we investigate the impact of a number of market reforms and policy changes in China on stock market anomalies. This is done by restricting our sample period to the 'split-share subsample', which covers the period 1 January, 2007 through 31 December, 2019. The years between 2000 and 2007 mark a significant period of reform. During these six years, China entered the World Trade Organization (WTO), directly opened up to foreign investors through QFII, and saw various influential regulatory changes by the China Securities Regulatory Commission (CSRC); see Carpenter, Lu, and Whitelaw (2021). This includes the launch of margin trading and short selling pilot programs in 2006.

Importantly, the CSRC also introduced the Split-Share Structure Reform in 2005, which relaxed restrictions on SOEs and brought a large proportion of non-tradable shares to the market. This reform was executed by 80% of firms by 2007; see Qiao (2019). Indeed, Table 1 reports that the proportion of non-tradable shares falls to 20% in the subsequent years. The split-share reform also sparked China's secondary privatization wave with the percentage of SOEs steadily dropping down to 30% after 2007. In addition, accounting standards more closely adhering to the International Financial Reporting Standards (IFRS) were rolled out in 2007. As such, the post-2007 period is characterized by higher liquidity, transparency, and data reliability, making 2007 an important economic breakpoint.

Table 8 contains the anomaly returns and t-statistics for the pre- and post-split share subsamples. Figure A3 in Appendix A contains anomaly returns for each five-year period of our sample period, for a more granular overview of anomaly performance over time. Most anomalies relying on fundamental information such as BM, EP, and OCP have become slightly weaker and are no longer statistically significant, partially due to the lower power in the shorter sample period. For example, the BM effect has a 1.01% per month (or 12% per year) excess return, but the corresponding t-statistic is 1.94, slightly below the critical value of two. Hsu et al. (2018) also observe a similar attenuation of the value effect and partially attribute this to value crashing during the global financial crisis. In addition, recent asset pricing literature has come to recognize a significant drawdown in the value effect in developed markets; see Arnott, Harvey, Kalesnik, and Linnainmaa (2021). Even though factor premia tend to be lowly correlated across regions, it is plausible that this downturn has partly spilled over to other markets including China. An explanation put forward in McLean and Pontiff (2016) is that anomalies become weaker over time because investors learn from academic publications, even though Jacobs and Müller (2020) find that post-publication decline in anomaly performance is mostly a US phenomenon.

In addition to some value characteristics, residual momentum and seasonal effects have lost a part of their excess returns, in a few cases leading to statistical insignificance. The connected-firm momentum by Ali and Hirshleifer (2020) is weak with 0.25% per month (t-statistic 0.65). The characteristics that are more linked to short-term anomalies, such as reversal, abnormal turnover, and short-term volatility are strong(er) and remain statistically significant, even in this relatively short recent sample period.

Finally, a few words of caution when it comes to empirical findings on the Chinese A-share market. Hsu et al. (2018) estimate that 50 years of data is required to achieve significance for a broad range of US anomalies. They contrast this with the 20-year sample period available to them in China. Similarly, Liu, Stambaugh, and Yuan (2019, p. 58) note "*Nevertheless, our 17-year period is somewhat shorter than is typical of US studies, so any of our statements about statistical insignificance of an anomaly must be tempered by this power consideration.*" Blitz (2020) also shows that academic factors in developed markets have had poor returns over the last decade, suggesting that short sample periods may not always reveal the long-run factor premiums. Finally, Hu et al. (2019, p. 6) remark "*It is fair to point out that the relatively short sample and the substantial time variation in market conditions in Chinese stock markets should make us cautious about the robustness of any empirical results.*" Even though the empirical results we present in this paper are strong, we have to caution that these are based on a short sample period in which the China A-share market has transformed into a more mature market.

7. Conclusions

Our research aims to shed light on the similarities and differences with respect to the existence of anomalies in the China A-share market and other markets. With respect to the existence of factors, we find strong evidence for value, low-risk, and trading anomalies. Evidence for anomalies in the size, quality and past return categories is substantially weaker, with the exception of a strong residual momentum and reversal effect. We are the first to present robust out-of-sample evidence for return seasonalities and residual reversal effects, while the evidence for connected firm momentum is weak.

Differences could be driven by three specifics of the China A-share market. Short-selling was prohibited in the beginning of our sample period, and allowed for a group of stocks towards the end of our sample period, but is much more expensive compared to most developed markets. We find that excess returns of the long and short side are of the same magnitude, suggesting that limits to arbitrage are at most a partial explanation of the existence of anomalies. Since state-owned enterprises constitute a substantial part of the China A-share market, this could affect the existence of anomalies. Even though we find that characteristics of SOEs and non-SOEs can be substantially different, this hardly affects the existence of anomalies. This indicates that asset managers do not need to treat both types of companies differently in order to harvest factor premiums. Finally, we find that prior to stock market reforms the anomalies returns were somewhat higher, but that they are still substantially positive afterwards for most factors. The reason that several characteristics lose statistical significance is related to the short sample period that reduces that statistical power to reject the null hypothesis.

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Figure 1: Industry composition of non-state-owned enterprises and state-owned enterprises

The two figures on the left side contain the information of the non-state-owned enterprises (SOEs) and the two figures on the right side the information of the SOEs. The two figures on the top count the number of stocks in each industry and the two figures at the bottom are the market-capitalization weighted industry compositions.

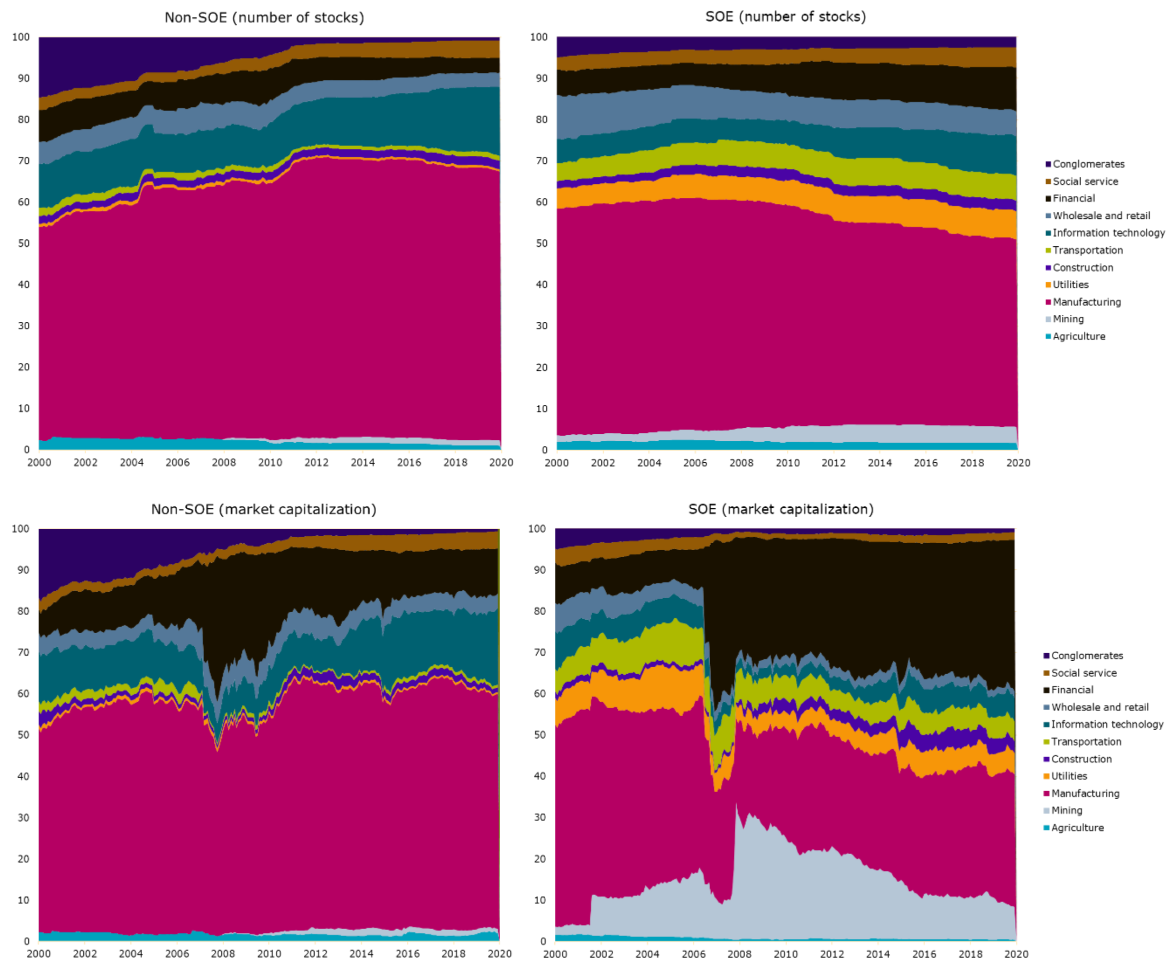


Table 1: Summary statistics

This table reports yearly summary statistics for China A-shares from 1990 to 2019. Reported are the number of listed firms (Firms), aggregate market capitalization of all A-shares (Market cap), average firm size (Firm size), the number of state-owned enterprises as a percentage of total listed firms (% of SOE), the percentage of non-tradable shares (% Non-tradable), and the return (Market return) and volatility (Market volatility) of a value-weighted market portfolio of all stocks. Market capitalization and firm size are in USD billions. All statistics except for return and volatility are year-end statistics. Returns are annual returns and volatility is the annualized monthly volatility.

