Anomalies in Chinese A-Shares

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Abstract

We apply well-studied factor strategies from the U.S. equity anomalies literature to Chinese A-shares, demonstrating which factors have worked and which have not over the last two decades since the opening of China's stock markets. We find while a number of traditional factors like value and size appear to work well in China, other factors are less effective, including A-shares momentum which works in the *opposite* direction. Our analysis reconciles conflicting results from the prior A-shares anomalies literature and explains differences in U.S. and Chinese factor investing experiences on the basis of unique features of China's evolving investing landscape, including issues related to regulation, financial reporting standards, differences in market microstructure, and investor behavior. After reviewing evidence on the performance of specific factor strategies applied to A-shares, we demonstrate ways in which a deep institutional knowledge of China's financial markets leads to more effective investment strategies through factor design and portfolio construction tailored to novel features of A-shares. Our findings will be of interest to researchers of equity anomalies and to those developing quantitative strategies for Chinese equities.

1 Introduction

Over the last few decades, beginning with financial liberalization policies initiated in the 1980s, China's capital markets have expanded rapidly. Its stock markets, essentially nonexistent prior to December 1990, have grown to become the second-largest in the world behind the U.S., totaling over $7 trillion in market capitalization as of the end of 2016.[1] At the same time, even as recent changes to restrictions on foreign investment have provided offshore investors with new access to China's domestic stock markets, those considering an allocation to Chinese equities still face a range of challenges in allocating to the Chinese equity market. The relatively short market history often makes statistical analyses inconclusive, while the evolving and uncertain regulatory environment creates doubts regarding the relevance of historical data. Substantial differences in market microstructure, such as the retail investor participation rate, transactions costs, and market liquidity, also have a significant effect on the implementation and performance of traditional investment strategies applied to Chinese stocks.

With growing expectation for inclusion of Chinese stocks into global equity benchmarks[2], asset owners must assess whether standard systematic approaches to generate excess equity returns are equally valid in China. The appeal of such cross-sectional "factor" strategies stems from lower direct costs for investment management and lower indirect costs associated with governance and due diligence. In a market where uncertainty and non-transparency are high, such features are particularly compelling. As such, the principal aim of this study is to develop a better understanding of the degree to which anomalies from the literature on U.S. equity markets generalize to stocks in China. In other words, we seek to answer the following question: What works and what doesn't when it comes to factor investing in China? As we will see, some well-known factors reliably carry over to Chinese stocks, while a number of other popular strategies do not, with some producing performance *counter* to that observed in the U.S. market, underscoring the importance of this research for investors considering an allocation to Chinese equities.

1.1 Reconciling prior research

Of course, our study is not the first to examine factor strategies applied to Chinese stocks. Within a few years of the country's mainland exchanges opening, academics began publishing replications of popular U.S. factor strategies in China. Unfortunately, the emerging literature on Chinese equity anomalies has yielded troublesome disparities, particularly with respect to the magnitude and significance of the premium to a number of widely used factors, raising questions about the robustness of these results. These inconsistencies arise from the exceedingly short samples employed, combined with subtle differences in start/end dates, as well as variations in factor definitions from one paper to another. Our research will address many of these issues while reconciling apparent discrepancies in the existing literature where possible.

1.2 Challenges to factor research in China

A more critical shortcoming of much prior research in this area is a failure on the part of many studies to recognize that evaluating factor strategies in Chinese equities requires more than constructing simple long-short portfolios and measuring historical average returns and associated *t*-stats. Indeed, Cheung, Hoguet, and Ng (2014) point to a range of considerations that prevent investors from drawing straightforward conclusions from traditional quantitative analysis of Chinese stocks. For one, China's domestic equity market offers a very short sample of returns and accounting data. Those data that are available are subject to evolving reporting standards and punctuated by numerous changes in regulations and instances of government intervention. Further complicating matters, China's market is segmented into multiple share classes with varying levels of liquidity, and strict constraints on ownership and trading. Short sales only became possible in 2010, and trading suspensions—in many cases imposed voluntarily by a firm's managers—are a relatively common occurrence, which negatively impacts price formation and market liquidity. Shareholder rights in China are also evolving and high levels of state ownership have the potential to exacerbate corporate governance issues. Finally, given retail investors account for 85% of all trades in the Chinese equity market[3], the potentially biased behaviors of individual investors are likely to have a more important impact on Chinese stock returns and anomalies than one observes in developed markets. We will show that applying knowledge of distinctive features of the Chinese financial landscape leads to a better understanding of the differences between U.S. and Chinese factor returns.

1.3 Some background on Chinese A-shares

Before we examine factor strategies using Chinese equity data, it is useful to review the segmented structure of China's equity markets.[4] Chinese stocks trade on two mainland exchanges, the Shanghai Stock Exchange (SSE), typified by large, state-owned financial and industrial firms, and the Shenzhen Stock Exchange (SZSE), located adjacent to Hong Kong, which lists a greater proportion of new-economy growth firms. Domestic equities consist of two share classes: A-shares, previously restricted to ownership by domestic investors, and B-shares, originally held exclusively by foreign investors. In addition to shares traded onshore, there exist H-shares, representing firms incorporated in China and listed in Hong Kong, and a range of securities issued by Chinese firms both incorporated and listed overseas, including those in Hong Kong (called Red and P chips), Singapore (S chips), and the United States (N chips). For roughly the first decade of trading in Chinese stocks, due to the prohibition on foreigners holding A-shares, offshore investors seeking equity exposure to China's economy had no choice but to purchase "unrestricted" securities—B-shares, H-shares, and the "Chips"—or to invest in the stock of non-Chinese multinational companies doing significant business in China.[5] This changed in 2002, when China began its Qualified Foreign Institutional Investors (QFII) program, allowing foreign investors to invest directly in A-shares. The recent expansion of QFII quotas and the introduction of Stock Connect have contributed to an increased interest in Chinese A-shares among foreign investors, as well as a decline in the relevance of B-shares—now rarely issued—and other unrestricted shares. As such, we will focus exclusively on Chinese A-shares in our analysis of factor investing in China.

2 Factor investing in A-shares

As a prelude to the more detailed discussion of A-shares factor performance in the sections that follow, **Table 1** reports A-shares and U.S. long-short factor returns associated with a broad range of stock characteristics corresponding to various dimensions of cross-sectional return predictability that have received significant attention in the U.S. equity anomalies literature. We test each strategy by first sorting A-shares and U.S. stocks into decile portfolios, then forming long-short portfolios by purchasing stocks in the top decile on each characteristic and shorting those in the bottom decile. To ensure we're working with sufficiently liquid stocks that investors could actually implement our strategies, our universe consists of the top 80% of stocks in each country based on market capitalization—"all-but-tiny" stocks, to use the language of Fama and French (2008a). We report returns to equal- and value-weighted versions of each factor.[6] Rebalancing takes place annually or monthly, depending on the signal. We will describe the data and make a thorough analysis of results for each of the factors shortly. For now, we simply offer a few general observations which serve to motivate discussion of the results.

First, while our full-sample U.S. results largely line up with those in the past literature, the performance of A-shares factor strategies is something of a mixed bag. Based on the full A-shares sample, beginning in 1995, we observe that some signals performed quite well (size, value, accruals, and reversals), others posted weak, albeit positive returns (profitability, NOA, and low volatility), and two popular factors seem not to have worked at all (asset growth and momentum). Much of this study will be concerned with rationalizing the similarities and differences between anomaly returns for A-shares and U.S. stocks based on a deep knowledge of those distinctive features of China's investing landscape with ramifications for factor investing.

Second, when evaluating A-shares over a more recent sample—using data beginning in 2008, which should be more representative of present market conditions after major financial and accounting reforms we describe later—we observe a number of interesting changes. While some signals produce roughly the same effect as before (gross profitability, NOA, and low beta), most effects are stronger (size, asset growth, momentum, and short-term reversal) or weaker (book-to-price, sales-to-price, accruals, low-volatility, and long-term reversal), and several anomalies actually show *opposite* performance when going from one sample to another (earnings-to-price, dividend yield, and operating profitability). These differences first and foremost illustrate the sensitivity of factor returns evaluated over relatively short samples (we employ 22 years of data, at most, in our analysis of A-shares versus 52 years for U.S. stocks). Moreover, these differences highlight the effect developments in things like accounting standards and the regulatory environment might have on factor strategy performance. In the case of accruals, as we will see, changes in accounting standards rather easily explain the signal's diminished performance in recent years, and understanding of China's securities regulations suggests an enhanced implementation of the traditional accruals strategy for Chinese stocks.

Finally, it is unsurprising that over the shorter 2008-2016 sample the statistical significance of most results is substantially diminished; now only size, change in book value, and short-term reversal show statistical significance in A-shares. Similarly, while most of the well-known anomalies exhibit strong returns over the full sample in the U.S., covering 1965-2016, when we evaluate those same U.S. factor returns over a simulated ten-year sample, using data taken from each ten-year sub-period over the last five decades, the results are also less robust. This simple comparison offers an argument against a rush to conclude that a lack of significance necessarily implies the absence of an effect. Rather, it raises the question: If only the history of Chinese data had as much time to unfurl as the U.S. sample, would A-shares factor returns compare more favorably with those observed in developed markets?

Investors contemplating an allocation to Chinese equities likely prefer not to wait another thirty years for a sample of sufficient size to yield higher *t*-stats. In the meantime, we indicate in Table 1 the number of years needed in our sample for each factor to attain statistical significance, assuming estimates from the short sample hold true going forward. For many U.S. signals calculated over the simulated short sample, the number of years necessary to achieve significance is no greater than the actual size of the full sample for U.S. stocks: around 50 years. On the other hand, it is interesting to note in the case of the value factor, supposing all we had observed was a typical decade of returns, we likely would have spuriously concluded that an effect was absent for U.S. stocks.

What about for A-shares? The low-volatility effect is an interesting case. Based on estimates from our recent sample, we would need well upward of 200 years of data to achieve a decent *p*-value. It seems difficult to make the case that the lack of significance for the low-volatility effect in China is based solely on the length of our recent sample. For other factors—accruals and NOA, valuation-based signals since 1995, or price-based signals in recent years—the required sample length is reasonably low, suggesting that with more data we *might* expect some of these factors to present with higher statistical confidence. The question as to whether we *should* expect estimated means and standard errors from our existing A-shares sample to persist in the future can only be answered through closer examination of the theoretical basis for each anomaly's performance given our knowledge of Chinese equity markets. After all, the *t*-stats may be low because the factors do not work, and not because of a lack of statistical power. The theoretical basis for these anomalies is a subject to which we will turn after saying a few words about our data and choice of factors.

2.1 Data

To evaluate factor strategies applied to Chinese equities, we collect returns and accounting variables for all A-shares stocks from the China Stock Market and Accounting Research (CSMAR) database. Because Chinese listed firms must report prior-year financial results before the end of April, we rebalance factors constructed using accounting variables annually, at the beginning of May.[7] We collect stock returns and financial statements for firms in our sample from May 1995 through December 2016. To understand the choice of start date, it is important to note that while China's equity markets opened for trading in 1990, it is clear from **Table 2**, which presents summary data on Chinese equity markets since inception, that only in the mid-1990s were there enough listed A-shares available to form factor portfolios of reasonable size for practical implementation.[8] We employ an internally calculated investable market cap-weighted benchmark using all available A-shares stocks in CSMAR as our A-shares market benchmark, and our risk-free proxy is the Chinese 12-month deposit rate, which we obtain from CSMAR. For the sake of comparison, we collect U.S. stock returns and accounting data from CRSP and Compustat, respectively, beginning in January 1963 and ending in December 2016. We use data from Kenneth French's website for the U.S. market benchmark and risk-free rate. We rebalance annual strategies for the U.S. in July of each year.

As mentioned before, we usually break out A-shares results using returns beginning in May 2008 to assess factor performance in a more recent sample. We split the data at this point in time because the previous few years saw major changes in both trading regulations and financial reporting standards that could bias results based on market and financial data from earlier years. In 2005, China's financial regulatory body, the China Securities Regulatory Commission (CSRC), instituted a Split-Share Structure Reform to relax trading restrictions on shares of listed State-Owned Enterprises (SOEs). Prior to this reform, as Table 2 indicates, roughly two-thirds of shares outstanding in the market for A-shares were held directly by the State or other government entities and could not be legally traded, resulting in lower liquidity and the obvious agency problems arising when majority shareholders cannot benefit from an increasing share price (Beltratti, Bortolotti, and Caccavaio 2012). By 2007, however, most listed firms had completed the process of bringing previously non-tradable shares to market, mitigating these problems for stocks in the later sample period. In February 2006, China's Ministry of Finance announced a new set of accounting standards requiring firms with listed A-shares to adopt, by 2007, accounting practices substantially conforming to International Financial Reporting Standards (IFRS). These changes in accounting standards resulted in a lower incidence of accruals-based earnings management and higher-quality financial reports with more "value relevance" to investors (Ho, Liao, and Taylor 2015). Given these changes in the regulatory and reporting environment, we view 2007 as an important breakpoint in the data, and will later consider the implications of these developments for particular factor strategies.