Year	Firms	Market cap	Firm size	% of SOE	% Non-tradable	Market return	Market volatility
1990	6	-	-	-	-	-	-
1991	13	3	0.22	61.5	62.7	74	59
1992	53	19	0.37	52.8	80.2	145.1	108.2
1993	177	58	0.33	63.3	79.6	-13	72.8
1994	287	42	0.15	60.6	77.2	-28.6	133.6
1995	311	40	0.13	60.5	76.1	-13.4	37
1996	514	115	0.22	60.5	73.5	98.6	45.6
1997	719	206	0.29	61.8	71.9	26.6	31.8
1998	825	234	0.28	62.6	71.3	-5.1	22.4
1999	923	318	0.34	63.1	69.7	17.9	39.5
2000	1060	577	0.54	62.4	67.5	55.5	18.1
2001	1136	514	0.45	62.8	68.7	-23.4	19.2
2002	1199	455	0.38	63.1	68.8	-17.3	24.5
2003	1262	503	0.4	62.8	70.3	4.2	15.8
2004	1352	440	0.33	61.8	69.7	-15.5	20.4
2005	1356	394	0.29	61.8	68.5	-6.9	21.8
2006	1404	1129	0.8	61.1	73.1	134.4	28.6
2007	1526	4455	2.92	59	72.1	124.9	35.7
2008	1600	1772	1.11	57.2	63.2	-64.8	39.6
2009	1695	3561	2.1	55	38.4	91	33.1
2010	2039	3992	1.96	48	27.7	-7.4	24.9
2011	2318	3397	1.47	42.8	23.7	-24.3	16.4
2012	2470	3645	1.48	40.8	21.5	4.8	23.1
2013	2468	3902	1.58	40.7	16.8	3.8	21.1
2014	2591	6092	2.35	39.2	15.6	51.6	16.8
2015	2809	8172	2.91	36.8	21.8	32.3	40.1
2016	3031	7301	2.41	34.9	23	-12.3	32.2
2017	3466	8658	2.5	31.5	21.1	3.9	8.9
2018	3566	6325	1.77	31	18.9	-27.5	14
2019	3750	8487	2.26	30	18.7	29.1	20.1

Table 2: Comparison of non-SOE and SOE firms.

This table reports summary statistics for non-SOE (Panel A) and SOE (Panel B) firms from January 2000 through December 2019. Reported in CNY billion are total A-shares market capitalization (Size), book value (Book), Earnings, and Sales. Book-to-market (BM), earnings-to-price (EP), sales-to-price (SP), asset growth (Inv), return on equity (ROE), operating profitability (OP), and daily volatility over the past year (Vol) are in percentages. Susp denotes the number of suspended trading days over the past year. 25%, 50%, and 75% denote percentiles.

	Size	**Book**	**Earnings**	**Sales**	**BM**	**EP**	**SP**	**Inv**	**ROE**	**OP**	**Vol**	**Susp**
Panel A: Non-SOEs												
Mean	7.71	2.4	0.23	2.73	31.37	1.09	40.38	79.45	7.89	4.55	2.93	15.83
25%	2.27	0.57	0.02	0.4	15.67	0.76	10.93	1.39	3.29	3.29	2.28	0
50%	4.09	1.07	0.07	0.92	26.71	1.86	22.73	10.99	7.39	8.25	2.75	2
75%	7.74	2.18	0.18	2.21	42.93	3.3	46.21	26.88	11.89	13.78	3.34	10
Panel B: SOEs												
Mean	15.43	9.53	1.11	11.29	43.85	2.15	74.94	61.06	6.67	4.4	2.76	11.01
25%	2.2	0.64	0.02	0.61	21.19	0.76	18.69	-0.12	2.48	2.16	2.11	0
50%	4.13	1.37	0.08	1.58	35.41	2.1	39.9	8.24	6.62	7.62	2.59	2
75%	9.28	3.51	0.28	4.77	56.97	4.07	83.88	20.61	11.1	13.61	3.21	5

Table 3: Factor characteristics

This table provides an overview of the accounting and stock characteristics used to construct the factors alongside a description and the corresponding anomaly category. A more detailed description can be found in Appendix B. Characteristics with a minus sign are expected to be negative predictors of returns, i.e., a higher value results in lower future returns.

Category	Characteristic	Sign	Short description
Size	SIZE	-	Total A-share market capitalization
Value	BM	+	Book-to-market ratio
	EP	+	Earnings-to-price ratio
	SP	+	Sales-to-price ratio
	DP	+	Dividend-to-price ratio
	CP	+	Cash flow-to-price ratio
	OCP	+	Operating cash flow-to-price ratio
Quality	ROE	+	Return on equity
	GP	+	Gross profitability
	OP	+	Operating profit
	INV ASSET	-	Asset growth
	INV BOOK	-	Book value growth
	ACC	-	Accruals
	TOTAL ACC	-	Total accruals
	NOA	-	Net operating assets
Risk	VOL 1M	-	Volatility (20 days)
	VOL 3Y	-	Volatility (36 months)
	BETA	-	Systematic market risk (250 days)
	IVOL	-	Idiosyncratic volatility (250 days)
	MAX	-	Maximum daily return (20 days)
Past returns	MOM	+	Momentum (12 months excl last month)
	RES MOM	+	Residual momentum (12 months excl last month)
	CF MOM	+	Connected-firm momentum (12 months excl last)
	REV 1M	-	Short-term reversal (1 month)
	RES REV 1M	-	Residual short-term reversal (1 month)
	REV LT	-	Long-term reversal (60 months excl last 12)
	SEAS	+	Same-month return
	SEAS REV	-	Other-month return
	SEAS DIFF	+	Same-month-return minus other-month return
Trading	TURN	-	Turnover (250 days)
	ABN TURN	-	Abnormal turnover (250 days)
	ILLIQ	+	Illiquidity

Table 4: Anomaly returns

This table reports average long-short portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. The left side contains equally weighted returns, the right side contains market value-weighted returns. We display three holding periods; 1, 6, and 12 months. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	Equally weighted						**Market value-weighted**					
	Hold = 1 month		Hold = 6 months		Hold = 12 months		Hold = 1 month		Hold = 6 months		Hold = 12 months	
Anomaly	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE	0.59	1.36	0.33	0.71	0.37	0.72	0.64	1.21	0.37	0.63	0.34	0.53
BM	**1.12**	3.02	0.80	1.81	0.79	1.77	**1.06**	2.38	0.66	1.33	0.70	1.44
EP	**1.10**	3.41	**0.79**	2.16	0.76	1.84	**1.09**	2.53	**0.97**	2.07	0.89	1.66
SP	**0.93**	3.34	**0.78**	2.63	**0.89**	2.72	**0.80**	2.21	0.77	1.89	**0.97**	2.04
DP	**0.76**	2.71	**0.60**	2.05	**0.66**	2.15	0.75	1.87	0.49	1.15	0.55	1.27
CP	**0.51**	2.74	0.35	1.75	0.31	1.61	0.58	1.76	0.51	1.67	0.47	1.63
OCP	**0.78**	2.78	**0.70**	2.35	**0.76**	2.31	0.74	1.88	0.61	1.43	0.64	1.34
ROE	0.54	1.82	0.53	1.50	0.49	1.18	0.62	1.61	0.59	1.29	0.36	0.68
GP	**0.63**	2.18	0.58	1.64	0.60	1.59	0.64	1.78	0.64	1.49	0.53	1.12
OP	**0.59**	2.21	0.53	1.72	0.47	1.30	0.31	1.08	0.34	1.15	0.14	0.47
INV ASSET	-0.55	-2.61	-0.44	-1.74	-0.19	-0.68	-0.49	-1.86	-0.50	-1.65	-0.27	-0.71
INV BOOK	-0.40	-1.89	-0.17	-0.71	-0.06	-0.19	-0.17	-0.62	-0.02	-0.06	0.01	0.02
ACC	-0.09	-0.68	-0.03	-0.20	-0.03	-0.20	-0.17	-0.77	-0.14	-0.68	-0.11	-0.54
TOTAL ACC	0.22	1.31	0.17	1.14	0.17	1.11	0.31	1.03	0.22	0.73	0.23	0.84
NOA	0.08	0.39	0.25	1.24	0.40	1.80	0.45	1.40	0.57	1.68	**0.74**	2.03
VOL 1M	**1.08**	3.77	**0.75**	2.63	**0.63**	2.48	**1.07**	2.72	0.77	1.98	0.46	1.23
VOL 3Y	**0.90**	2.99	**0.90**	2.98	**0.85**	2.87	**0.84**	2.10	**0.85**	2.04	0.64	1.58
BETA	0.36	1.18	0.37	1.27	0.30	1.12	0.55	1.30	0.29	0.71	0.19	0.46
IVOL	**1.19**	3.93	**1.01**	3.26	**0.76**	2.32	**1.10**	2.51	0.88	1.88	0.67	1.34
MAX	**1.20**	5.20	**0.64**	3.29	**0.44**	2.55	**0.96**	2.55	0.60	1.97	0.26	0.92
MOM	0.33	0.92	0.19	0.50	0.11	0.30	0.35	0.79	0.28	0.69	0.27	0.69
RES MOM	**0.66**	3.36	0.32	1.66	0.18	0.89	**0.59**	2.11	0.32	1.31	0.15	0.63
CF MOM	0.46	1.54	0.22	1.31	0.31	1.91	0.61	1.72	0.35	1.59	**0.44**	2.47
REV 1M	**1.42**	4.35	0.23	1.37	-0.06	-0.39	0.80	1.88	0.19	0.92	-0.18	-1.01
RES REV 1M	**1.18**	4.72	0.09	0.78	-0.05	-0.59	0.56	1.63	0.11	0.82	-0.05	-0.44
REV LT	**0.71**	2.18	0.62	1.71	0.51	1.22	0.81	1.92	0.69	1.44	0.58	1.10
SEAS	**0.42**	2.79	-0.13	-1.47	-0.14	-1.43	0.59	1.93	-0.23	-1.36	-0.19	-1.34
SEAS REV	**0.81**	3.28	**0.56**	2.08	0.60	1.99	**0.75**	2.06	0.51	1.28	0.52	1.23
SEAS DIFF	**0.89**	4.16	0.45	1.96	**0.51**	2.13	**0.90**	2.83	0.44	1.29	0.44	1.22
TURN	**0.88**	3.26	**0.62**	2.36	0.42	1.46	0.69	1.56	0.52	1.12	0.39	0.81
ABN TURN	**1.72**	5.50	**0.62**	2.69	**0.49**	2.36	**1.33**	3.22	**0.62**	2.11	0.31	1.30
ILLIQ	**1.24**	3.35	0.64	1.64	0.49	1.05	0.71	1.50	0.33	0.62	0.17	0.27

Table 5: Turnover and break-even transaction costs

This table reports turnover ("Turn") and break-even transaction costs ("B-E") over the sample period January 2000 through December 2019. The left side contains equally weighted returns, the right side contains market value-weighted returns. Turnover is defined as two-way turnover and is in percentage per month. The break-even transaction costs are in percentages per trade. We display three holding periods; 1, 6, and 12 months. Anomaly variable definitions are provided in Table 3 and in Appendix B.

	Equally-weighted						Market value-weighted					
	Hold = 1 month		Hold = 6 months		Hold = 12 months		Hold = 1 month		Hold = 6 months		Hold = 12 months	
Anomaly	Turn	B-E	Turn	B-E	Turn	B-E	Turn	B-E	Turn	B-E	Turn	B-E
SIZE	115.28	0.51	32.59	1.02	19.10	1.93	103.75	0.62	29.40	1.26	17.28	1.97
BP	76.67	1.47	27.57	2.88	17.92	4.44	69.72	1.53	25.28	2.60	16.52	4.24
EP	85.06	1.30	34.81	2.28	21.91	3.48	79.92	1.36	32.48	2.99	19.74	4.49
SP	65.73	1.42	24.00	3.24	15.77	5.61	56.43	1.41	21.92	3.52	14.50	6.68
DP	74.80	1.02	32.56	1.83	22.47	2.92	67.67	1.10	28.80	1.69	20.00	2.73
CP	100.32	0.50	48.32	0.73	29.58	1.05	86.20	0.68	42.62	1.21	26.67	1.75
OCP	91.24	0.85	42.20	1.66	25.71	2.94	80.32	0.92	37.47	1.63	23.04	2.77
ROE	68.70	0.78	32.13	1.64	22.16	2.21	58.66	1.06	29.45	2.01	20.54	1.73
GP	59.44	1.06	26.62	2.17	17.59	3.43	52.79	1.21	25.56	2.50	16.84	3.17
OP	79.24	0.74	33.99	1.55	19.39	2.45	53.45	0.59	25.03	1.34	13.32	1.03
INV ASSET	84.99	-0.64	42.40	-1.05	28.75	-0.65	74.81	-0.65	40.52	-1.23	28.13	-0.95
INV BOOK	82.21	-0.49	41.77	-0.42	29.21	-0.19	73.12	-0.23	40.80	-0.05	28.99	0.03
ACC	71.91	-0.13	37.15	-0.08	29.76	-0.10	60.79	-0.27	34.02	-0.41	28.96	-0.37
TOTAL ACC	66.74	0.33	33.66	0.52	26.69	0.64	53.46	0.58	29.55	0.75	24.86	0.94
NOA	57.21	0.13	27.26	0.92	21.28	1.89	41.98	1.07	21.65	2.61	17.95	4.13
VOL 1M	265.43	0.41	53.93	1.39	28.16	2.23	244.98	0.44	49.43	1.56	25.58	1.80
VOL 3Y	66.52	1.35	27.90	3.23	19.41	4.39	55.49	1.51	24.13	3.52	17.31	3.70
BETA	91.18	0.39	38.02	0.97	24.87	1.22	76.69	0.72	33.85	0.85	22.35	0.83
IVOL	82.36	1.45	37.28	2.70	25.36	3.00	60.56	1.82	29.38	3.01	20.52	3.25
MAX	323.45	0.37	58.06	1.11	29.74	1.48	305.34	0.32	54.66	1.11	27.86	0.94
MOM	149.10	0.22	49.97	0.37	30.89	0.37	154.79	0.23	49.94	0.56	30.35	0.88
RES MOM	180.49	0.37	53.85	0.59	31.50	0.57	185.47	0.32	53.33	0.59	31.29	0.48
CF MOM	299.61	0.15	57.43	0.38	30.86	1.01	327.40	0.19	59.22	0.58	30.89	1.41
REV 1M	355.26	0.40	60.24	0.38	30.67	-0.19	358.66	0.22	60.63	0.32	30.79	-0.58
RES REV 1M	361.93	0.33	60.76	0.15	30.80	-0.17	362.02	0.15	60.86	0.19	30.61	-0.16
REV LT	96.56	0.73	34.40	1.81	22.88	2.24	89.17	0.90	32.74	2.09	21.96	2.66
SEAS	366.76	0.11	59.96	-0.22	15.21	-0.89	369.72	0.16	58.98	-0.39	13.95	-1.39
SEAS REV	163.80	0.50	34.67	1.62	16.54	3.61	144.50	0.52	29.07	1.74	14.27	3.61
SEAS DIFF	253.74	0.35	45.85	0.98	16.21	3.18	239.34	0.38	40.83	1.09	14.02	3.11
TURN	61.04	1.45	28.64	2.15	20.20	2.10	44.88	1.54	23.06	2.26	16.98	2.31
ABN TURN	254.16	0.68	60.64	1.02	31.69	1.54	263.55	0.51	60.70	1.01	31.83	0.96
ILLIQ	148.54	0.83	37.60	1.70	21.43	2.28	118.86	0.59	30.17	1.10	17.46	0.95

Table 6: Size-neutral and industry-neutral anomaly returns

This table reports average long-short portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. Portfolio returns are equally weighted (for value-weighted, see Table C2). The left side contains size-neutral returns, the right side contains industry-neutral returns. We display three holding periods; 1, 6, and 12 months. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	Size-neutral						**Industry-neutral**					
	Hold = 1 month		Hold = 6 months		Hold = 12 months		Hold = 1 month		Hold = 6 months		Hold = 12 months	
Anomaly	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE	-	-	-	-	-	-	0.57	1.47	0.36	0.89	0.39	0.90
BM	**1.02**	3.06	0.67	1.75	0.65	1.62	**1.16**	3.73	**0.81**	2.30	**0.79**	2.10
EP	**1.20**	4.92	**0.88**	3.41	**0.89**	2.92	**1.03**	4.03	**0.70**	2.43	**0.69**	2.09
SP	**0.98**	3.77	**0.80**	2.95	**0.82**	2.76	**0.97**	3.71	**0.83**	2.84	**0.88**	2.74
DP	**0.67**	2.90	**0.58**	2.30	**0.64**	2.47	**0.90**	3.95	**0.73**	3.08	**0.70**	3.00
CP	**0.46**	2.65	**0.37**	2.03	0.30	1.64	**0.51**	3.50	**0.37**	2.31	0.25	1.55
OCP	**0.76**	3.14	**0.74**	2.83	**0.81**	2.78	**0.87**	4.07	**0.68**	2.97	**0.68**	2.69
ROE	**0.74**	3.31	**0.60**	2.49	**0.55**	2.11	0.46	1.64	0.43	1.32	0.37	1.02
GP	**0.71**	2.83	**0.64**	2.06	0.65	1.95	**0.63**	2.55	0.57	1.95	0.57	1.81
OP	**0.67**	3.37	**0.58**	2.62	**0.53**	2.19	**0.50**	2.45	0.47	1.91	0.49	1.71
INV ASSET	-0.70	-3.66	**-0.53**	-2.58	-0.30	-1.40	-0.54	-2.87	-0.43	-1.98	-0.19	-0.82
INV BOOK	-0.42	-2.26	-0.27	-1.39	-0.18	-0.81	-0.40	-2.07	-0.20	-0.91	-0.06	-0.24
ACC	-0.11	-0.84	-0.05	-0.34	-0.06	-0.38	0.04	0.46	0.03	0.37	0.00	-0.01
TOTAL ACC	0.20	1.30	0.15	1.07	0.14	1.00	0.21	1.60	0.12	0.94	0.15	1.15
NOA	0.07	0.36	0.25	1.43	0.33	1.67	0.22	1.83	**0.35**	3.07	**0.38**	2.96
VOL 1M	**1.05**	4.24	**0.73**	3.10	**0.66**	3.12	**1.14**	4.62	**0.72**	3.14	**0.62**	3.27
VOL 3Y	**0.82**	3.22	**0.82**	3.21	**0.78**	2.95	**0.84**	3.57	**0.80**	3.40	**0.81**	3.61
BETA	0.14	0.56	0.26	1.04	0.22	0.92	0.18	0.67	0.22	0.85	0.20	0.87
IVOL	**1.06**	4.09	**0.96**	3.72	**0.72**	2.53	**1.20**	5.23	**1.03**	4.52	**0.83**	3.51
MAX	**1.19**	6.15	**0.58**	3.45	**0.42**	2.60	**1.26**	6.70	**0.61**	3.82	**0.41**	2.78
MOM	0.33	1.07	0.14	0.44	0.06	0.17	0.11	0.37	0.12	0.37	-0.03	-0.10
RES MOM	**0.68**	3.63	0.35	1.99	0.22	1.19	**0.59**	3.70	0.31	1.88	0.11	0.66
CF MOM	0.40	1.58	0.23	1.96	**0.24**	2.09	0.25	1.31	0.14	1.00	0.07	0.61
REV 1M	**1.63**	5.66	0.18	1.34	-0.03	-0.24	**1.48**	5.22	0.24	1.59	0.00	-0.02
RES REV 1M	**1.09**	4.78	0.09	0.79	-0.06	-0.69	**1.32**	6.10	0.14	1.41	0.02	0.29
REV LT	0.39	1.58	0.48	1.86	0.33	1.29	**0.64**	2.33	0.64	1.98	0.50	1.38
SEAS	**0.38**	2.77	-0.03	-0.41	-0.03	-0.55	**0.39**	2.80	-0.16	-2.20	-0.11	-1.37
SEAS REV	0.43	2.00	0.35	1.76	**0.38**	2.00	**0.70**	3.45	**0.46**	2.03	0.45	1.78
SEAS DIFF	**0.63**	3.36	0.30	1.76	**0.35**	2.32	**0.79**	4.05	0.37	1.96	0.39	1.96
TURN	**1.24**	5.77	**0.87**	4.40	**0.64**	2.33	**0.89**	3.95	**0.61**	2.81	0.47	1.97
ABN TURN	**1.74**	6.62	**0.58**	3.08	**0.44**	2.54	**1.64**	6.19	**0.57**	2.68	**0.44**	2.38
ILLIQ	**1.33**	6.29	**0.67**	3.80	**0.44**	2.35	**1.26**	3.92	0.64	1.93	0.55	1.40