2.2 Factors

The first step in testing factor strategies for Chinese equities is to identify firm characteristics which might predict differences in the cross-section of future A-shares stock returns. We begin our search for factors in the empirical literature, considering only those predictive characteristics with a robust history of academic research. In **Table 3**, we provide a representative list of factors identified in prior research along with the associated characteristics we use to validate each factor's efficacy in A-shares.[9] Predictors preceded by a minus sign are those variables hypothesized to have an inverse relationship with future stock returns; we transform these predictors such that corresponding high-minus-low trading strategies should, in theory, produce positive expected returns. In the last column, we indicate the rebalancing frequency for each predictor. We will describe each factor more fully in the course of presenting our results, and offer full details on the calculation of all predictive characteristics in Appendix A, as well as a brief literature review for each anomaly in Appendix B.

In **Table 4**, we provide summary statistics for all 17 of the predictors calculated using data on Chinese A-shares through December 2016. The rapid growth in China's markets throughout our sample is evident in the distributions of a number of our firm characteristics. Positive median values for ∆ASSET and ∆BOOK, for example, reflect the consistent expansion in Chinese firms' balance sheets over the last two decades. Likewise, an average P/E ratio of 40 could also be seen as reflecting the strong growth expected of Chinese equities over the period covered by our study (U.S. stocks in our universe had an average P/E ratio of around 16 over the same horizon). Owing to a sizable fraction of companies in our sample not paying dividends, we report a value of zero for the bottom quartile of the dividend yield, D/P.

2.3 Results

For each category of the factors above, we provide detailed commentary on the results in Table 1. When evaluating the relationships among factors described below, it will be useful to consult **Table 5**, which reports correlations across value-weighted factor returns over the full sample period. In most cases, an understanding of the Chinese investing landscape and a close reading of the prior literature help to place our findings in perspective. For several factors we supplement portfolio sorts with additional evidence to gain deeper insight into the performance of those strategies when applied to A-shares.

2.3.1 Value

Over the full sample, A-shares exhibit a strong value effect. Value-weighted returns associated with sorts on various valuation ratios range from 5.7% per year (dividend yield) to 11.7% per year (sales-to-price). The past literature on value strategies in A-shares is somewhat divided, although most prior studies offer at least marginal evidence of a relationship between book-to-price ratios and future returns.[10] In terms of explaining these positive findings, Huang, Yang, and Zhang (2013) reported a strong book-to-price effect in A-shares, but found that value stocks in China actually exhibited *lower* default risk than growth firms, contradicting the usual risk-based rationalization of the value premium. Given the observation by Ng and Wu (2006) that Chinese retail investors prefer holding growth stocks, a behavioral story seems plausible for those studies seeming to confirm the overvaluation of A-shares "glamour" stocks. Alternative specifications of the value strategy have received less attention, and the evidence that does exist on earnings-to-price, sales-to-price, and dividend-to-price ratios is less consistent.[11] Cheung, Hoguet, and Ng (2014) find a positive dividend yield effect, and suggest that China's taxation of dividends but not capital gains might result in investors demanding a premium to hold dividend-paying stocks. Eun and Huang (2007) report a marginally significant positive relationship between earnings-to-price ratios and future returns, but also observe a weakly significant *negative* relationship between dividend yield and future returns, contradicting the usual finding of a positive dividend yield effect. They assert investors might accept lower returns on dividend-paying stocks, since payment of dividends signals a willingness of managers to return capital to investors. Of course, if unsophisticated investors irrationally disregard the value of this signal, such an explanation could also apply as a behavioral story for a positive D/P effect.

Turning to the more recent sample, we observe a substantially weaker value effect, with book-to-price and sales-to-price ratios producing positive, but insignificant returns since 2008, and earnings-to-price and dividend-to-price factors actually showing negative performance over the shorter sample. Some of this effect may stem from sensitivity of value strategies to the 2008 global financial crisis, which kicks off our shorter A-shares sample. It is also possible that the diminishing performance in A-shares value strategies is related to the changes in accounting standards and Split-Share Structure Reform that motivated our choice of 2007 as a breakpoint in our A-shares data. Liao, Liu, and Wang (2014) pointed out that prior to 2005, non-tradable shares of SOEs were not valued at market prices, but at the book value of a firm's assets. This gave majority shareholders a strong incentive to disregard tradable shareholder value and inflate the firm's balance sheet, which could easily lead to high book-to-market ratios for firms exposing minority investors to the most risk. Such abuses are often cited as a principal reason for the eventual enactment of Split-Share Structure Reform. Moreover, the accounting changes that took effect in 2007 resulted in an increase in the quality of financial reporting and greater reliance by investors on valuation measures calculated using data from firms' financial statements, which could also account for attenuation of the value effect in the post-2007 sample period. That said, given most A-shares turnover is due to trading by retail investors, one might reasonably wonder about the plausibility of any explanation predicated on investor sophistication in parsing financial statements and optimally trading off risk and return.

Another perspective on the weaker performance of A-shares value factors in recent years arises when considering changes in the relative valuation of growth and value stocks over time. In Panel A of **Figure 1**, we plot the aggregate price-to-book ratio for A-shares growth stocks (defined as the top quintile of firms, sorted on the P/B ratio) and value stocks (the bottom quintile of firms sorted on P/B) beginning in 2007.[12] In Panel B, we provide the same view of U.S. stocks in the period surrounding the dot-com bubble. Turning first to U.S. equities, we see clear time variation in the valuation spread between growth and value stocks, with inflection points around 1997 and 2000. The story in China is similar, with growth stocks periodically gaining and retreating in valuation relative to shares in the bottom-decile P/B portfolio. Given the valuation gains in growth stocks since 2013—and noting that most Chinese stocks do not pay a dividend—it is not surprising that value stocks have returned less to A-shares investors in the recent sample period. If history is a guide, this view also suggests value may yet see better day, as this relative valuation returns to its average level.

2.3.2 Size

We find a very strong size effect in A-shares. An investor buying the smallest stocks and shorting the largest firms produced value-weighted returns of 14.6% per year over the two decades covered by our analysis, results which are significant at the 5% level. Over the shorter sample beginning in 2008, the size anomaly produced even stronger performance, with a value-weighted size factor returning almost 25% per annum. Our finding with respect to firm size is consistent with past work on predictability in A-shares, with almost all studies of factor strategies confirming a size effect in Chinese stocks, regardless of the sample period.[13] Although Cheung, Hoguet, and Ng (2014) did not find evidence of a size effect from 2001 through 2013, they restricted their sample to stocks contained in the MSCI China A Index, which only includes large-cap and mid-cap companies.

What might account for the outperformance of small stocks in Chinese A-shares? Investigating the size effect prior to China's 2005 Split-Share Structure Reform, Wang and Xu (2004) calculate firm size using only tradable shares (we use total shares outstanding) and conclude that part of the size effect in the pre-reform years might relate to agency issues due to the fact that small firms were more likely to have large blocks of non-tradable shares, leading to less favorable corporate governance, for which rational investors should demand a premium. Given our recent sample covers a period in which this split-share structure no longer applies, the same rationale cannot explain those results. Huang, Yang, and Zhang (2013) proposed another risk-based explanation for the size effect. Estimating default probabilities for A-shares in a manner similar to Ohlson (1980), they found that size is highly correlated with default risk, and that controlling for default risk eliminated some—but not all—of the ability that size has to predict future returns. Thus at least some of the size premium might be attributable, as Fama and French (1993) suggest, to compensation for risk. Assuming size proxies for distress risk, Huang, Yang, and Zhang (2013) suggest one more reason we might observe higher returns for financially distressed A-shares firms. Because qualifying for an IPO in China has been historically difficult, many firms seeking external financing in the equity markets find it easier to merge with a firm on the verge of delisting, resulting in distressed companies often having substantial "shell value" as candidates for reverse mergers. A common behavioral story for the size effect is that unsophisticated investors exhibit an irrational demand for large-cap stocks and drive the price of large stocks too high. Ng and Wu (2006), analyzing data from Chinese brokerage accounts, reported that retail investors actually prefer small company stocks (they theorize small growth stocks are more attractive to investors with little capital and an inability to use leverage), contradicting this explanation in the case of A-shares.

Having identified a statistically significant pattern in the cross-section of stock returns, there is still a question as to whether the outperformance of size in A-shares might have led to inflation in the valuation of stocks on the long side of the factor portfolio. If so, a correction in prices would likely yield less stellar future returns, in which case we should be particularly wary about extrapolating the results of a favorable backtest. Turning again to Figure 1, in Panels C and D, we perform the same analysis of aggregate price-to-book ratios for Chinese and U.S. stocks in the small and large size factor portfolios that we previously undertook for the value factor.[14] In the U.S., small-cap stocks enjoyed a strong run relative to large-caps in the heyday of the tech boom, before crashing back to typical valuations in the wake of the dot-com bust. For A-shares, we observe a similar, if more subdued rise in the valuation of small-cap stocks since 2008, which likely explains some of the extreme returns to the A-shares size factor in recent years. By the end of our sample, with an aggregate price-to-book ratio of 3.1, small-cap stocks seemed expensive relative to large-caps, whose P/B ratio was only 1.1, leading a valuation-conscious investor to discount the size premium going forward. It is worth noting that the observed inflation in valuation ratios for small-cap firms is consistent with the preference of retail investors for small company stocks mentioned above, supporting a behavioral explanation for the run-up in small-cap shares since 2008.

2.3.3 Momentum/reversal

Turning to technical factors based on sorts of stocks according to past returns, we find the traditional intermediate-horizon momentum strategy fails for Chinese stocks, producing insignificant *negative* returns in the full sample period. At the same time, a factor trading on short-term reversal produces an equal-weighted return of 8.3% per year in the full sample, significant at the 5% level, while long-term reversal yields a marginally significant equal-weighted return of 8.5% per annum and a statistically significant value-weighted return of around 12% per year.[15] Our results on price-based factors are even more pronounced in the recent sample from 2008. Over that horizon, 12-month momentum produces negative returns of roughly 8-12% per year, with *t*-stats that suggest these results should be significant if they persisted over a moderately longer sample. The short-term reversal factor is extremely profitable in recent years, generating returns of over 20% per annum in our backtests; long-term reversals post returns of 6-8% per year since 2008. Taken together, these results indicate the presence of return reversals over *all* horizons in Chinese A-shares. On the other hand, as **Table 6** illustrates, implementing a price-based factor in A-shares can be costly due to the frequent trading required by such strategies (annualized two-way portfolio turnover approaches 1,000% for momentum, and exceeds 2,000% for short-term reversal).

The prior literature largely confirms our findings on returns-based strategies, although there are a handful of exceptions.[16] Given the extremely high turnover exhibited by A-shares—Eun and Huang (2007) calculate average annual turnover in excess of 480% from 1991 through 2004, and Chen, Kim, Nofsinger, and Rui (2007) reported that Chinese retail investors trade stocks almost four times more frequently than U.S. investors—it seems plausible that cycles of overreaction and correction might take place over shorter horizons in China, and this seems to be the usual explanation given by authors in the A-shares literature for the lack of a momentum effect. Of course, the same volatility that impairs medium-term momentum should facilitate strategies based on short-term reversals, explaining the effectiveness of short-horizon strategies in Chinese A-shares. **Table 7** provides a more comprehensive view of price-based strategies for A-shares and U.S. stocks over various formation and holdings periods, reporting the profits to a classic momentum strategy that longs past winners and shorts past losers. Our results bear out the dominance of reversals in A-shares over most typical look-back windows and investment horizons. While U.S. returns correspond perfectly to the usual short-term reversal (one-month formation period, one-month holding period) and medium-term momentum (look-back windows of 2 to 12 months and holding periods of greater than 1 month), A-shares show reversals over literally every specification, sorting stocks based on past returns ranging from one to twelve months, and over holding periods of up to one year. Interestingly, because returns to reversals persist for at least twelve months following portfolio formation, price-based A-shares strategies seem feasible even when rebalanced at lower frequencies.

In trying to better understand the results described above, it is worth noting that investor behavior might also account for at least part of the difference in price-based strategies evaluated for A-shares and U.S. stocks. Arkes, Hirshleifer, Jiang, and Lim (2010), found that Asian subjects are faster to adapt to prior gains and losses than their American counterparts, which is consistent with reversals, but not momentum. In support of this story, Chinese individual investors' portfolio holdings don't seem to map well to momentum strategies (Ng and Wu 2006). Chui, Titman, and Wei (2010) propose an alternative explanation for cross-country differences in the effectiveness of returns-based strategies on psychological grounds, citing evidence of cultural differences in individualism, a quality related to overconfidence and self-attribution bias, both of which have been implicated in behavioral models of momentum and reversals (for example, Daniel, Hirshleifer, and Subrahmanyam 1998). They find the individualism of a country's population is positively correlated with momentum profits in the country's stock markets, and weakly associated with the profitability of long-term price reversals. As expected, given China's classification as a relatively collectivist culture, the authors find no momentum effect for A-shares.