Table 7: Anomalies and short-sales constraints

This table reports average portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. The left side contains equally weighted (EW) portfolio returns and the value-weighted (VW) index, the middle contains value-weighted returns and the value-weighted index, the right contains equally weighted returns and the equally weighted index. The long leg denotes long-minus-index returns and the short leg denotes index-minus-short returns. The index is the either the equally weighted or market value-weighted average return of all China A-shares that pass our filters for eligibility in anomaly portfolios. The holding period is 1 month. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	EW returns - VW index				**VW returns - VW index**				**EW returns - EW index**			
	Long leg		Short leg		Long leg		Short leg		Long leg		Short leg	
	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE	0.63	1.65	-0.04	-0.37	0.63	1.65	0.01	0.07	**0.37**	2.23	0.22	0.76
BM	**0.72**	2.75	0.41	1.42	**0.69**	2.94	0.37	1.39	**0.46**	2.19	**0.66**	3.29
EP	**0.74**	3.64	0.36	1.08	**0.43**	2.02	**0.66**	2.31	**0.49**	2.09	**0.61**	4.54
SP	**0.63**	2.69	0.30	1.01	**0.43**	2.15	0.37	1.62	**0.38**	2.55	**0.55**	3.45
DP	**0.67**	3.48	0.09	0.31	**0.44**	2.14	0.31	1.31	**0.41**	2.44	**0.35**	2.42
CP	**0.58**	2.60	-0.07	-0.31	**0.62**	2.63	-0.04	-0.20	**0.32**	2.13	**0.19**	2.00
OCP	**0.78**	3.77	0.00	0.01	**0.52**	2.38	0.21	1.00	**0.52**	2.62	**0.26**	2.26
ROE	0.38	1.99	0.16	0.49	0.24	1.44	0.38	1.42	0.12	0.71	**0.42**	2.62
GP	**0.59**	2.50	0.03	0.12	**0.43**	2.02	0.21	0.95	0.34	1.88	**0.29**	2.16
OP	**0.44**	2.36	0.14	0.51	0.29	1.58	0.03	0.14	0.19	1.04	**0.40**	2.89
INV ASSET	-0.06	-0.22	-0.48	-1.98	-0.32	-1.55	-0.17	-0.93	-0.32	-2.79	-0.23	-1.73
INV BOOK	-0.06	-0.20	-0.34	-1.42	-0.18	-0.84	0.01	0.03	-0.31	-2.37	-0.09	-0.72
ACC	0.07	0.30	-0.16	-0.62	-0.13	-0.98	-0.03	-0.16	-0.19	-2.51	0.10	0.92
TOTAL ACC	0.33	1.53	-0.11	-0.41	0.21	1.49	0.10	0.45	0.08	0.81	0.14	1.11
NOA	0.29	1.46	-0.22	-0.84	0.33	1.82	0.12	0.64	0.04	0.30	0.04	0.33
VOL 1M	0.33	1.52	**0.75**	2.27	0.22	1.15	**0.85**	3.16	0.07	0.42	**1.01**	5.96
VOL 3Y	**0.56**	2.74	0.34	1.13	0.23	1.16	**0.61**	2.49	0.30	1.61	**0.60**	4.02
BETA	0.09	0.35	0.27	0.90	0.01	0.03	**0.55**	2.05	-0.17	-0.94	**0.53**	3.24
IVOL	**0.56**	2.83	0.63	1.98	0.32	1.53	**0.78**	3.04	0.31	1.63	**0.89**	5.65
MAX	0.46	1.83	**0.74**	2.62	0.13	0.64	**0.83**	3.51	0.20	1.43	**1.00**	7.68
MOM	0.33	1.18	0.00	0.01	0.18	0.71	0.17	0.60	0.07	0.35	0.26	1.39
RES MOM	**0.51**	2.11	0.15	0.58	**0.40**	2.20	0.20	0.94	**0.25**	2.12	**0.41**	3.37
CF MOM	**0.90**	3.61	-0.44	-1.83	**0.67**	2.40	-0.05	-0.24	**0.64**	2.59	-0.18	-0.96
REV 1M	**0.68**	2.24	**0.74**	2.78	0.25	1.00	**0.55**	2.14	**0.43**	2.38	**1.00**	4.92
RES REV 1M	**0.61**	2.41	**0.57**	2.35	0.38	1.78	0.17	0.81	**0.36**	3.20	**0.82**	4.66
REV LT	0.43	1.40	0.28	1.13	0.31	1.12	**0.49**	2.27	0.17	0.89	**0.54**	2.91
SEAS	0.36	1.42	0.06	0.24	0.28	1.43	0.31	1.62	0.10	0.99	**0.31**	2.80
SEAS REV	**0.60**	2.11	0.21	0.93	0.33	1.31	**0.42**	2.17	**0.34**	2.16	**0.47**	2.98
SEAS DIFF	**0.64**	2.32	0.25	1.11	0.40	1.83	**0.50**	2.91	**0.38**	2.71	**0.51**	3.75
TURN	0.28	1.83	0.60	1.97	0.09	0.51	**0.60**	2.07	0.03	0.14	**0.85**	7.24
ABN TURN	**0.62**	2.30	**1.10**	3.57	0.16	0.85	**1.17**	3.84	**0.36**	2.36	**1.36**	7.42
ILLIQ	**0.88**	2.60	**0.36**	2.54	0.60	1.92	0.10	0.61	**0.62**	4.10	**0.61**	2.52

Table 8: Anomalies and state-owned enterprises and post-reform

This table reports average portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. Portfolio returns are equally weighted (for value-weighted, see Table C5). The left side contains the subsamples state-owned enterprises (SOEs) and non-SOEs; the right contains the subsamples January 2000 to December 2006 and January 2007 to December 2019. The holding period is 1 month. The index is the equally weighted average return of all China A-shares that pass our filters for eligibility in anomaly portfolios. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	Non-SOE		SOE		2000-2006		2007-2019	
	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE	0.46	1.15	0.54	1.20	-0.42	-0.63	1.08	1.92
BM	**1.24**	3.10	**1.27**	3.52	**1.31**	2.92	1.01	1.94
EP	**1.01**	3.13	**1.26**	3.60	**1.42**	2.96	**0.94**	2.20
SP	**1.20**	4.31	**1.08**	4.40	**1.31**	5.24	0.69	1.73
DP	**0.88**	2.78	**0.72**	2.51	**1.05**	2.55	0.59	1.60
CP	0.26	1.03	**0.55**	2.76	**0.63**	3.14	0.44	1.66
OCP	**0.76**	2.62	**1.00**	3.88	**1.19**	3.42	0.57	1.48
ROE	0.62	1.91	0.52	1.64	0.54	0.92	0.51	1.51
GP	**0.75**	2.36	**0.59**	2.02	0.74	1.74	0.56	1.44
OP	0.55	2.00	0.59	1.99	0.62	1.11	0.56	1.93
INV ASSET	-0.74	-3.47	-0.33	-1.59	-0.76	-2.07	-0.49	-1.94
INV BOOK	-0.47	-2.49	-0.25	-1.05	-0.52	-1.28	-0.34	-1.34
ACC	-0.15	-0.78	-0.05	-0.35	0.09	0.58	-0.21	-1.13
TOTAL ACC	0.03	0.15	0.28	1.62	**0.61**	2.73	0.00	-0.01
NOA	-0.28	-1.34	**0.40**	2.06	0.33	1.60	-0.08	-0.27
VOL 1M	**1.12**	3.12	**1.01**	3.46	**0.89**	2.12	**1.16**	3.06
VOL 3Y	**0.85**	2.60	**0.97**	3.17	**1.17**	2.83	0.75	1.86
BETA	0.17	0.51	0.42	1.26	0.11	0.21	0.51	1.35
IVOL	**1.24**	3.88	**1.33**	4.38	**1.37**	3.44	**1.10**	2.64
MAX	**1.22**	4.31	**1.16**	4.72	**0.97**	2.78	**1.30**	4.34
MOM	0.38	1.04	0.06	0.15	1.00	1.76	0.02	0.03
RES MOM	**0.86**	3.27	**0.55**	2.57	**1.13**	4.09	0.44	1.71
CF MOM	-0.01	-0.01	0.32	0.94	**0.98**	2.17	0.25	0.65
REV 1M	**1.46**	4.47	**1.49**	4.13	0.60	1.34	**1.83**	4.22
RES REV 1M	**1.13**	3.66	**1.25**	4.83	**0.75**	2.47	**1.40**	4.07
REV LT	**1.35**	5.53	**1.20**	5.46	0.97	1.70	0.55	1.38
SEAS	-0.13	-0.47	**0.76**	4.15	0.20	0.90	**0.55**	2.78
SEAS REV	**0.83**	2.69	**0.90**	3.18	**1.01**	2.63	**0.70**	2.15
SEAS DIFF	**0.58**	2.11	**0.98**	3.94	**1.12**	3.34	**0.77**	2.73
TURN	**0.94**	3.31	**0.73**	2.38	**0.97**	3.04	**0.86**	2.27
ABN TURN	**1.87**	5.98	**1.65**	5.05	**1.72**	4.63	**1.72**	3.89
ILLIQ	**1.04**	3.00	**1.16**	3.07	0.29	0.48	**1.72**	3.81

Appendix A

Figure A1: Trading suspensions

This figure displays the number of companies with suspended A-shares as a percentage of the number of listed companies. The orange solid line uses all A-shares and the blue dashed line our sample that excludes the 30% smallest stocks, i.e. microcaps.

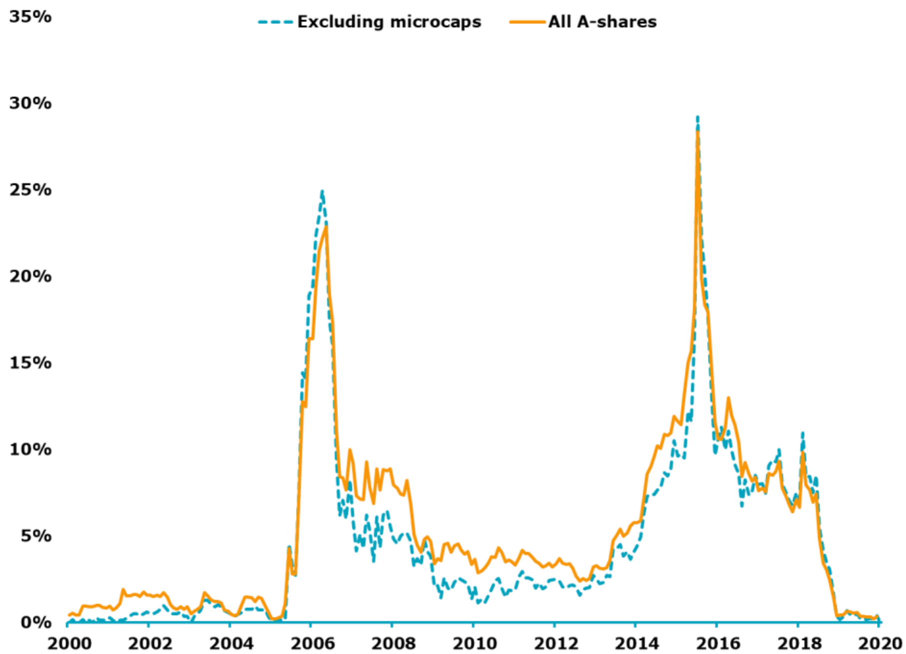


Figure A2: Total cash flows and operating cash flows for SOEs and non-SOEs

This figure displays the median operating cash flows (OCF) and total cash flows (CF) over time for state-owned enterprises (SOEs) and non-SOEs. Cash flows are reported in CNY million.