2.3.4 Low volatility

We test for risk-based anomalies in A-shares on the basis of three measures of the volatility in past stock returns. The results in Table 1 suggest over the full sample period, higher risk—whether systematic or firm-specific—predicts lower future returns for A-shares. Our finding that beta correlates negatively with future performance deviates relative to most studies testing the CAPM for Chinese stocks, which almost uniformly fail to identify a significant low-beta effect for A-shares.[17] With respect to other measures of risk, Drew, Naughton, and Veeraraghavan (2004) document an idiosyncratic volatility effect, while Eun and Huang (2007) and Cakici, Chan, and Topyan (2015) provide strong evidence of outperformance for stocks with both low idiosyncratic and low total volatility; Chen, Kim, Yao, and Yu (2010) report only a weakly significant idiosyncratic volatility effect.

Our findings for Chinese stocks are particularly hard to square with rational models of risk and return. Eun and Huang (2007) posit that because most Chinese retail investors are grossly underdiversified—an observation borne out in the analysis of Chen, Kim, Nofsinger, and Rui (2007), who find the individual investors in China hold, on average, portfolios consisting of only 2.6 stocks—they should, as the model of Merton (1987) suggests, rationally earn a premium for bearing firm-specific risk, although the data suggest they actually pay a *higher* price for stocks with high idiosyncratic risk. The authors cite small investment account balances, the lack of a developed mutual fund industry, and the speculative nature of retail investors' trading activity as contributing to the concentration in Chinese individual investors' portfolios. The massive size of retail investor holdings and state ownership relative to shares held by institutional investors also makes the usual explanation for the low-beta effect based on leverage-constrained mutual fund managers (Black 1972) less plausible. A more likely explanation seems to be a demand on the part of Chinese retail investors for stocks with lottery-like payoffs, which pushes the prices of risky stocks too high; Ng and Wu (2006) find that individual investors do tend to hold a greater proportion of risky shares, in support of this story.

2.3.5 Accruals/NOA

We employ two common measures of earnings quality and sustainability: total accruals and net operating assets (NOA).[18] In his seminal study of the accrual effect, Sloan (1996) pointed to unsophisticated investors' failure to account for earnings management as an important driver of profits to the accruals strategy. Because it seems unlikely Chinese retail investors will fare any better than U.S. institutions at gauging the effects of accounting manipulation on the persistence of firms' cash flows, high retail investor participation in Chinese equities implies the efficacy of A-shares strategies based on accounting conservatism will depend largely on whether or not Chinese firms manage earnings. Initial evidence on this question comes from a cross-country analysis by Leuz, Nanda, and Wysocki (2003), who showed earnings management is more pronounced in nations with less developed financial markets. Indeed, consistent with this finding, many studies in the academic accounting literature identify earnings management as a significant concern among Chinese firms.[19]

As **Figure 2** illustrates, the extent of earnings management in China is visibly apparent in the distribution of firms' earnings, which rarely go negative. The stark discontinuity at ROE = 0% suggests a strong preference on the part of Chinese firms to report small gains as opposed to small losses. Reported earnings in the U.S., by contrast, exhibit something closer to normality, although still show a slight kink around break-even earnings, suggesting at least some degree of earnings management by U.S. firms. Given clear evidence of earnings management by Chinese firms, even before running a backtest, we expect A-shares factors based on accounting conservatism to be particularly effective. As expected, the results in Table 1 indicate high accruals predict lower future stock returns in both the full and recent sample periods; judging by the *t*-stats, performance of accruals is somewhat weaker in the post-2007 sample. NOA provides marginally significant performance in both sample periods, as well.

Few past studies have examined factors based on accounting conservatism in A-shares. Chen, Kim, Yao, and Yu (2010) also tested both accruals and NOA factors, and found weak evidence of an inverse relationship between accruals and future stock performance, but strong support for the use of an A-shares NOA factor. On the other hand, Pincus, Rajgopal, and Venkatachalam (2007), in a study of the accrual effect in global markets—including Hong Kong and Taiwan, but omitting A-shares—found the accruals anomaly appears to be stronger in markets governed by common law, including those in Hong Kong and the U.S., than in markets governed by code law, like those in Taiwan and mainland China, which could account for the relative weakness of accruals factor returns in A-shares. We will have more to say about accruals when we address the impact of Chinese regulations and reforms on the design and performance of factor strategies in Section 3.1.

2.3.6 Investments

Over the full sample period, we find little support for the asset growth anomaly—the notion that growth in a firm's balance sheet predicts lower future returns—as neither ΔASSET nor ΔBOOK succeed in differentiating among good and bad stocks. That said, results in more recent years indicate a fairly strong effect, particularly when employed in a value-weighted strategy, where both asset growth signals generate nearly 9% per annum in outperformance. What factors might explain these seemingly conflicting results? If empire building by U.S. executives results in a negative relationship between asset growth and firm value, as Titman, Wei, and Xie, (2004) suggest, we might view the absence of such an effect in A-shares as evidence Chinese managers are not similarly engaged in expanding the firm's balance sheet for personal benefit. On the other hand, given managers of SOEs are subject to a "policy burden" that entails pursuing political and social objectives beyond maximizing shareholder value—promoting greater employment, for example—it seems more reasonable to assume, *ex ante*, over-investment is a very serious risk for Chinese firms. As **Figure 3** illustrates, SOEs do seem to exhibit behavior typical of firms undertaking inefficient investment, as state-owned companies show higher levels of debt issuance (consistent with SOEs having easier access to loans from state-owned banks) and significantly lower efficiency in employing those assets than non-SOEs. These effects appear particularly pronounced in the years after the global financial crisis, which would account for stronger asset growth factor performance in the recent sample. Past studies focusing on the operating performance of SOEs relative to private listed firms in China strongly support this view.[20]

Checking in with the prior literature, one finds mixed evidence on the asset growth effect in A-shares. Titman, Wei, and Xie (2013) analyzed data covering the period from 2000 through 2010, and found no significant relationship between total asset growth and future stock returns in China (if anything, returns in their sample appeared to be *higher* for stocks with greater asset growth, although those results were not statistically significant). Analyzing a range of other countries, they concluded the asset growth effect is most pronounced in countries with more developed financial markets, and the strength of the effect seems to have little relation to corporate governance or trading costs—all factors that should suggest against finding a straightforward relationship between asset growth and returns in Chinese markets. Watanabe, Xu, Yao, and Yu (2013) obtained similar results over a longer sample, covering 1990-2010.

By contrast, Yao, Yu, Zhang, and Chen (2011) documented a significant relationship between total asset growth and stock returns for A-shares stocks, from 1994 through 2007, but in a cross-country analysis confirmed the effect is generally weaker in countries with more homogeneous asset growth rates and a greater reliance on bank financing, both of which apply in the case of Chinese firms. The strongest evidence for an asset growth effect in A-shares comes from Wang, Liu, Lee, and Wang (2015), who report that the effect is most prevalent for state-owned firms, and companies with high cash flows and low debt. These conclusions are more consistent with evidence of SOE over-investment and correspond most closely with our backtest over the more recent sample, as large SOEs will certainly exert a greater impact on the factor returns in Table 1, given our universe of relatively large Chinese firms—particularly our value-weighted specifications, which show the greatest investment effect.

2.3.7 Profitability

Our evidence for a gross profitability effect in A-shares—whereby more profitable companies should outperform less profitable firms—is quite weak. A related signal based on operating profitability is even less effective in China; in the more recent sample period, the OP signal actually yields returns with the wrong sign. These outcomes are roughly consistent with work by Sun, Wei, and Xie (2014), who reported that gross profitability fails to predict future stock returns in China from 1994 through 2009. Examining gross profitability around the world, the authors found the effect tends to be strongest in developed countries, countries with low levels of political risk, and countries in which firms enjoy easier access to investment capital, providing a rationale for the absence of a significant effect in our A-shares sample. The authors' cross-country analysis also revealed that returns to gross profitability are *not* greater in countries with more severe limits to arbitrage—contrary to the prediction of theories associating the gross profitability effect with mispricing—further weakening the case for observing significant factor performance in China, where short sale constraints and high idiosyncratic volatility should, in principal, make mispricing riskier to exploit, leading to higher returns for strategies based on behavioral effects.

On the other hand, although the predictive value of gross profitability is weak in our sample of Chinese stocks, if profitability factor returns bear low correlation to those based on other signals we've investigated, profitability might still serve as a useful addition to a multi-factor A-shares strategy. Indeed, in his original study of the gross profitability effect in the U.S., Novy-Marx (2013) demonstrated that one of the principal benefits of a long-short factor based on gross profitability is the complementary nature of the strategy with respect to a traditional value factor; over his study's sample period of 1963-2010, gross profitability and value factor returns actually had a correlation of −0.57. In light of this finding, and because firms ranking favorably on gross profitability tend to have high price-to-book ratios, we might view gross profitability as a way of identifying "good" growth firms. Consistent with these arguments, we observe in Table 5 that the correlations between A-shares value and profitability factors are quite low; in our data, gross profitability and book-to-price have a coefficient of −0.52, which is essentially identical to what Novy-Marx (2013) observed for U.S. stocks, leaving the door open for inclusion of profitability-based signals as part of a diversified A-shares factor strategy.

3 How is factor investing in China different?

In the course of describing the results for tests of traditional anomalies in Chinese equities, we touched upon a number of novel and interesting aspects of the marketplace as they apply to factor investing. In fact, a principal aim of this study has been to highlight some of the many market-specific considerations affecting factor strategies applied to A-shares. In this section, we will show that beyond informing one's interpretation of a backtest, the features that make China's markets unique demand attention when building effective factor strategies for Chinese stocks, from signal design to portfolio construction. For the sake of illustration, we will focus on two specific areas of interest: nuances of China's securities regulations, and the high level of state ownership of listed firms.

3.1 A case study in A-shares factor research: Regulation and reforms

Our analysis in the preceding section made it clear how important a deep institutional knowledge can be when it comes to interpreting the results of A-shares factor research. Accruals-based factor strategies provide an excellent case study by which to explore the role an understanding of issues such as China's regulatory environment and changes to financial reporting standards plays in shaping the implementation of A-shares strategies.

3.1.1 Accounting for "big bath" firms in accruals factor design

In our discussion of returns to the accruals and NOA factors, we referenced loss avoidance by Chinese firms, clearly evidenced in Figure 2, when assessing the usefulness of these signals for A-shares. It turns out Chinese firms have good reason to manage earnings to avoid losses. Li, Niu, Zhang, and Largay (2011) described China's rather unique delisting regulations, which stipulate that a firm experiencing two years of consecutive annual losses or negative stockholders' equity receives "special treatment (ST)" status, after which a third loss results in trading suspension, and a fourth in delisting. They pointed out that these rules incentivize distressed firms to use earnings management, particularly by taking a "big bath" in the form of negative abnormal accruals. Li, Niu, Zhang, and Largay (2011) suggested this form of earnings management results in many distressed firms appearing in the low-accrual portfolio—which, according to an accruals-based factor strategy, should contain undervalued firms. When the authors removed "big bath" firms from the low-accrual portfolio, they found a stronger A-shares accrual effect in a short sample, from 1998-2002.

We also find the low-accrual portfolio of Chinese stocks contains a high proportion of "big bath" firms. From 1999 through 2016, approximately 90% of loss firms in the bottom decile of accruals are big bath stocks, even though big bath stocks make up only around 50% of the overall population of A-shares loss firms, potentially confounding traditional tests for an accrual effect in China.[21] As Li, Niu, Zhang, and Largay (2011) indicate, one obvious method of accounting for the presence of big bath firms in accruals-based portfolio sorts is simply to remove all firms reporting a loss in the year over which we measure accruals before sorting stocks into decile portfolios. The first two rows of **Table 8** present returns to the "classic" total accruals factor tested earlier for A-shares stocks, and a modified factor, excluding loss firms. For equal-weighted factor returns, particularly in the early sample, the accruals strategy applied to firms with non-negative earnings performs better than the baseline accruals strategy, consistent with the argument that big bath loss firms add noise to the standard A-shares accruals signal. These results support the exclusion of loss firms when playing the accruals anomaly in A-shares, based on regulatory concerns unique to Chinese stocks, and serve as a good example of the manner by which a deeper understanding of Chinese markets might lead to more effective factor design.

3.1.2 The impact of China's 2006 accounting reforms on factor returns

As mentioned at the outset of this study, when evaluating investment strategies in A-shares, one is already working with a rather limited sample period, not to mention a small cross-section of stocks in the Chinese equity markets' early years. These difficulties are compounded when one considers the speed with which

China's financial landscape has evolved during this relatively brief history. We have already discussed a seemingly important break in the data, which occurred in 2006-2007, when China instituted major accounting reforms that brought its accounting standards toward compliance with IFRS. In the context of accounting accruals, we have also cited research by Ho, Liao, and Taylor (2015), who studied the implications of these accounting changes and concluded reforms resulted in a reduction in accruals-based earnings management—a development which clearly poses a potential threat to factor strategies whose performance is predicated on differences in earnings quality across firms.

To evaluate the significance of accounting reforms for accruals-based factor investing in China, in Table 8, we provide factor returns for the classic accruals strategy, the variation on accruals tailored to Chinese stocks through the exclusion of loss firms, and the NOA strategy. The table presents results both before and after China's 2006 accounting reforms, which became effective beginning with firms' 2007 financial data, and for the full accruals sample, covering 2000-2016. We observe that for both of the accruals factors, performance does appear to abate in the period after reforms. On the other hand, we note point estimates for the accruals strategies are still positive in the post-2007 sample, while the NOA factor—which might be seen as a more comprehensive measure of earnings sustainability—actually delivers more significant abnormal returns after accounting changes. Our analysis indicates the potential sensitivity of factor returns to China's continuing financial development, while supporting a diversified approach to factor investing whose performance is robust to a changing environment.

3.2 A case study in A-shares portfolio construction: State ownership

Perhaps the most obvious distinction between equity investing in the U.S. and China is the major role state ownership plays in the market for A-shares and the management of many Chinese firms. Bai, Liu, Song, and Zhang (2004) noted that one of the Chinese government's principal motives in establishing equity markets in the first place was to assist SOEs in raising external capital and to provide state-owned firms with more incentive to improve operating performance. As Table 2 makes clear, even after decades of privatization, over 50% of A-shares market cap was classified as deriving from SOEs as of the end of 2016. We have already seen one way in which state-ownership might affect factor returns, based on some evidence the A-shares asset growth effect might be exacerbated by over-investment on the part of SOEs, suggesting a better understanding of SOEs could be useful in A-shares factor design. In fact, an extensive academic literature studies the implications of state-ownership for other issues ranging from corporate governance and operating performance to financial constraints and the quality of financial reporting.[22] Unfortunately, a thorough treatment of the differences between SOEs and private listed firms in China is beyond the scope of this study. Nevertheless, it is worth discussing how investors might address at least some of these differences at the level of factor portfolio construction.

Two basic differences between SOEs and non-SOEs have clear potential to affect the performance of our factor strategies. First, as can be seen in **Figure 4**, the shares of state-owned firms have traded at perennially lower valuation multiples than those of private listed firms in China. As such, sorting on value-oriented signals has the effect of tilting one's portfolio toward SOEs. Second, as we noted earlier, a sizeable proportion of state-owned shares were historically non-tradable, and the state has little reason to actively trade the unrestricted portion of its shares. These static holdings result in the shares of SOEs exhibiting relatively low liquidity and, consequently, persistently low levels of volatility. Research on U.S. factor strategies has shown that calculating signals in an industry-neutral manner—ranking stocks within industries rather than across industries to account for differences in signal values specific to each industry—often leads to better risk-adjusted performance (Asness, Porter, and Stevens 2000). This suggests one high-level approach to addressing differences between SOEs and non-SOEs in terms of the factors tested in Section 2 is to construct SOE-neutral A-shares factor portfolios.

In **Table 9**, we provide factor returns over the recent sample for the baseline strategies presented in Table 1, along with strategies employing the same factors according to either industry-neutral or SOE-neutral construction.[23] Consistent with past research on U.S. equities, even without adjusting for risk, we observe that for a number of signals industry-neutrality enhances performance. The benefits are perhaps most notable in the case of risk-based factors, which Asness, Frazzini, and Pedersen (2014) demonstrated are particularly conducive to an industry-neutral implementation. When we calculate factor returns according to an SOE-neutral implementation, we find a majority of signals—including those associated with value and low-volatility—do perform better, consistent with differences between state-owned and private listed firms suggested above. These findings serve to reinforce the idea that distinctive features of China's financial markets, including high levels of state ownership, will play an important part in the implementation of A-shares factor strategies, even at the level of portfolio construction.

4 Conclusions

This study set out to determine whether equity factors commonly employed by investors in other markets might be applied in devising profitable investment strategies for Chinese A-shares. We systematically tested a diverse set of factors against a carefully constructed sample of stock returns and accounting data covering the last two decades of activity in Chinese equity markets. We identified a number of strategies that carry over quite well from U.S. stocks to A-shares, but found several traditional factors yielded surprising results when applied to Chinese stocks. Along the way, we addressed the range of challenges facing researchers studying quantitative investment strategies in A-shares and attempted to better understand deviations from the U.S. experience on the basis of features we believe make China's investing landscape unique. Beyond yielding specific insights into factor performance in A-shares, our analysis underscores two important considerations for researchers and investors in Chinese stocks. First, we note naïve application of U.S. strategies to Chinese stocks may lead to undesirable results, as not all strategies familiar to U.S. investors outperform in A-shares and—even worse—some actually work in the opposite direction. Moreover, our work reveals that a thoughtful approach to factor design and portfolio construction based on knowledge specific to A-shares and the related financial landscape has the potential to produce superior outcomes for investors.

5 Notes

1. According to data from World Federation of Exchanges, 2017.
2. See, for example: Rabouin (2016).
3. For instance: Shen and Goh (2015), Hilliard and Zhang (2015).
4. Alford and Lau (2014) provide a more detailed overview of the structure of China's equity markets, as well as recommendations for foreign investors seeking exposure to Chinese stocks.
5. This was problematic for foreign investors because B-shares and stocks listed offshore have proved to be a rather poor proxy for the overall performance of Chinese equities. Alford and Lau (2014) found that unrestricted shares "span" only a quarter of the return opportunities provided by A-shares from 2001 to 2013. The unrestricted shares provide insufficient access because roughly two-thirds of Chinese listed companies, representing over 40% of market capitalization, only issued A-shares. Furthermore, firms with unrestricted stock are substantially different from the average firm in China. Specifically, a capitalization-weighted portfolio invested in only unrestricted stocks tilts substantially toward services and away from manufacturing, relative to a cap-weighted portfolio of A-shares. Additionally, B-shares are generally thinly traded and thus illiquidity tends to meaningfully drive that market's return attributes (Chen, Lee, and Rui 2001). These observations argue that a portfolio excluding A-shares cannot be representative of the Chinese equity market beta, nor its other investment characteristics.
6. Value-weighted returns usually serve as a better estimate of an investor's actual returns when implementing factor strategies, since cap-weighted portfolio performance is less likely to be driven by the returns of small, volatile stocks and more robust to transaction costs, given that large stocks are usually more liquid and less expensive to trade. Interestingly, this intuition might fail in some

cases for A-shares factor strategies, particularly prior to the 2005 non-tradable share reforms, as the largest Chinese firms are often state-owned enterprises (SOEs) which, due to restrictions on trading and limited turnover in shares held by the state, can frequently be *less* liquid than non-SOEs.

7. When rebalancing portfolios, to ensure backtested strategies would have actually been tradable, we account for stocks under trading suspension and prohibit purchase of "Special Treatment" shares, as designated by the CSRC, for which there are additional restrictions on trading. For annually rebalanced strategies, any dividends paid during each year are assumed reinvested in the stocks that pay them until the next rebalance date.

8. Carpenter, Lu, and Whitelaw (2016) similarly consider A-shares factor performance and also begin their analysis in 1995, making our choice of start date conducive to comparison of results across papers. Most other previous studies of A-shares anomalies use far shorter samples—sometimes by choice, but more often as a result of coming earlier in the literature—leading to difficulty drawing sharp inferences and results that are highly sensitive to the precise specification of tests and vary considerably from one study to the next, as we will see when we discuss individual factors.

9. It is worth noting that the inclusion of multiple predictive characteristics for a single factor—for example, employing book-to-price, dividend-to-price, earnings-to-price, and sales-to-price as measures of valuation—is an important feature of our approach to factor selection, since doing so allows us to better identify factors that are robust to changes in the way we define a given variable. If the factor performance associated with a particular anomaly is extremely sensitive to the way in which we specify our tests, we might question whether our theoretical understanding of the anomaly is correct and should proceed with caution when making out-of-sample forecasts on the basis of our findings. Using a broad set of characteristics in our analysis also provides a more complete picture of the relationships among various sources of predictability, helping us to determine, for example, which factors are most likely to complement one another if applied within the same portfolio.

10. Prior research indicating a strong book-to-market effect includes: Wang (2004), Wong, Tan, and Liu (2006), Eun and Huang (2007), Wang and Di Iorio (2007), Wu (2011a), Huang, Yang, and Zhang (2013), Cakici, Chan, and Topyan (2015), Hilliard and Zhang (2015), and Carpenter, Lu, and Whitelaw (2016). Others offer results merely suggestive of book-to-market's predictability: Wang and Xu (2004), Chen, Kim, Yao, and Yu (2010), and Cheung, Hoguet, and Ng (2014). Drew, Naughton, and Veeraraghavan (2003), studying only stocks on the Shanghai Stock Exchange, find that *low* book-to-market stocks outperform.

11. We have focused on explanations for significant findings on alternative versions of the value effect, but a number of papers in the literature reported the absence of such an effect. For example, Wang

and Di Iorio (2007) test for profits when sorting by cash-flow-to-price and dividend yield, but find none. Likewise, Chen, Kim, Yao, and Yu (2010) fail to detect any relationship between earnings-to-price or cash-flow-to-price ratios and future stock performance.

12. We calculate the aggregate price-to-book ratio for each portfolio as the ratio of capitalization-weighted firm size to capitalization-weighted book value.
13. Prior studies documenting a size effect in A-shares include: Drew, Naughton, and Veeraraghavan (2003), Wang (2004), Wang and Xu (2004), Wong, Tan, and Liu (2006), Eun and Huang (2007), Wang and Di Iorio (2007), Chen, Kim, Yao, and Yu (2010), Wu (2011a), Huang, Yang, and Zhang (2013), Cakici, Chan, and Topyan (2015), Hilliard and Zhang (2015), and Carpenter, Lu, and Whitelaw (2016).
14. In this analysis, we define large-cap A-shares as the top 300 firms by market capitalization, and small-cap stocks as the next-largest 500 firms; for U.S. stocks, large-cap and small-cap stocks are those in the top and bottom quintiles, respectively, sorted on market capitalization.
15. Because our long-term reversal signal uses three years of past returns, we begin employing this signal in 1996, when enough price data become available.
16. Studies finding no momentum effect include: Wang (2004), Wong, Tan, and Liu (2006), Chen, Kim, Yao, and Yu (2010), Chui, Titman, and Wei (2010), Li, Qiu, and Wu (2010), Wu (2011b), and Cheung, Hoguet, and Ng (2014). Other studies report some evidence of significant medium-term momentum in A-shares returns, including: Kang, Liu, and Ni (2002), Naughton, Truong, and Veeraraghavan (2008), Cakici, Chan, and Topyan (2015), and Carpenter, Lu, and Whitelaw (2016). Studies showing profits to short-term reversals include: Kang, Liu, and Ni (2002), Li, Qiu, and Wu (2010), Wu (2011b), Cakici, Chan, and Topyan (2015), and Carpenter, Lu, and Whitelaw (2016). Finally, Wang (2004) finds some evidence of reversals at longer horizons.
17. See, for example: Wang and Xu (2004), Wong, Tan, and Liu (2006), Eun and Huang (2007), Wang and Di Iorio (2007), Cheung, Hoguet, and Ng (2014), Cakici, Chan, and Topyan (2015), and Carpenter, Lu, and Whitelaw (2016).
18. As our measure of accounting accruals, we employ total accruals, as defined in Hribar and Collins (2002), using information from the cash flow statement; as such, our accruals signal begins in 2000, when these data are available from CSMAR. Following the past accruals literature, we exclude financial firms, for which earnings management is likely to take a fundamentally different form than it does in other industries. Given massive IPO underpricing in A-shares—Tian (2011) reported average first-day returns of 247% for offerings conducted from 1992-2007—we also drop firm-year observations in which a firm first issued shares. In the U.S., because the cash flow statement is only

available after 1987, we report accruals based on the original method in Sloan (1996), which uses information from the balance sheet.

19. For example: Aharony, Lee, and Wong (2000), Chen and Yuan (2004), and Jian and Wong (2010).
20. See, for instance: Wu, Wu, and Rui (2010), Chen, Sun, Tang, and Wu (2011), and Wu, Wu, Zhou, and Wu (2012).
21. We adopt the standard of Li, Niu, Zhang, and Largay (2011), who defined "big bath" firms as those falling in the bottom quintile of stocks sorted on abnormal accruals, calculated as in Xie (2001).
22. See, for instance: Sun and Tong (2003), Fan, Wong, and Zhang (2007), Wang and Wu (2011), Liu, Uchida, and Yang (2012)—to name but a few.
23. We present industry-neutral results corresponding to portfolios formed by sorting stocks on each factor separately, *within each industry*, based on industry classification codes issued by the CSRC and employing industry weights according to a benchmark consisting of the top 80% of A-shares by market capitalization. We build SOE-neutral portfolios by sorting stocks on each factor separately, *within the set of SOEs* and *within the set of non-SOEs*. Because our data covering SOEs only reach back to 2004, Table 9 shows results for the recent sample period.