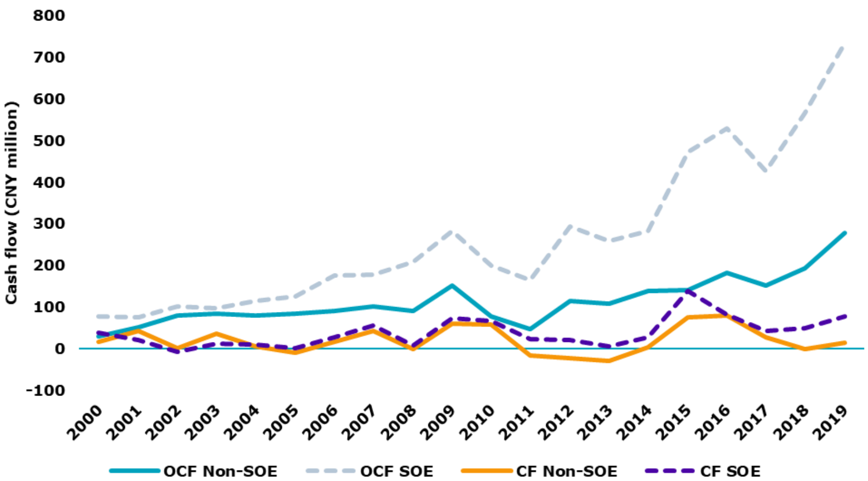
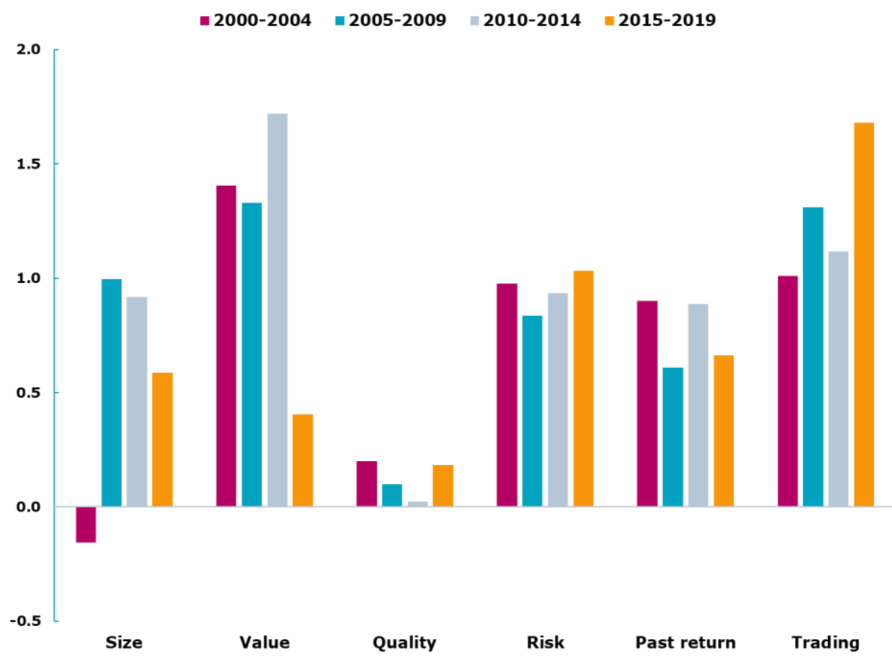


Figure A3: Anomaly group performance for five-year periods

This figure reports average excess portfolio returns (% per month) for six anomaly groups for each five-year period over the period 2000 to 2019. Size contains only SIZE; Value contains BM, EP, SP, DP, CP, OCP; Quality contains ROE, GP, OP, INV ASSET, INV BOOK, ACC, TOTAL ACC, NOA; Risk contains VOL 1M, VOL 3Y, BETA, IVOL, MAX; Past returns contains MOM, RES MOM, CF MOM, REV 1M, RES REV 1M, REV LT, SEAS, SEAS REV, SEAS DIFF; Trading contains TURN, ABN TURN, ILLIQ. Anomaly variable definitions are provided in Table 3 and in Appendix B.



Appendix B: Detailed description of factor characteristics

This section details how the anomaly characteristics are calculated. As mentioned in Section 3.1, all data used comes from CSMAR and Institutional Brokers Estimate System (IBES). IBES data is only used to obtain analyst coverage data necessary to calculate CF MOM. All other data is obtained from CSMAR. With the exception of the accounting variables, all variables are updated monthly using end-of-month data.

The frequency of accounting characteristics varies across categories. All variables in the value and quality categories are calculated based on the most recently reported financial statements. Specifically, semi-annual statements are used prior to January 2002, while quarterly statements are used after this date. Valuation ratios are updated monthly using a firm's end-of-month market value. Variables in the accruals category are based on annual reports and thus updated yearly.

Size

- SIZE. Following Hsu et al. (2018), SIZE is calculated as the natural logarithm of a firm's end-of-month total A-share market capitalization.

Value

- *BM*. Following Liu, Stambaugh, and Yuan (2019), book-to-market is calculated as the ratio of book value to market value. Book value is defined as common shareholder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests. Market value refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. We exclude firms with negative book values.
- *EP*. Following Liu, Stambaugh, and Yuan (2019), earnings-to-price is calculated as the ratio of total earnings to price. Total earnings is defined as net profit excluding minority interest income. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. We exclude firms with negative earnings.
- *SP*. Following Hsu et al. (2018), sales-to-price is calculated as the ratio of total sales to price. Total sales is equal to operating revenue. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price.
- *DP*. Following Hsu et al. (2018), dividend-to-price is calculated as the ratio of total dividends to price. Total dividends is calculated as the total monetary value of dividends paid out to shareholder's over the previous reporting period. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. We exclude firms that do not pay dividends.
- *CP*. Following Liu, Stambaugh, and Yuan (2019), cash-flow-to-price is calculated as the ratio of total cash flow to price. Total cash flow is calculated as the net increase in cash or cash equivalents over the previous reporting

period. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. We exclude firms with negative cash flows.

- *OCP*. Operating-cash-flow-to-price is calculated as the ratio of operating cash flow to price. Operating cash flow is calculated as the net increase in operating cash flow over the previous reporting period. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. We exclude firms with negative operational cash flows.

Quality

- *ROE*. Following Haugen and Baker (1996) and Liu, Stambaugh, and Yuan (2019), return on equity is calculated as the ratio of total earnings to book equity value. Total earnings is defined as net profit excluding minority interest income. Book value is defined as common shareholder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests.
- *GP*. Following Novy-Marx (2013), gross profitability is calculated as the ratio of gross profit to total assets. Gross profit is defined as operating revenue minus operating costs.
- *OP*. Following Fama and French (2015), operating profit is calculated as the ratio of operating profit excluding interest expense to book value. Interest expense is excluded by subtracting total interest expense from operating profit. Book value is defined as common shareholder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests.
- *INV ASSET*. Following Hou, Xue, and Zhang (2020), asset growth is calculated as the quarter-to-quarter asset growth rate, i.e., the difference between total assets in the previous two quarters divided by total assets two quarters ago.
- *INV BOOK*. Following Hou, Xue, and Zhang (2020), book value growth is calculated as the quarter-to-quarter book value growth rate, i.e., the difference between total book value in the previous two quarters divided by total book value two quarters ago. Book value is defined as common share-holder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests.
- *ACC*. Following Liu, Stambaugh, and Yuan (2019), Sloan (1996) firm-level accruals are calculated as

$$ACC = 2 \times Accrual_t/(TA_{t-1} + TA_t)$$

$$Accrual_t = (\Delta CA_t - \Delta Cash_t) - (\Delta CL_t - \Delta STD_t - \Delta TP_t) - DP_t$$

where TA_t is total assets, $Cash_t$ is the balance of cash and cash equivalents, CL_t is current liabilities, STD_t is the sum of notes payable and long-term debt due within one year, TP_t is taxes payable, DP_t is the sum of depreciation of fixed assets, oil and gas assets, and bearer biological assets, and intangible asset amortization. Δ denotes the year-on-year difference and *t* denotes the year.

- *TOTAL ACC*. Following Hribar and Collins (2002), total accruals is calculated as the difference between earnings in year *t* and operating cash flows in year *t*, scaled by total assets in year *t*.

- *NOA*. Following Liu, Stambaugh, and Yuan (2019), net operating assets is calculated as net operating assets in year t scaled by total assets in year *t-1*. The numerator is calculated as the difference between operating assets and operating liabilities. Operating assets is defined as total assets minus balance sheet cash, minus short-term investment. Operating liabilities represents total assets minus short-term loans, minus long-term loans, minus minority interest, minus common shareholder's equity excluding minority interest.

Risk

- *VOL 1M*. Following Ang, Hodrick, Xing, and Zhang (2006), one-month volatility is calculated as the standard deviation of daily stock returns over the past twenty trading days.
- *VOL 3Y*. Following Blitz and Van Vliet (2007), three-year volatility is calculated as the standard deviation of monthly stock returns over the past 36 months.
- *BETA*. Following Hsu et al. (2018), market beta is used as a proxy for systematic risk. BETA is defined as the estimated slope coefficient from a regression of daily excess stock returns over the past 250 trading days on an intercept and the daily returns from the value-weighted market portfolio. The value-weighted market portfolios is calculated using all available A-share stocks.
- *IVOL*. Following Hsu et al. (2018), idiosyncratic volatility is calculated as the standard deviation of residuals from a regression of daily excess stock returns over the past 250 trading days on an intercept and the daily returns from the value-weighted market, size, and value factor.
- *MAX*. Following Bali, Cakici, and Whitelaw (2011), the maximum daily return over the past twenty trading days equals the highest adjusted daily return over this period. Daily returns are adjusted in two ways. First, to account for a possible downward bias caused by trade suspensions, daily returns on suspended trading days are set equal to -99. Second, as suggested by Cheema, Nartea, and Man (2020), we aggregate the daily returns after a stock hits the upper price limit.