6 References

Aharony, Joseph, Chi-Wen Jevons Lee, and Tak Jun Wong. "Financial packaging of IPO firms in China." *Journal of Accounting Research* 38, no. 1 (2000): 103-126.

Alford, Andrew W., and Alison W. Lau. "A Foreign Investor's Guide to Accessing the Chinese Equity Market." *The Journal of Portfolio Management* 41, no. 5 (2014): 31-40.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. "The cross-section of volatility and expected returns." *The Journal of Finance* 61, no. 1 (2006): 259-299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. "High idiosyncratic volatility and low returns: International and further US evidence." *Journal of Financial Economics* 91, no. 1 (2009): 1-23.

Arkes, Hal R., David Hirshleifer, Danling Jiang, and Sonya S. Lim. "A cross-cultural study of reference point adaptation: Evidence from China, Korea, and the US." *Organizational Behavior and Human Decision Processes* 112, no. 2 (2010): 99-111.

Asness, Clifford S., Andrea Frazzini, and Lasse H. Pedersen. "Low-risk investing without industry bets." *Financial Analysts Journal* 70, no. 4 (2014): 24-41.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen. "Value and momentum everywhere." *The Journal of Finance* 68, no. 3 (2013): 929-985.

Asness, Clifford S., R. Burt Porter, and Ross L. Stevens. "Predicting stock returns using industry-relative firm characteristics." *Working Paper* (2000).

Bai, Chong-En, Qiao Liu, Joe Lu, Frank M. Song, and Junxi Zhang. “Corporate governance and market valuation in China.” *Journal of Comparative Economics* 32, no. 4 (2004): 599-616.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler. “Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly.” *Financial Analysts Journal* 67, no. 1 (2011): 40-54.

Baker, Nardin L., and Robert A. Haugen. “Low risk stocks outperform within all observable markets of the world.” *Working Paper* (2012).

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri V. Nikolaev. “Deflating profitability.” *Journal of Financial Economics* 117, no. 2 (2015): 225-248.

Banz, Rolf W. “The relationship between return and market value of common stocks.” *Journal of Financial Economics* 9, no. 1 (1981): 3-18.

Basu, Sanjoy. “Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis.” *The Journal of Finance* 32, no. 3 (1977): 663-682.

Beltratti, Andrea, Bernardo Bortolotti, and Marianna Caccavaio. “The stock market reaction to the 2005 split share structure reform in China.” *Pacific-Basin Finance Journal* 20, no. 4 (2012): 543-560.

Black, Fischer. “Capital market equilibrium with restricted borrowing.” *The Journal of Business* 45, no. 3 (1972): 444-455.

Black, Fischer, Michael C. Jensen, and Myron Scholes. 1972. “The Capital Asset Pricing Model: Some Empirical Tests.” In *Studies in the Theory of Capital Markets.* Edited by Michael C. Jensen. New York: Praeger.

Bradshaw, Mark T., Scott A. Richardson, and Richard G. Sloan. “The relation between corporate financing activities, analysts’ forecasts and stock returns.” *Journal of Accounting and Economics* 42, no. 1 (2006): 53-85.

Cakici, Nusret, Kalok Chan, and Kudret Topyan. “Cross-sectional stock return predictability in China.” *The European Journal of Finance* (2015): 1-25.

Carpenter, Jennifer N., Fangzhou Lu, and Robert F. Whitelaw. “The real value of China’s stock market.” *NBER Working Paper w20957* (2015).

Chen, Gong-Meng, Kenneth A. Kim, John R. Nofsinger, and Oliver M. Rui. “Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors.” *Journal of Behavioral Decision Making* 20, no. 4 (2007): 425-451.

Chen, Gong-Meng, Bong-Soo Lee, and Oliver Rui. “Foreign ownership restrictions and market segmentation in China’s stock markets.” *Journal of Financial Research* 24, no. 1 (2001): 133-155.

Chen, Kevin CW, and Hongqi Yuan. “Earnings management and capital resource allocation: Evidence from China’s accounting-based regulation of rights issues.” *The Accounting Review* 79, no. 3 (2004): 645-665.

Chen, Shimin, Zheng Sun, Song Tang, and Donghui Wu. “Government intervention and investment efficiency: Evidence from China.” *Journal of Corporate Finance* 17, no. 2 (2011): 259-271.

Chen, Xuanjuan, Kenneth A. Kim, Tong Yao, and Tong Yu. “On the predictability of Chinese stock returns.” *Pacific-Basin Finance Journal* 18, no. 4 (2010): 403-425.

Cheung, Christopher, George Hoguet, and Sunny Ng. “Value, Size, Momentum, Dividend Yield, and Volatility in China’s A-Share Market.” *The Journal of Portfolio Management* 41, no. 5 (2014): 57-70.

Chui, Andy CW, Sheridan Titman, and KC John Wei. “Individualism and momentum around the world.” *The Journal of Finance* 65, no. 1 (2010): 361-392.

Collins, Daniel W., Guojin Gong, and Paul Hribar. “Investor sophistication and the mispricing of accruals.” *Review of Accounting Studies* 8, no. 2-3 (2003): 251-276.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill. “Asset growth and the cross-section of stock returns.” *The Journal of Finance* 63, no. 4 (2008): 1609-1651.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. “Investor psychology and security market under-and overreactions.” *The Journal of Finance* 53, no. 6 (1998): 1839-1885.

Daniel, Kent D., and Tobias J. Moskowitz. “Momentum Crashes.” *NBER Working Paper* w20439 (2014).

Daniel, Kent, and Sheridan Titman. “Market reactions to tangible and intangible information.” *The Journal of Finance* 61, no. 4 (2006): 1605-1643.

De Bondt, Werner, and Richard H. Thaler. “Does the Stock Market Overreact?.” *The Journal of Finance* 40, no. 3 (1985): 793-805.

Dechow, Patricia M., Natalya V. Khimich, and Richard G. Sloan. “The accrual anomaly.” In *The handbook of equity market anomalies: translating market inefficiencies into effective investment strategies*, edited by Leonard Zacks, 23-61. New Jersey: John Wiley & Sons, 2011.

Dichev, Ilia D. “Is the risk of bankruptcy a systematic risk?.” *The Journal of Finance* 53, no. 3 (1998): 1131-1147.

Drew, Michael E., Tony Naughton, and Madhu Veeraraghavan. “Firm size, book-to-market equity and security returns: Evidence from the Shanghai Stock Exchange.” *Australian Journal of Management* 28, no. 2 (2003): 119-139.

Drew, Michael E., Tony Naughton, and Madhu Veeraraghavan. “Is idiosyncratic volatility priced?: Evidence from the Shanghai Stock Exchange.” *International Review of Financial Analysis* 13, no. 3 (2004): 349-366.

Eun, Cheol S., and Wei Huang. “Asset pricing in China’s domestic stock markets: Is there a logic?.” *Pacific-Basin Finance Journal* 15, no. 5 (2007): 452-480.

Fama, Eugene F., and Kenneth R. French. “The cross-section of expected stock returns.” *The Journal of Finance* 47, no. 2 (1992): 427-465.

Fama, Eugene F., and Kenneth R. French. “Common risk factors in the returns on stocks and bonds.” *Journal of Financial Economics* 33, no. 1 (1993): 3-56.

Fama, Eugene F., and Kenneth R. French. “Profitability, investment and average returns.” *Journal of Financial Economics* 82, no. 3 (2006): 491-518.

Fama, Eugene F., and Kenneth R. French. “Dissecting anomalies.” *The Journal of Finance* 63, no. 4 (2008a): 1653-1678.

Fama, Eugene F., and Kenneth R. French. “Average returns, B/M, and share issues.” *The Journal of Finance* 63, no. 6 (2008b): 2971-2995.

Fama, Eugene F., and Kenneth R. French. “Size, value, and momentum in international stock returns.” *Journal of Financial Economics* 105, no. 3 (2012): 457-472.

Fama, Eugene F., and Kenneth R. French. “International tests of a five-factor asset pricing model.” *Fama-Miller Working Paper* (2015).

Fan, Joseph PH, Tak Jun Wong, and Tianyu Zhang. “Politically connected CEOs, corporate governance, and Post-IPO performance of China’s newly partially privatized firms.” *Journal of Financial Economics* 84, no. 2 (2007): 330-357.

Frazzini, Andrea, and Lasse Heje Pedersen. “Betting against beta.” *Journal of Financial Economics* 111, no. 1 (2014): 1-25.

Graham, Benjamin, and David L. Dodd. *Security analysis: principles and technique.* McGraw-Hill, 1934.

Green, Jeremiah, John RM Hand, and Mark T. Soliman. “Going, going, gone? The apparent demise of the accruals anomaly.” *Management Science* 57, no. 5 (2011): 797-816.

Griffin, John M., and Michael L. Lemmon. “Book–to–market equity, distress risk, and stock returns.” *The Journal of Finance* 57, no. 5 (2002): 2317-2336.

Haugen, Robert A., and Nardin L. Baker. “Case closed.” In *Handbook of Portfolio Construction*, pp. 601-619. Springer US, 2010.

Haugen, Robert A., and A. James Heins. “Risk and the rate of return on financial assets: Some old wine in new bottles.” *Journal of Financial and Quantitative Analysis* 10, no. 5 (1975): 775-784.

Hilliard, Jitka, and Haoran Zhang. “Size and price-to-book effects: Evidence from the Chinese stock markets.” *Pacific-Basin Finance Journal* 32 (2015): 40-55.

Hirshleifer, David, Kewei Hou, and Siew Hong Teoh. “The accrual anomaly: risk or mispricing?.” *Management Science* 58, no. 2 (2012): 320-335.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang. “Do investors overvalue firms with bloated balance sheets?.” *Journal of Accounting and Economics* 38 (2004): 297-331.

Ho, Li-Chin Jennifer, Qunfeng Liao, and Martin Taylor. “Real and Accrual-Based Earnings Management in the Pre-and Post-IFRS Periods: Evidence from China.” *Journal of International Financial Management & Accounting* 26, no. 3 (2015): 294-335.

Hong, Harrison, and Jeremy C. Stein. “A unified theory of underreaction, momentum trading, and overreaction in asset markets.” *The Journal of Finance* 54, no. 6 (1999): 2143-2184.

Hribar, Paul, and Daniel W. Collins. “Errors in estimating accruals: Implications for empirical research.” *Journal of Accounting Research* 40, no. 1 (2002): 105-134.

Huang, Yujia, Jiawen Yang, and Yongji Zhang. “Value premium in the Chinese stock market: free lunch or paid lunch?.” *Applied Financial Economics* 23, no. 4 (2013): 315-324.

Jegadeesh, Narasimhan. “Evidence of predictable behavior of security returns.” *The Journal of Finance* 45, no. 3 (1990): 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman. “Returns to buying winners and selling losers: Implications for stock market efficiency.” *The Journal of Finance* 48, no. 1 (1993): 65-91.

Jian, Ming, and Tak Jun Wong. “Propping through related party transactions.” *Review of Accounting Studies* 15, no. 1 (2010): 70-105.

Kang, Joseph, Ming-Hua Liu, and Sophie Xiaoyan Ni. “Contrarian and momentum strategies in the China stock market: 1993–2000.” *Pacific-Basin Finance Journal* 10, no. 3 (2002): 243-265.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny. “Contrarian investment, extrapolation, and risk.” *The Journal of Finance* 49, no. 5 (1994): 1541-1578.

Lehmann, Bruce N. “Fads, Martingales, and Market Efficiency.” *The Quarterly Journal of Economics* 105, no. 1 (1990): 1-28.

Leuz, Christian, Dhananjay Nanda, and Peter D. Wysocki. “Earnings management and investor protection: an international comparison.” *Journal of Financial Economics* 69, no. 3 (2003): 505-527.

Lev, Baruch, and Doron Nissim. “The persistence of the accruals anomaly.” *Contemporary Accounting Research* 23, no. 1 (2006): 193-226.

Li, Xi, Ying Becker, and Didier Rosenfeld. “Asset growth and future stock returns: International evidence.” *Financial Analysts Journal* 68, no. 3 (2012): 51-62.

Li, Yuanpeng, Jianjun Niu, Ran Zhang, and James A. Largay. “Earnings management and the accrual anomaly: Evidence from China.” *Journal of International Financial Management & Accounting* 22, no. 3 (2011): 205-245.

Li, Bin, Judy Qiu, and Yanhui Wu. “Momentum and seasonality in Chinese stock markets.” *Journal of Money, Investment and Banking* 17 (2010): 24-36.

Liao, Li, Bibo Liu, and Hao Wang. “China’s secondary privatization: Perspectives from the Split-Share Structure Reform.” *Journal of Financial Economics* 113.3 (2014): 500-518.