Past returns

- *MOM*. Following Jegadeesh and Titman (1993), momentum at month *t* is calculated as the cumulative monthly stock return over the previous twelve months excluding the most recent month.
- *RES MOM*. Following Blitz, Huij, and Martens (2011) and Lin (2019), residual momentum is calculated in three steps. First, monthly excess stock returns over the past 36 months are regressed on the Fama and French (1993) three-factor model. Note that only stocks with a complete 36-month return history are included in the rolling window regressions. Second, residual returns are calculated as the difference between observed excess returns and fitted excess returns. Third, the residual returns from the previous twelve months excluding the most recent month are scaled by their standard deviation of the same period. Residual momentum is then calculated as the mean of the standardized residual returns.
- *CF MOM*. Following Ali and Hirshleifer (2019), connected-firm momentum is calculated as the past return on a portfolio of firms connected through analysts. For a given stock *i* and month *t*, the CF MOM portfolio return is

computed using the weighted average return of all stocks linked to stock *i* through common analyst coverage in the past month. Specifically, the return is calculated as

$$CF\ MOM_{i,t} = \frac{1}{\sum_{j=1}^{N} n_{i,j}} \sum_{j=1}^{N} n_{i,j} Ret_{j,t}$$

in which $Ret_{j,t}$ is the month-*t* return of stock *j*, $n_{i,j}$ denotes the number of analysts covering both stock *i* and stock *j*, and *N* is the total number of stocks connected to stock *i* in month *t*. To identify analyst coverage, we make use of detail file in the IBES database.

- *REV 1M*. Following Jegadeesh (1990), short-term reversal is calculated as the cumulative stock return over the past twenty trading days.
- *RES REV 1M*. Following Blitz, Huij, Lansdorp, and Verbeek (2013) residual reversal is calculated in three steps. First, monthly excess stock returns over the past 36 months are regressed on the Fama and French (1993) three-factor model. Note that only stocks with a complete 36-month return history are included in the rolling window regressions. Second, residual returns are calculated as the difference between observed excess returns and fitted excess returns. Third, residual reversal is calculated as the residual return in the most recent month scaled by the 36-month residual return standard deviation.
- *REV LT*. Following De Bondt and Thaler (1985), long-term reversal is calculated as the cumulative monthly stock return over the past five years excluding the previous year, i.e., month *t* = 60 to month *t*-13.
- *SEAS*. Following Heston and Sadka (2008, 2010) and Keloharju, Linnainmaa, and Nyberg (2016), seasonal return is defined as a stock's average historical same-month return. To calculate historical same-month returns, stock returns are first cross-sectionally demeaned to account for differences in the availability of historical data across stocks. In particular, demeaning ensures that average same-month returns of stocks with varying data histories are comparable. Then, the average return is calculated over the stock's series of same-calendar-month returns. We require at least a five-year return history to include a stock and calculate the average using up to twenty years of historical data.
- *SEAS REV*. Following Keloharju, Linnainmaa, and Nyberg (2021), seasonal return reversals is defined as a stock's average historical other-month return. To calculate historical other-month returns, stock returns are first cross-sectionally demeaned to account for differences in the avail-ability of historical data across stocks. For each other month of the year, the average return is calculated up to twenty years back. The other-month return is calculated by taking the sum over all other-month averages. For example, if the current month is January, the sum of the average February-December returns is calculated. We require at least a five-year return history to include a stock and calculate the average using up to twenty years of historical data.
- *SEAS DIFF*. Following Keloharju, Linnainmaa, and Nyberg (2021), seasonal return differences are calculated as the difference between historical average same-month returns and average other-month returns. That is, SEAS minus SEAS REV.

Trading

- *TURN*. Following Liu, Stambaugh, and Yuan (2019), turnover is calculated as the average of the daily share turnover over the past 250 trading days. Daily share turnover is the ratio of the number of shares traded to the total number of shares outstanding.
- *ABN TURN*. Following Liu, Stambaugh, and Yuan (2019), abnormal turnover is calculated as the average daily share turnover over the past twenty trading days scaled by the average daily share turnover over the past 250 trading days. Daily share turnover is the ratio of the number of shares traded to the total number of shares outstanding.
- *ILLIQ*. Following Amihud (2002), illiquidity is calculated as the average stock illiquidity over the past twenty trading days. Stock illiquidity at day t is defined as

$$Illiq_t = |Ret_t|/Volume_t$$

where $|Ret_t|$ is the absolute value of the stock's daily return and $Volume_t$ is the dollar trading volume on day t, i.e., total number of shares traded times close price.

Appendix C: Additional tables

Table C1: Anomaly alphas

This table reports CAPM alphas alongside their Newey and West (1987) t-statistics over the sample period Jan 2000 through Dec 2019. The left side contains equally weighted portfolio returns, the right side contains market value-weighted portfolio returns. We display three holding periods; 1, 6, and 12 months. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive. For the equally weighted returns, we use the equally weighted market portfolio, while for the value-weighted returns, we use the value-weighted market portfolio, both including all China A-shares that pass our filters so that are eligible for anomaly portfolio construction.

	Equally weighted						**Value-weighted**					
	Hold = 1 month		Hold = 6 months		Hold = 12 months		Hold = 1 month		Hold = 6 months		Hold = 12 months	
Anomaly	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE	0.52	1.26	0.27	0.60	0.30	0.60	0.50	1.00	0.24	0.44	0.20	0.33
BM	**1.08**	2.99	0.71	1.69	0.68	1.58	**1.05**	2.41	0.62	1.28	0.64	1.32
EP	**1.16**	3.66	**0.81**	2.33	0.76	1.90	**1.24**	2.96	**1.07**	2.38	0.95	1.85
SP	**0.92**	3.37	**0.74**	2.64	**0.82**	2.78	**0.77**	2.20	0.70	1.86	**0.83**	2.04
DP	**0.79**	2.93	**0.59**	2.14	**0.63**	2.21	**0.81**	2.14	0.53	1.35	0.58	1.43
CP	**0.49**	2.79	0.32	1.73	0.29	1.56	0.60	1.91	0.50	1.75	0.43	1.62
OCP	**0.80**	2.95	**0.70**	2.44	**0.72**	2.33	**0.85**	2.29	0.70	1.73	0.69	1.53
ROE	**0.62**	2.10	0.58	1.70	0.53	1.29	**0.74**	2.04	0.68	1.59	0.46	0.91
GP	**0.78**	2.99	**0.71**	2.25	**0.74**	2.13	**0.79**	2.36	0.78	1.95	0.68	1.52
OP	**0.65**	2.43	0.56	1.86	0.49	1.35	0.26	0.90	0.28	0.99	0.08	0.29
INV ASSET	-0.56	-2.77	-0.44	-1.77	-0.18	-0.67	-0.48	-1.88	-0.48	-1.66	-0.24	-0.67
INV BOOK	-0.44	-2.17	-0.19	-0.81	-0.06	-0.21	-0.23	-0.87	-0.06	-0.17	-0.02	-0.04
ACC	-0.08	-0.62	-0.01	-0.10	-0.02	-0.10	-0.14	-0.68	-0.10	-0.54	-0.07	-0.38
TOTAL ACC	0.25	1.58	0.19	1.31	0.18	1.21	0.42	1.54	0.30	1.06	0.28	1.07
NOA	0.07	0.39	0.24	1.29	0.38	1.85	0.53	1.76	0.62	1.97	**0.78**	2.23
VOL 1M	**1.27**	4.27	**0.91**	3.36	**0.76**	3.25	**1.28**	3.28	**0.95**	2.62	0.64	1.95
VOL 3Y	**1.10**	3.92	**1.06**	3.89	**0.99**	3.58	**1.09**	2.99	**1.07**	2.92	**0.85**	2.42
BETA	**0.58**	2.02	0.53	1.96	0.46	1.75	**0.84**	2.08	0.54	1.57	0.45	1.32
IVOL	**1.32**	4.54	**1.08**	3.74	**0.82**	2.67	**1.32**	3.39	**1.06**	2.57	0.84	1.88
MAX	**1.32**	5.69	**0.73**	3.94	**0.52**	3.22	**1.20**	3.46	**0.76**	2.71	0.41	1.65
MOM	0.39	1.08	0.26	0.72	0.20	0.52	0.45	1.04	0.38	0.94	0.35	0.87
RES MOM	**0.65**	3.26	0.32	1.67	0.19	0.97	**0.66**	2.39	0.37	1.53	0.20	0.82
CF MOM	0.41	1.38	0.21	1.22	0.27	1.81	0.54	1.53	0.32	1.47	**0.38**	2.43
REV 1M	**1.40**	4.26	0.20	1.20	-0.08	-0.55	0.81	1.99	0.15	0.75	-0.21	-1.21
RES REV 1M	**1.16**	4.49	0.09	0.82	-0.05	-0.64	0.55	1.64	0.11	0.82	-0.06	-0.55
REV LT	**0.68**	2.14	0.59	1.71	0.48	1.19	0.75	1.89	0.64	1.46	0.54	1.07
SEAS	**0.42**	2.92	-0.13	-1.42	-0.13	-1.32	0.57	1.93	-0.23	-1.44	-0.18	-1.36
SEAS REV	**0.81**	3.47	**0.56**	2.19	**0.58**	2.01	**0.79**	2.30	0.55	1.50	0.55	1.37
SEAS DIFF	**0.90**	4.37	**0.45**	2.08	**0.51**	2.21	**0.94**	3.09	0.47	1.50	0.46	1.39
TURN	**1.02**	3.89	**0.71**	2.94	0.51	1.96	**0.89**	2.16	0.67	1.59	0.53	1.22
ABN TURN	**1.82**	6.12	**0.69**	2.83	**0.52**	2.47	**1.45**	3.81	**0.66**	2.20	0.34	1.42
ILLIQ	**1.28**	3.66	0.64	1.70	0.48	1.07	0.65	1.47	0.25	0.49	0.08	0.15