Liu, Chunyan, Konari Uchida, and Yufeng Yang. “Corporate governance and firm value during the global financial crisis: Evidence from China.” *International Review of Financial Analysis* 21 (2012): 70-80.

Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin. “Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs.” *Journal of Accounting and Economics* 42, no. 1 (2006): 3-33.

Merton, Robert C. “Presidential address: A simple model of capital market equilibrium.” *The Journal of Finance* 42 (1987): 483-510.

Naughton, Tony, Cameron Truong, and Madhu Veeraraghavan. “Momentum strategies and stock returns: Chinese evidence.” *Pacific-Basin Finance Journal* 16, no. 4 (2008): 476-492.

Ng, Lilian, and Fei Wu. “Revealed stock preferences of individual investors: Evidence from Chinese equity markets.” *Pacific-Basin Finance Journal* 14, no. 2 (2006): 175-192.

Novy-Marx, Robert. “The other side of value: The gross profitability premium.” *Journal of Financial Economics* 108, no. 1 (2013): 1-28.

Ohlson, J. A. “Financial Ratios and the Probabilistic Prediction of Bankruptcy.” *Journal of Accounting Research* 18, no. 1 (1980).

Pincus, Morton, Shivaram Rajgopal, and Mohan Venkatachalam. “The accrual anomaly: International evidence.” *The Accounting Review* 82, no. 1 (2007): 169-203.

Rabouin, Dion. “FTSE Russell declines to add China A shares to emerging market index.” *Reuters*, Sep. 29, 2016.

Rouwenhorst, K. Geert. “Local return factors and turnover in emerging stock markets.” *The Journal of Finance* 54, no. 4 (1999): 1439-1464.

Shen, Samuel and Brenda Goh. “China stock market freezing up as sell-off gathers pace.” *Reuters*, Jul. 8, 2015.

Sloan, Richard G. “Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?.” *The Accounting Review* 71, no. 3 (1996): 289-315.

Sun, Qian, and Wilson HS Tong. “China share issue privatization: the extent of its success.” *Journal of Financial Economics* 70, no. 2 (2003): 183-222.

Sun, Lei, Kuo-Chiang John Wei, and Feixue Xie. “On the Explanations for the Gross Profitability Effect: Insights from International Equity Markets.” In *Asian Finance Association (AsianFA) 2014 Conference Paper.* 2014.

Tian, Lihui. “Regulatory underpricing: Determinants of Chinese extreme IPO returns.” *Journal of Empirical Finance* 18, no. 1 (2011): 78-90.

Titman, Sheridan, KC John Wei, and Feixue Xie. “Capital investments and stock returns.” *Journal of Financial and Quantitative Analysis* 39, no. 04 (2004): 677-700.

Titman, Sheridan, KC John Wei, and Feixue Xie. “Market development and the asset growth effect: International evidence.” *Journal of Financial and Quantitative Analysis* 48, no. 5 (2013): 1405-1432.

Van Dijk, Mathijs A. “Is size dead? A review of the size effect in equity returns.” *Journal of Banking & Finance* 35, no. 12 (2011): 3263-3274.

Vassalou, Maria, and Yuhang Xing. “Default risk in equity returns.” *The Journal of Finance* 59, no. 2 (2004): 831-868.

Wang, Changyun. “Relative strength strategies in China’s stock market: 1994–2000.” *Pacific-Basin Finance Journal* 12, no. 2 (2004): 159-177.

Wang, Yuenan, and Amalia Di Iorio. “The cross section of expected stock returns in the Chinese A-share market.” *Global Finance Journal* 17, no. 3 (2007): 335-349.

Wang, Xia, and Min Wu. “The quality of financial reporting in China: An examination from an accounting restatement perspective.” *China Journal of Accounting Research* 4, no. 4 (2011): 167-196.

Wang, Fenghua, and Yexiao Xu. “What determines Chinese stock returns?.” *Financial Analysts Journal* 60, no. 6 (2004): 65-77.

Wang, Yifeng, Cheyuan Liu, Jen-Sin Lee, and Yanming Wang. “The relation between asset growth and the cross-section of stock returns: Evidence from the Chinese stock market.” *Economic Modelling* 44 (2015): 59-67.

Watanabe, Akiko, Yan Xu, Tong Yao, and Tong Yu. “The asset growth effect: Insights from international equity markets.” *Journal of Financial Economics* 108, no. 2 (2013): 529-563.

Wong, Kie Ann, Ruth Seow Kuan Tan, and Wei Liu. “The cross-section of stock returns on the Shanghai Stock Exchange.” *Review of Quantitative Finance and Accounting* 26, no. 1 (2006): 23-39.

Wu, Hong. “The value and size effect—are there firm-specific-risks in China’s domestic stock markets?.” *International Journal of Economics and Finance* 3, no. 3 (2011a): 26.

Wu, Yangru. “Momentum trading, mean reversal and overreaction in Chinese stock market.” *Review of Quantitative Finance and Accounting* 37, no. 3 (2011b): 301-323.

Wu, Wenfeng, Chongfeng Wu, and Oliver M. Rui. “Ownership and the value of political connections: Evidence from China.” *European Financial Management* 18, no. 4 (2012): 695-729.

Wu, Wenfeng, Chongfeng Wu, Chunyang Zhou, and Jun Wu. “Political connections, tax benefits and firm performance: Evidence from China.” *Journal of Accounting and Public Policy* 31, no. 3 (2012): 277-300.

Wu, Jin Ginger, Lu Zhang, and X. Zhang. “The q-Theory Approach to Understanding the Accrual Anomaly.” *Journal of Accounting Research* 48, no. 1 (2010): 177-223.

Xie, Hong. “The mispricing of abnormal accruals.” *The Accounting Review* 76, no. 3 (2001): 357-373.

Yao, Tong, Tong Yu, Ting Zhang, and Shaw Chen. “Asset growth and stock returns: Evidence from Asian financial markets.” *Pacific-Basin Finance Journal* 19, no. 1 (2011): 115-139.

Zhang, Lu. “The value premium.” *The Journal of Finance* 60, no. 1 (2005): 67-103.

Appendix A: Variable definitions for A-shares characteristics

Type	Variable	Name	Description
Size	$SIZE_t$	Natural log of firm size	Natural log of the firm's total A-share market value of equity from CSMAR, as of the end of April in year *t*. CSMAR also provides firm market value calculated according to the free float, but we believe that calculating size based on total shares outstanding provides a clearer measure of the firm's market value, particularly after the Split-Share Structure Reform of 2005.
Valuation	B/P_t	Book-to-price ratio	Book value of equity for year $t-1$, divided by its total market cap. as of the end of April in year *t*.
	E/P_t	Earnings-to-price ratio	Earnings for year $t-1$, divided by its total market cap. as of the end of April in year *t*.
	S/P_t	Sales-to-price ratio	Sales for year $t-1$, divided by its total market cap. as of the end of April in year *t*.
	D/P_t	Dividend-to-price ratio	Dividends for year $t-1$, divided by its total market cap. as of the end of April in year *t*. We drop firm-year observations for stocks not paying dividends in year $t-1$.
Profitability	GP_t	Gross profitability	(Sales − COGS) for fiscal year ending at $t-1$, divided by total assets at the end of year $t-1$.
	OP_t	Operating profitability	(Sales − COGS − SG&A − Interest expense) for fiscal year ending at $t-1$, divided by book value of equity at the end of year $t-1$.
Investments	$\Delta ASSET_t$	Change in total assets	Percentage change in total assets from the beginning to the end of the fiscal year ending at $t-1$.
	$\Delta BOOK_t$	Change in book equity	Percentage change in book equity from the beginning to the end of the fiscal year ending at $t-1$.
Accounting Conservatism	ACC_t	Accruals	Following the definition of total accruals in Hribar and Collins (2002), earnings less operating cash flows, for fiscal year ending at $t-1$, scaled by total assets at the beginning of year $t-1$.
	NOA_t	Net operating assets	Operating assets less operating liabilities for fiscal year ending at $t-1$, scaled by total assets at beginning of year $t-1$.

Appendix A: Variable definitions for A-shares characteristics, continued

Type	Variable	Name	Description
Risk	VOL_t	Total risk	The standard deviation of daily stock returns over the previous year.
	$BETA_t$	Systematic risk	The slope coefficient from a regression of daily excess stock returns over the previous year against corresponding daily returns for an internally calculated capitalization-weighted market benchmark consisting of all available A-shares.
	$I\text{-}VOL_t$	Idiosyncratic risk	The variance of residuals from a regression of daily excess stock returns over the previous year against corresponding daily returns for an internally calculated capitalization-weighted market benchmark consisting of all available A-shares.
Returns-based	MOM_t	Momentum	The stock's cumulative return from month $t-12$ to month $t-2$.
	$REV\text{-}ST_t$	Short-term reversal	The stock's return over the previous month.
	$REV\text{-}LT_t$	Long-term reversal	The stock's cumulative return from month $t-60$ to month $t-13$.

Appendix B: Background on anomalies

Our study investigates in Chinese A-shares a range of cross-sectional equity anomalies with significant prior literature in the U.S. Here, we provide a brief review of past research related to these anomalies. We attempt to offer some detail on the origin of each anomaly, as well as rational or behavioral stories posited as explanations for the performance of the corresponding factor strategies.

B.1 Size

Banz (1981) was the first to document a "size" effect in U.S. equity data, reporting that firms with higher market capitalization significantly underperform small company stocks. Fama and French (1993) attributed the premium offered by small-cap stocks to the undiversifiable risk borne by small firms which, due to capital constraints, have greater difficulty weathering macroeconomic shocks. Follow-up research confirmed the size effect in later samples (Fama and French 1992) and a number of studies found evidence of a relationship between firm size and stock returns outside the U.S. (Rouwenhorst 1999, Fama and French 2012). However, more recent work has shown significant attenuation of the size effect in the U.S. beginning in the 1980s and some researchers have questioned how consistently firm size performs in predicting international stock returns (see Van Dijk 2011, which provides a survey of the historical literature on firm size). We measure firm size [**SIZE**] as the natural log of total market capitalization.

B.2 Value

For many years, professional investors have advocated a strategy calling for the purchase of stocks with low price relative to various measures of fundamental value (Graham and Dodd 1934). Beginning with Basu (1977), who found that high price-to-earnings ratios predict lower future stock returns, many academics have systematically tested this approach, proposing ratios of fundamental accounting variables to market price as indicators of relatively cheap or expensive stocks. Subsequent research has identified other indicators of valuation that seem to capture the same premium, including book-to-price, cash-flow-to-price, sales-to-price, and dividend-to-price (Lakonishok, Shleifer, and Vishny 1994). Fama and French (1993) again proposed a risk-based explanation for the "value" effect, suggesting that the high return on value stocks represents compensation for bearing undiversifiable distress risk, although follow-up studies have failed to establish a consistent link between valuation ratios and default risk (compare, for example, Vassalou and Xing 2004 with Dichev 1998, Griffin and Lemmon 2002). Zhang (2005) proposed that the value premium actually compensates investors for the cost of disinvesting during an economic downturn for capital-intensive firms. On the other hand, Lakonishok, Shleifer, and Vishny (1994) favored a behavioral basis for the value effect, positing that investors naively extrapolate recent sales growth into the future, while showing irrational pessimism toward firms with poor recent performance, resulting in overvaluation of high-growth, "glamour" stocks. However one chooses to explain the value phenomenon, it has proven to be extremely robust, generating profits over time, across asset classes, and throughout the world (Fama and French 2012, Asness, Moskowitz, and Pedersen 2013). In our analysis, we consider four common valuation measures: book-to-price [**B/P**], earnings-to-price [**E/P**], sales-to-price [**S/P**], and dividend yield [**D/P**].

B.3 Profitability

Based on a simple dividend discount model with clean surplus accounting, Fama and French (2006) proposed that in addition to low current valuations (as reflected in high book-to-market ratios, for example) predicting higher future returns, greater future earnings should also predict higher returns going forward holding other variables constant. This intuition, they claimed, suggests the existence of a complement to the value effect: profitable firms should outperform unprofitable firms. Using current net income as a proxy for future profitability, however, Fama and French (2006) found little evidence of a "profitability" effect. Novy-Marx (2013) argued that net income is a poor signal of future profitability, because the accounting treatment of earnings penalizes firms for any investments recognized as expenses, even if those investments lead to future growth in the firm's cash flows. He showed that gross profitability [**GP**]—measured as sales, less cost of goods sold (COGS), scaled by total assets—is a much cleaner measure of future profitability and serves as a strong positive predictor of future stock returns. Because high-gross-profitability firms tend to exhibit growth characteristics, the strategy serves as a hedge when implemented alongside a value portfolio. Ball, Gerakos, Linnainmaa, and Nikolaev (2015) pointed out that selling, general, and administrative expenses (SG&A) are largely associated with current income and that managers have discretion when allocating expenses between SG&A and COGS. They proposed employing operating profitability—essentially gross profits, less SG&A, again scaled by total assets—as a sorting variable and found that it significantly outperforms gross profitability in predicting future returns. The model motivating Fama and French (2006) implies a risk-based story for the profitability effect, in which risky firms reinvest a smaller fraction of earnings due to a high discount rate, and thereby show greater profitability. Alternatively, profitability might simply serve as a means of distinguishing among rationally and irrationally priced growth stocks. Internationally, Fama and French (2015) find evidence of a relationship between operating profitability [**OP**]—which they defined as operating profits scaled by book value—and future returns in North America, Europe, and Asia Pacific, but not in Japan.

B.4 Investments

A number of studies have shown that, on average, firms experiencing investment and growth suffer lower future returns. Titman, Wei, and Xie (2004), for example, demonstrated that capital investment is inversely related to future stock performance, while Bradshaw, Richardson, and Sloan (2006) documented poor stock returns for firms with positive net external financing. Cooper, Gulen, and Schill (2008) employed the change in total assets [**ΔASSET**] as a catch-all composite measure of firm growth, and found it to be a strong negative predictor of future returns. Related research has shown that changes in the book value of a firm's equity [**ΔBOOK**] can be useful in refining predictions based solely on the firm's book-to-market ratio (Daniel and Titman 2006, Fama and French 2006, 2008b). A standard rational explanation for asset growth effects, called the *q*-theory of investments, attributes a firm's asset growth to falling discount rates, which make the firm's projects more profitable but, of course, also imply lower future expected returns (Wu, Zhang, and Zhang 2010 give a more thorough account of this argument in the context of modeling the related accruals anomaly, described below). Such effects could also arise from investors' irrational extrapolation of past growth rates into the future, as described by Lakonishok, Shleifer, and Vishny (1994). Titman, Wei, and Xie (2004), on the other hand, viewed the negative relationship between investment and subsequent returns as evidence that investors might systematically underreact to overinvestment resulting from managers' empire building. Li, Becker, and Rosenfeld (2012) and Fama and French (2015) found evidence of an asset growth effect in markets outside the U.S., whereas Titman, Wei, and Xie (2013) report stronger predictability in countries with more developed financial markets, and little connection between the asset growth effect and measures of corporate governance, casting some doubt on the "empire building" hypothesis described above.

B.5 Accounting conservatism

Sloan (1996) showed that accruals, the non-cash component of current earnings, are less persistent than earnings attributable to a firm's cash flows, but that investors seem to fixate on the firm's reported earnings without appreciating this distinction. As a result, firms with high accruals are systematically overvalued relative to firms with low accruals such that high accruals predict low future stock returns. We use a firm's total accruals [**ACC**]—defined as net income minus operating cash flows, taken from the cash flow statement, scaled by total assets—which Hribar and Collins (2002) demonstrate is less noisy than operating accruals estimated from the balance sheet. In related research, Hirshleifer, Hou, Teoh, and Zhang (2004) demonstrated that high net operating assets [**NOA**], which measures the cumulative difference between operating income and free cash flow, serves as an even stronger predictor of lower future returns than accruals, again suggesting that some inattentive investors fail to account for long-term earnings management when valuing stocks. Pincus, Rajgopal, and Venkatachalam (2007) found that the accruals anomaly persists through time and in other countries, particularly those with reporting standards that permit extensive use of accrual accounting. Hirshleifer, Hou, and Teoh (2011) tested a risk-based explanation for the accruals anomaly, but found that comovement with an accrual factor-mimicking portfolio failed to explain the cross-section of stock returns. Sloan (1996) took a behavioral perspective, attributing the accruals effect to errors in valuation by unsophisticated investors. He found that the accruals strategy generates roughly half of its profits around firms' public earnings announcements, supporting the view that the accruals anomaly reflects a mispricing that only becomes apparent to investors when future earnings fail to match their biased expectations. Green, Hand, and Soliman (2010) documented attenuation in accruals anomaly returns in more recent years, consistent with at least part of the strategy's performance having been "arbitraged away" by sophisticated investors since the original paper's publication. Collins, Gong, and Hribar (2003) likewise showed that stocks with higher institutional ownership are priced more efficiently with respect to accruals. Finally, in the same vein, Lev and Nissim (2006) and Mashruwala, Rajgopal, and Shevlin (2006) identified typical extreme-accruals stocks as small, illiquid, and volatile, characteristics that constitute limits to arbitrage, which might explain the strategy's persistence. A survey by Dechow, Khimich, and Sloan (2011) provides a more detailed overview of the vast literature on accounting accruals.

B.6 Risk

Anomalies based on risk initially emerged as a result of early tests of the CAPM, which demonstrated, contrary to the model's prediction, that stocks with low levels of systematic risk, measured as the beta from regressing a stock's past excess returns against those of a market proxy, actually performed on par with—and sometimes better than—stocks with high systematic risk (Black 1972, Black, Jensen, and Scholes 1972, Haugen and Heinz 1975). Follow-up research demonstrated that not only has high systematic risk continued to predict lower future returns (Baker, Bradley, and Wurgler 2011, Frazzini and Pedersen 2014), but high idiosyncratic risk—which, because it can be completely eliminated through proper diversification, rational models suggest should not constitute a priced risk—also predicts lower future performance (Ang, Hodrick, Xing, and Zhang 2006). Given the apparent "low-beta" and "idiosyncratic volatility" effects, it should come as little surprise that total volatility is inversely related to future stock performance, as well: the so-called "low-vol" effect (Haugen and Baker 2010, Baker, Bradley, and Wurgler 2011). Black (1972) provided a rational explanation for the low-beta and low-vol effects, suggested that institutional investors subject to borrowing constraints might overweight high-beta stocks in order to indirectly lever up portfolio returns. Baker, Bradley, and Wurgler (2011) reviewed a number of behavioral stories for these effects, including irrational investor demand for risky stocks with lottery-like payoffs, and concluded that the strategy's persistent success could stem from rational institutional investors' inability to exploit the anomaly due to the high tracking error it creates for funds managing to a benchmark. The idiosyncratic volatility effect is more difficult to explain. Merton (1987) demonstrated that investors forced to hold imperfectly diversified portfolios should demand higher returns for stocks with greater firm-specific risk, but the idiosyncratic volatility effect actually runs counter to this intuition. Ang, Hodrick, Xing, and Zhang (2009) and Baker and Haugen (2012) provide international evidence for the low-vol and idiosyncratic volatility effects. In addition to total risk [**VOL**], we include systematic risk [**BETA**] and idiosyncratic risk [**I-VOL**] as risk-based predictors of future returns.

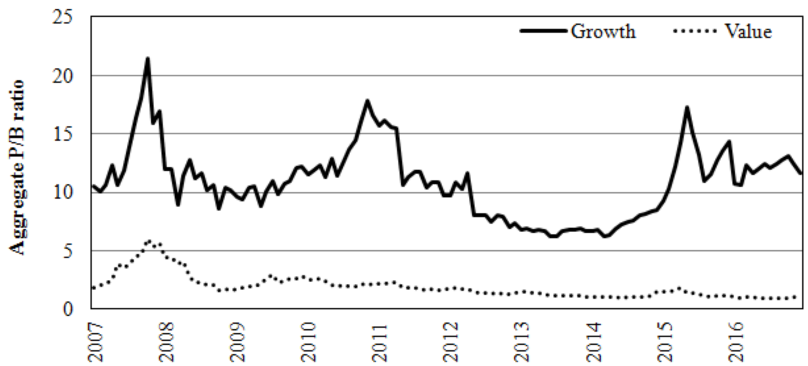
B.7 Past returns

Strategies based on past price data depend on the formation period over which one evaluates prior returns. Over intermediate horizons, from roughly three months to one year, Jegadeesh and Titman (1993) found past winners continue to outperform while past losers continue to underperform: in other words, there appears to be medium-term "momentum" [**MOM**] in stock prices. On the other hand, forming portfolios on the basis of just the last month's stock return, Lehmann (1990) and Jegadeesh (1990) documented short-term "reversals" [**REV-ST**], such that higher returns over the last one week or one month predict lower future returns. Over much longer horizons, from three to five years, De Bondt and Thaler (1985) found evidence of long-term "reversals" [**REV-LT**] in returns. Common behavioral explanations for momentum and reversals usually hinge on some combination of short-run underreaction to information, resulting in price continuation, and eventual overreaction, which sends prices too high or low, leading to an inevitable reversal when investors realize that they have erred. Widely cited theoretical models of such behavior are given by Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). Rational explanations for the persistence of returns-based strategies include the observation by Daniel and Moskowitz (2013) that occasional "momentum crashes" represent a significant source of risk in traditional momentum strategies, and the fact that the high turnover of such strategies typically results in substantial trading costs, making factors based on past returns relatively difficult to implement, in practice. Momentum, like the value effect, has been highly robust through time and across the globe (Chui, Titman, and Wei 2010, Fama and French 2012, Asness, Moskowitz, and Pedersen 2013).

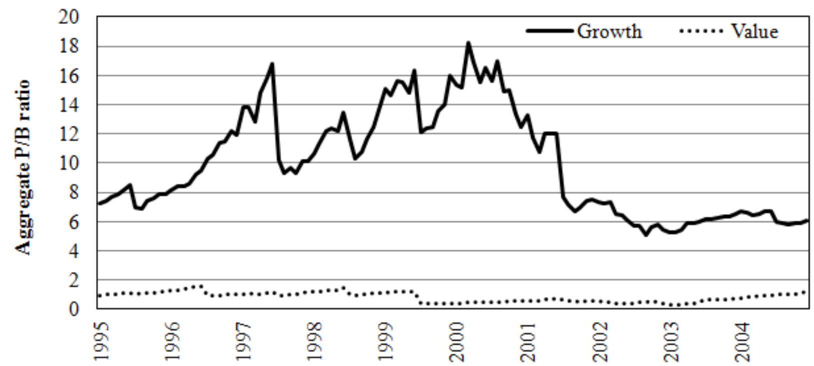
Figure 1: Valuation inflation in factor portfolios, A-shares and U.S. stocks.

The graphs below plot valuation inflation in A-shares over a recent sample (2007-2016) and in U.S. stocks around the dot-com bubble (1995-2004) for portfolios of stocks associated with the value and size anomalies. We measure valuation inflation using aggregate price-to-book ratios, calculated as the ratio of capitalization-weighted firm size to capitalization-weighted book value, for various subsets of stocks. For A-shares and U.S. stocks, we define "growth" and "value" stocks as the top and bottom quintile of firms, sorted on the price-to-book ratio. In China, we define "large" and "small" stocks as the top 300 firms by market capitalization and the next-largest 500 firms, respectively; in the U.S., "large" stocks are the top quintile of firms sorted on market cap, and "small" stocks are the bottom quintile.

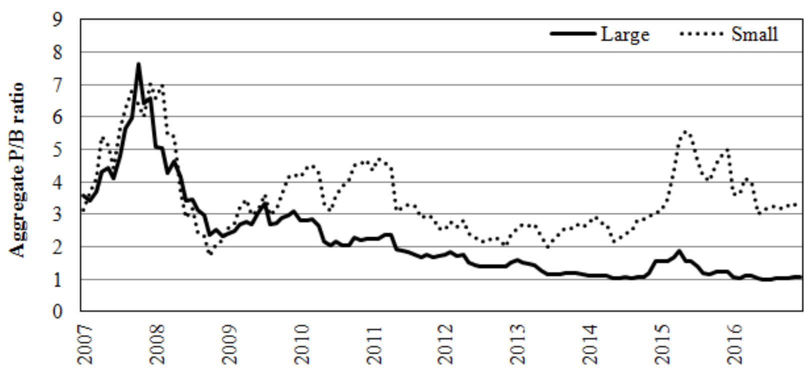
Panel A. Price-to-book inflation in Chinese stocks, 2007-2016: Value vs. growth.



Panel D. Price-to-book inflation in U.S. stocks, 1995-2004: Value vs. growth.



Panel C. Price-to-book inflation in Chinese stocks, 2007-2016: Small-cap vs. large-cap.



Panel D. Price-to-book inflation in U.S. stocks, 1995-2004: Small-cap vs. large-cap.