Table C2: Size-neutral and industry-neutral anomaly returns (value-weighted)

This table reports average long-short portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. Portfolio returns are value-weighted (for equally weighted, see Table 6). The left side contains size-neutral returns, the right side contains industry-neutral returns. We display three holding periods; 1, 6, and 12 months. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	Size-neutral						**Industry-neutral**					
	Hold = 1 month		Hold = 6 months		Hold = 12 months		Hold = 1 month		Hold = 6 months		Hold = 12 months	
Anomaly	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE							0.62	1.23	0.47	0.87	0.46	0.78
BM	**0.98**	2.28	0.57	1.18	0.62	1.28	**1.10**	2.79	0.81	1.95	**0.92**	2.13
EP	**1.47**	3.71	**1.09**	2.71	**0.97**	2.17	**1.19**	3.03	**0.98**	2.30	**0.92**	2.01
SP	**0.86**	2.35	**0.85**	2.25	**0.86**	2.01	**0.82**	2.34	**0.85**	2.12	**0.85**	1.99
DP	0.64	1.76	0.37	0.96	0.45	1.13	**1.04**	2.84	**0.89**	2.46	0.69	1.85
CP	0.40	1.28	0.38	1.33	0.41	1.56	0.42	1.74	0.50	1.83	0.25	1.20
OCP	**0.97**	2.85	**0.89**	2.38	**0.99**	2.44	**0.97**	3.03	**0.77**	2.40	**0.71**	2.04
ROE	**0.71**	2.47	**0.68**	2.23	0.60	1.83	0.60	1.78	0.57	1.44	0.35	0.79
GP	**0.70**	2.11	0.68	1.69	0.63	1.52	0.60	1.74	0.52	1.30	0.40	0.93
OP	0.52	1.70	0.45	1.49	0.25	0.87	0.44	1.44	0.29	0.88	0.30	0.82
INV ASSET	-0.70	-2.77	-0.72	-2.47	-0.53	-1.57	-0.56	-2.31	-0.36	-1.34	-0.18	-0.56
INV BOOK	-0.16	-0.59	-0.20	-0.67	-0.27	-0.76	-0.13	-0.56	0.06	0.22	0.11	0.30
ACC	-0.22	-1.13	-0.17	-0.91	-0.13	-0.67	0.11	0.57	-0.03	-0.17	-0.10	-0.53
TOTAL ACC	0.22	0.80	0.08	0.30	0.13	0.49	0.37	1.48	0.21	0.85	0.20	0.87
NOA	0.41	1.30	0.46	1.43	0.54	1.56	**0.41**	1.99	**0.56**	2.93	**0.65**	3.08
VOL 1M	**0.77**	2.18	0.52	1.47	0.30	0.88	**0.98**	2.60	0.56	1.55	0.32	0.92
VOL 3Y	**0.94**	2.56	0.73	1.85	0.57	1.54	**0.93**	2.67	0.75	1.81	0.70	1.69
BETA	0.25	0.68	0.09	0.25	0.04	0.11	0.16	0.38	-0.03	-0.06	-0.01	-0.03
IVOL	**0.91**	2.28	0.71	1.61	0.52	1.12	**0.96**	2.39	**0.91**	2.06	0.74	1.59
MAX	**0.72**	2.20	0.38	1.37	0.16	0.58	**0.74**	2.34	0.53	1.75	0.15	0.55
MOM	0.40	1.08	0.29	0.75	0.24	0.64	0.30	0.77	0.26	0.67	0.11	0.32
RES MOM	**0.64**	2.45	0.28	1.12	0.25	1.01	0.41	1.58	0.25	1.04	0.11	0.43
CF MOM	0.65	1.97	0.31	1.59	**0.30**	2.14	0.12	0.43	0.06	0.36	-0.15	-1.05
REV 1M	**0.91**	2.67	0.10	0.57	-0.16	-0.95	**0.71**	2.25	0.15	0.79	-0.11	-0.70
RES REV 1M	0.49	1.60	0.06	0.41	-0.05	-0.52	**0.71**	2.43	0.11	0.76	0.03	0.37
REV LT	0.59	1.73	0.59	1.70	0.55	1.60	**0.81**	2.18	0.68	1.56	0.56	1.17
SEAS	0.55	1.79	-0.19	-1.29	-0.11	-0.96	**0.64**	2.38	-0.21	-1.32	-0.15	-1.12
SEAS REV	0.45	1.45	0.36	1.12	0.33	1.06	0.60	1.92	0.38	1.11	0.34	0.94
SEAS DIFF	0.61	1.99	0.32	1.06	0.31	1.07	**0.78**	2.62	0.27	0.90	0.28	0.89
TURN	0.75	1.89	0.55	1.33	0.35	0.73	0.70	1.81	0.51	1.24	0.45	1.05
ABN TURN	**1.35**	4.04	**0.55**	2.26	0.29	1.55	**1.12**	3.45	**0.53**	2.02	0.23	1.15
ILLIQ	0.40	1.19	-0.08	-0.22	-0.23	-0.52	0.85	1.98	0.42	0.90	0.29	0.55

Table C3: Anomaly decile returns

This table reports average decile portfolio returns over the sample period January 2000 through December 2019. Portfolio returns are equally weighted within each anomaly decile. Anomaly deciles are arranged based on their expected sign such that expected D1 returns are lower than D10 returns. The holding period is 1 month. Anomaly variable definitions are provided in Table 3 and in Appendix B. The color green indicates high returns, while red indicates low returns.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
SIZE	0.81	0.94	0.78	0.95	0.83	0.93	1.04	1.09	1.23	1.40
BP	0.37	0.78	0.72	0.84	0.93	1.08	1.14	1.33	1.34	1.49
EP	0.42	0.64	0.78	0.93	1.07	1.11	1.20	1.35	1.39	1.52
SP	0.48	0.85	0.87	0.87	0.87	1.07	1.17	1.12	1.28	1.41
DP	0.68	0.89	0.94	1.03	1.01	1.08	1.13	1.34	1.34	1.44
CP	0.85	0.86	0.94	0.96	1.07	1.11	1.06	1.06	1.13	1.35
OCP	0.77	0.62	0.93	1.05	0.99	1.10	1.07	1.27	1.21	1.55
ROE	0.61	0.82	0.85	0.95	0.93	1.14	1.17	1.13	1.27	1.15
GP	0.74	0.76	0.86	0.83	0.94	0.95	1.12	1.15	1.28	1.37
OP	0.63	0.77	0.83	0.91	0.99	1.13	1.15	1.20	1.20	1.22
INV ASSET	1.26	1.17	1.04	1.15	1.02	1.10	1.05	0.98	0.84	0.71
INV BOOK	1.12	1.18	1.02	1.14	1.16	1.20	1.02	0.93	0.84	0.72
ACC	0.94	1.05	1.04	1.02	1.10	1.06	1.17	1.05	0.96	0.84
TOTAL ACC	0.89	0.97	0.94	1.09	0.97	1.00	1.09	1.15	1.09	1.11
NOA	0.99	1.08	0.93	1.14	1.07	1.08	0.99	0.95	1.01	1.07
VOL 1M	0.03	0.59	0.93	1.11	1.25	1.28	1.18	1.31	1.24	1.10
VOL 3Y	0.43	0.71	0.93	1.01	1.08	1.10	1.18	1.18	1.22	1.33
BETA	0.50	0.75	0.96	1.12	1.16	1.28	1.19	1.17	1.22	0.86
IVOL	0.19	0.79	1.00	0.93	1.04	1.21	1.20	1.31	1.29	1.27
MAX	0.03	0.52	0.82	0.90	1.23	1.24	1.39	1.39	1.33	1.23
MOM	0.77	0.93	1.05	1.02	1.14	1.11	1.06	1.09	0.95	1.10
RES MOM	0.62	0.84	0.89	1.07	0.94	0.95	1.13	1.16	1.26	1.29
CF MOM	1.21	1.27	1.18	1.47	1.13	1.16	1.51	1.33	1.43	1.67
REV 1M	0.03	0.44	0.76	0.93	1.09	1.15	1.33	1.36	1.45	1.46
RES REV 1M	0.21	0.60	0.77	0.98	1.03	1.10	1.28	1.28	1.52	1.39
REV LT	0.49	0.80	0.96	1.00	1.03	0.97	1.09	1.20	1.21	1.20
SEAS	0.72	0.69	0.85	1.00	1.09	0.98	1.14	1.10	1.22	1.14
SEAS REV	0.56	0.66	0.89	0.72	1.09	1.14	1.05	1.13	1.32	1.37
SEAS DIFF	0.52	0.72	0.72	0.96	0.92	1.02	1.09	1.26	1.32	1.41
TURN	0.18	0.70	0.94	1.02	1.26	1.18	1.31	1.35	1.24	1.06
ABN TURN	-0.33	0.61	0.82	1.17	1.15	1.22	1.42	1.37	1.41	1.39
ILLIQ	0.42	0.55	0.61	0.84	1.02	0.91	1.07	1.37	1.57	1.65

Table C4: Anomalies for each size decile

This table reports average long-short portfolio returns over the sample period January 2000 through December 2019. Portfolio returns are equally weighted within each size decile. The holding period is 1 month. Anomaly variable definitions are provided in Table 3 and in Appendix B. The color green indicates positive excess returns, while red indicates negative excess returns.

	Small	D2	D3	D4	D5	D6	D7	D8	D9	Large
SIZE										
BM	1.01	1.30	1.84	0.87	0.81	0.96	0.98	0.83	0.41	1.24
EP	0.87	1.18	0.96	0.48	1.17	1.25	1.19	1.46	1.39	1.82
SP	1.09	0.86	0.97	0.41	1.19	0.87	1.16	1.13	0.93	1.24
DP	0.74	0.52	1.12	1.00	0.50	0.77	0.58	0.21	0.68	0.81
CP	0.15	0.43	0.32	0.69	0.65	0.17	0.44	0.47	0.66	0.28
OCP	0.42	0.70	0.29	0.15	1.05	1.16	0.62	1.31	0.73	1.01
ROE	0.83	0.71	0.28	0.95	0.67	1.04	0.99	0.57	0.87	0.49
GP	0.43	0.64	0.61	0.58	0.53	0.76	0.98	0.83	1.12	0.63
OP	1.06	0.84	0.19	0.68	0.48	0.87	0.91	0.69	0.87	0.13
INV ASSET	-0.66	-0.74	-1.06	-0.84	-0.56	-0.48	-0.75	-0.88	-0.70	-0.37
INV BOOK	-0.25	-0.78	-0.56	-0.72	-0.18	-0.19	-0.66	-0.51	-0.36	0.03
ACC	-0.44	0.54	-0.01	0.13	0.01	-0.47	-0.35	0.01	-0.28	-0.16
TOTAL ACC	-0.34	0.06	0.01	-0.20	0.46	0.31	0.22	0.88	0.13	0.31
NOA	-0.02	-0.37	-0.30	-0.09	0.01	-0.09	0.50	-0.07	0.02	1.06
VOL 1M	1.26	1.97	1.10	1.16	1.37	1.01	1.04	0.83	0.28	0.49
VOL 3Y	0.90	0.50	0.21	0.57	0.98	1.07	0.91	0.96	0.92	1.13
BETA	-0.49	-0.02	-0.69	0.49	0.32	0.63	0.48	0.49	0.09	0.08
IVOL	1.10	1.24	1.54	1.07	1.36	0.87	0.91	1.08	0.67	0.74
MAX	1.80	1.73	1.40	1.51	1.40	1.03	0.90	1.11	0.37	0.63
MOM	0.21	0.32	0.03	0.35	0.11	0.45	0.27	0.31	0.78	0.37
RES MOM	0.40	0.21	0.86	0.35	0.81	0.39	0.57	0.87	1.37	0.81
CF MOM	-0.06	0.27	0.53	-0.20	1.57	-0.56	0.38	0.08	0.44	0.56
REV 1M	2.40	2.45	2.08	1.81	1.78	1.88	0.93	1.21	0.85	0.94
RES REV 1M	1.84	2.21	1.53	1.37	1.14	1.01	0.73	1.11	0.11	-0.06
REV LT	-0.42	-0.14	0.94	0.23	0.28	0.79	0.26	0.63	0.26	1.04
SEAS	0.60	0.68	0.60	-0.01	0.48	0.10	0.18	0.41	0.75	-0.07
SEAS REV	0.41	0.57	1.11	-0.25	-0.04	0.74	-0.35	1.05	0.52	0.47
SEAS DIFF	0.70	0.80	1.40	0.17	0.27	0.78	-0.31	1.19	0.66	0.49
TURN	1.81	1.56	1.24	1.44	1.51	1.86	1.05	1.03	0.27	0.59
ABN TURN	2.29	2.24	2.27	1.84	1.96	1.94	1.40	1.50	1.19	0.75
ILLIQ	2.09	1.77	1.71	1.74	1.47	1.53	1.12	1.41	0.71	-0.24

Table C5: Anomalies and state-owned enterprises and post-reform (value-weighted)

This table reports average portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. Portfolio returns are value-weighted (for equally weighted, see Table 8). The left side contains the subsamples state-owned enterprises (SOEs) and non-SOEs; the right contains the subsamples January 2000 to December 2006 and January 2007 to December 2019. The holding period is 1 month. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	Non-SOE		SOE		2000-2006		2007-2019	
	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE	0.58	1.23	0.60	1.13	-0.61	-0.79	1.23	1.76
BM	**1.07**	2.25	**1.16**	2.61	**1.39**	2.41	0.84	1.41
EP	**1.12**	2.65	**1.29**	2.89	**1.99**	3.04	0.63	1.14
SP	**1.45**	4.31	**0.92**	2.34	**1.41**	3.21	0.39	0.81
DP	**1.02**	2.25	**0.82**	2.10	1.01	1.82	0.60	1.13
CP	0.43	1.07	0.59	1.74	0.23	0.61	0.77	1.70
OCP	0.59	1.42	**1.10**	2.87	**1.72**	2.72	0.20	0.41
ROE	0.53	1.32	0.73	1.72	0.73	1.11	0.59	1.21
GP	0.70	1.73	0.66	1.63	0.82	1.78	0.53	1.05
OP	0.26	0.78	0.39	1.25	0.00	0.00	0.48	1.33
INV ASSET	-0.83	-2.94	-0.49	-1.77	-0.72	-1.62	-0.38	-1.12
INV BOOK	-0.46	-1.62	-0.17	-0.59	-0.56	-1.10	0.02	0.05
ACC	-0.20	-0.82	-0.15	-0.60	-0.04	-0.13	-0.21	-0.69
TOTAL ACC	0.01	0.04	0.30	0.92	**1.09**	2.73	-0.09	-0.23
NOA	0.08	0.22	0.51	1.63	**0.93**	2.96	0.19	0.41
VOL 1M	**0.99**	2.35	**1.12**	2.75	0.56	1.06	**1.28**	2.40
VOL 3Y	**0.97**	2.40	**0.97**	2.40	**1.34**	2.27	0.62	1.20
BETA	0.48	1.10	0.54	1.28	0.24	0.39	0.75	1.31
IVOL	0.90	1.96	**1.30**	2.93	**1.90**	3.56	0.76	1.26
MAX	**0.91**	2.52	**0.88**	2.17	0.52	1.11	**1.15**	2.20
MOM	0.59	1.33	0.07	0.16	1.12	1.64	-0.05	-0.09
RES MOM	**0.99**	2.75	0.46	1.53	**1.06**	2.57	0.38	1.08
CF MOM	0.32	0.55	0.46	1.29	**1.42**	2.64	0.22	0.49
REV 1M	0.86	1.99	0.83	1.84	-0.14	-0.25	**1.24**	2.13
RES REV 1M	0.49	1.29	0.63	1.78	-0.09	-0.19	**0.92**	2.09
REV LT	0.54	1.20	**0.91**	2.21	0.91	1.22	0.71	1.35
SEAS	-0.07	-0.19	**0.73**	2.23	0.45	1.53	0.66	1.50
SEAS REV	**1.08**	2.76	0.69	1.71	**1.18**	2.09	0.47	0.99
SEAS DIFF	**0.89**	2.17	**0.79**	2.26	**1.20**	2.54	0.70	1.65
TURN	0.56	1.53	0.75	1.60	**1.47**	3.07	0.33	0.52
ABN TURN	**1.58**	3.98	**1.21**	2.91	**1.08**	2.48	**1.48**	2.52
ILLIQ	0.37	0.85	0.65	1.38	-0.49	-0.62	**1.29**	2.24

Table C6: Anomalies and state-owned enterprises (size-neutral)

This table reports average size-neutral portfolio returns alongside their Newey and West (1987) t-statistics over the sample period January 2000 through December 2019. The left side contains equally weighted portfolio returns, the right side contains market value-weighted portfolio returns. Each panel is further split into state-owned enterprises (SOE) and non-SOE subsamples. The holding period is 1 month. Anomaly variable definitions are provided in Table 3 and in Appendix B. Significance at the 5% level is indicated in bold when the coefficient is of the expected sign, i.e., positive.

	Equally weighted				**Value-weighted**			
	Non-SOE		SOE		Non-SOE		SOE	
	Return	t-stat	Return	t-stat	Return	t-stat	Return	t-stat
SIZE								
BP	**0.82**	2.44	**1.15**	3.87	0.72	1.69	**0.97**	2.33
EP	**1.01**	3.86	**1.32**	5.11	**1.19**	3.47	**1.46**	3.62
SP	**0.91**	3.60	**1.01**	4.94	**1.02**	3.34	0.69	1.84
DP	**0.74**	3.06	**0.62**	2.72	**0.86**	2.22	0.58	1.71
CP	**0.62**	2.64	0.34	1.76	0.60	1.61	0.35	1.01
OCP	**0.55**	2.11	**0.97**	4.62	0.54	1.40	**1.05**	3.22
ROE	**0.89**	3.88	**0.62**	2.58	**0.74**	2.67	**0.73**	2.16
GP	**0.91**	3.31	**0.62**	2.53	**0.88**	2.23	**0.81**	2.34
OP	**0.79**	3.99	**0.67**	3.00	0.40	1.48	**0.62**	2.02
INV ASSET	-0.97	-4.80	-0.48	-2.79	-0.99	-3.47	-0.66	-2.41
INV BOOK	-0.53	-2.88	-0.36	-1.87	-0.44	-1.65	-0.30	-1.10
ACC	-0.14	-0.84	-0.07	-0.51	-0.19	-0.83	-0.09	-0.36
TOTAL ACC	0.06	0.31	0.14	0.87	-0.07	-0.23	0.08	0.25
NOA	-0.22	-1.14	**0.31**	2.03	0.07	0.19	0.46	1.62
VOL 1M	**1.12**	3.54	**0.92**	3.91	**0.85**	2.24	0.69	1.91
VOL 3Y	**0.86**	3.05	**0.78**	3.11	**0.99**	2.72	**0.91**	2.38
BETA	0.10	0.37	0.18	0.67	0.53	1.34	0.39	0.98
IVOL	**1.14**	4.01	**1.15**	4.67	**0.79**	2.02	**1.00**	2.48
MAX	**1.05**	4.26	**1.14**	5.41	**0.70**	2.04	**0.71**	2.14
MOM	0.48	1.48	0.14	0.47	0.65	1.65	0.40	1.03
RES MOM	**0.84**	3.42	**0.59**	2.93	**1.09**	3.26	**0.59**	2.16
CF MOM	0.37	0.76	0.28	1.06	0.77	1.33	0.57	1.79
REV 1M	**1.49**	5.13	**1.54**	5.02	**1.16**	3.11	**0.71**	2.15
RES REV 1M	**1.04**	3.81	**1.23**	5.13	**0.70**	2.09	0.57	1.82
REV LT	0.06	0.26	**0.51**	2.08	0.15	0.45	0.47	1.30
SEAS	-0.03	-0.14	**0.56**	4.03	0.07	0.24	0.39	1.29
SEAS REV	0.32	1.46	**0.49**	2.16	0.45	1.35	0.23	0.70
SEAS DIFF	0.42	1.96	**0.60**	2.91	0.51	1.44	0.29	0.94
TURN	**1.13**	4.58	**1.11**	5.13	0.63	1.82	**0.75**	2.04
ABN TURN	**1.69**	6.39	**1.62**	6.24	**1.09**	3.06	**1.08**	3.30
ILLIQ	**1.31**	4.90	**1.22**	5.45	0.65	1.69	0.25	0.69