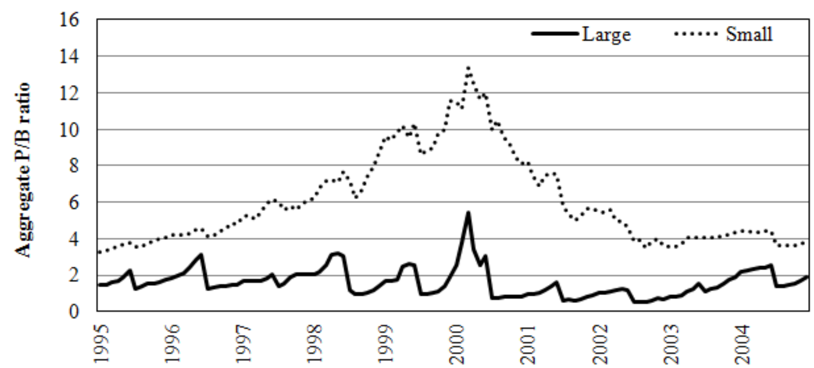
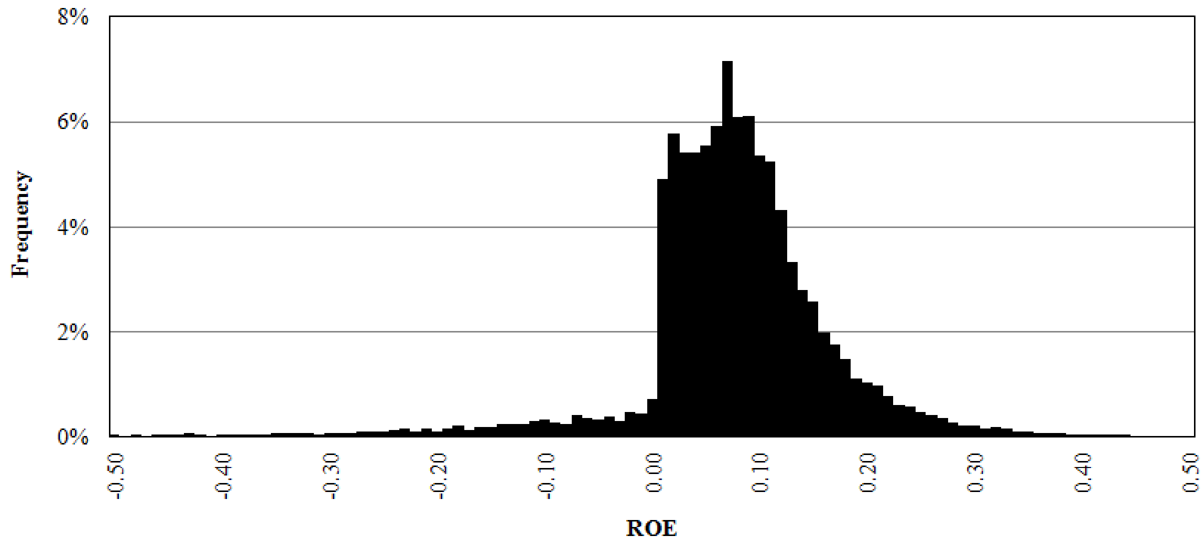


Figure 2: Distribution of return on equity (ROE) for Chinese and U.S. firms.

Panel A. We plot the distribution of annual return on equity (ROE) for A-shares listed firms, from 1998-2016, plotting values of ROE ranging from −50% to 50% for the sake of clarity. The kink in the distribution occurs around ROE = 0%.



Panel B. We plot the distribution of annual return on equity (ROE) for U.S. firms, from 1963-2016, plotting values of ROE ranging from −50% to 50%. Once again, the kink in the distribution occurs around ROE = 0%, although it is less pronounced.

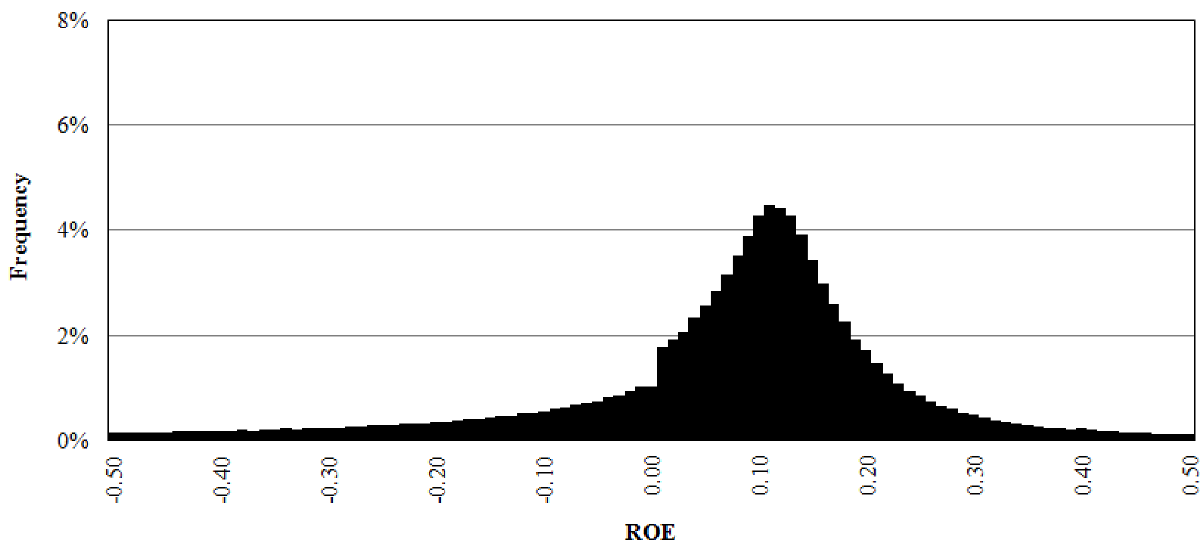
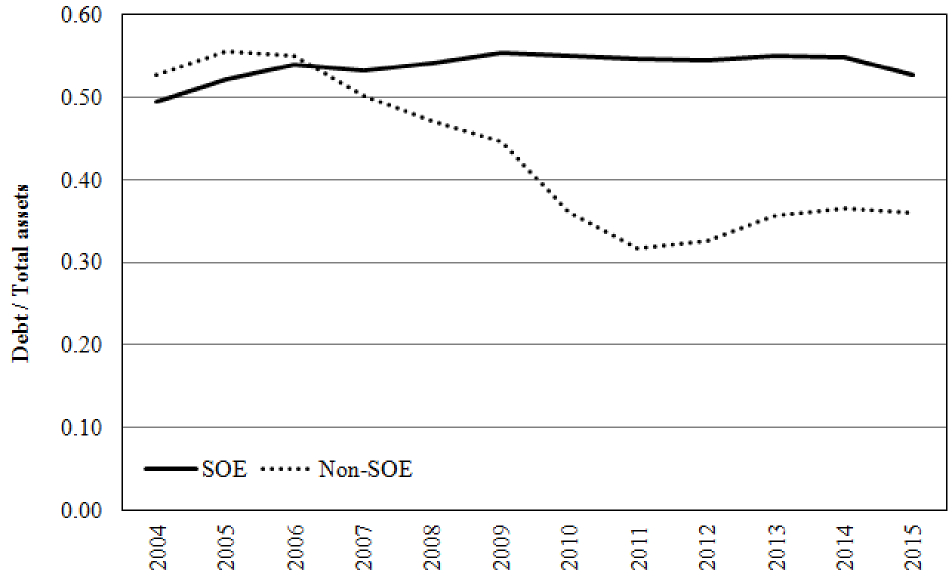


Figure 3: Evidence of over-investment by state-owned Chinese firms, 2004-2015.

Panel A. Borrowing by state-owned and private listed firms in China, measured by the debt-to-assets ratio.



Panel B. Operating efficiency of state-owned and private listed firms in China, measured by asset turnover.

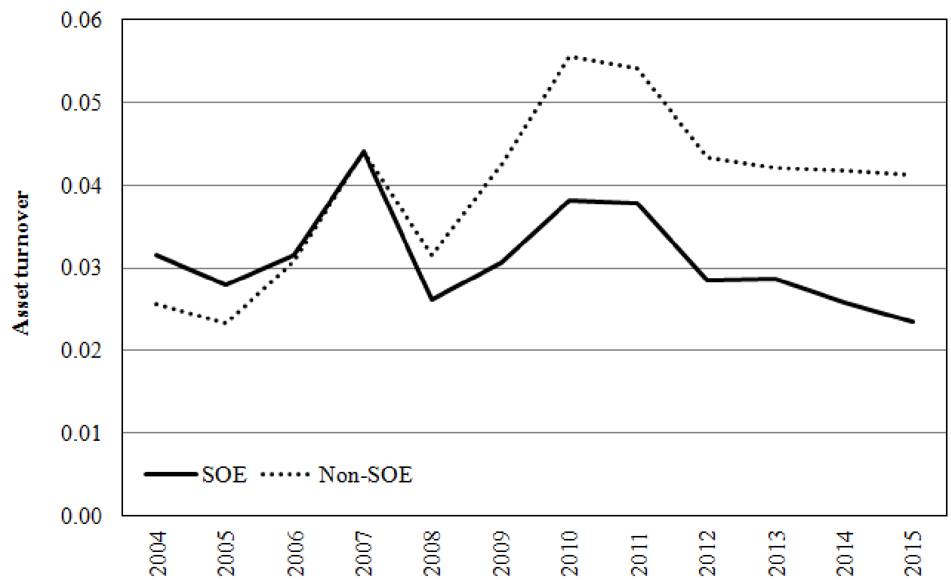


Figure 4: Price-to-earnings ratios of A-shares corresponding to state-owned and private listed firms.

The plot shows value-weighted average price-to-earnings ratios of SOE and non-SOE firms with listed A-shares, over the period from Feb. 2005 through Dec. 2016. State-owned firms typically trade at lower valuation multiples than private listed firms during our sample.

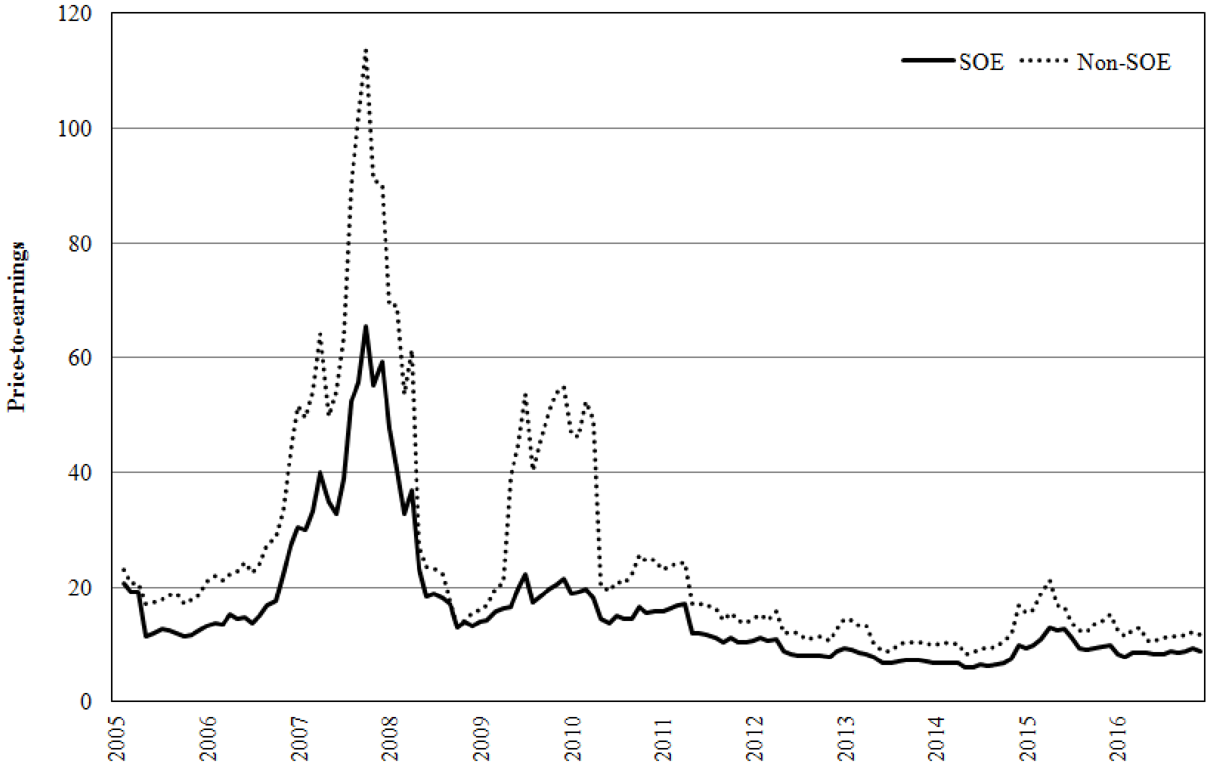


Table 1: Factor returns for A-shares and U.S. stocks.

The table presents annualized equal- (EW) and value-weighted (VW) mean returns for a range of factor strategies described in the text, for Chinese and U.S. stocks, over various time periods, with *t* -statistics in parentheses. In both China and the U.S., the universe is made up of the largest 80% of stocks, by market capitalization. In China, the data necessary to construct ACC are only available as of 2000; REV-LT is available beginning in 1996. For annual signals, we rebalance A-shares strategies in May, and rebalance U.S. strategies in July. We simulate a short sample for U.S. stocks with length similar to that of the recent A-shares sample by averaging means and *t* -stats for each 10-year sub-period in the U.S. data, from 1967-2016. For both A-shares samples and the short U.S. sample, we show the implied number of years required to achieve a p -value less than 0.05 based on the in-sample VW factor returns and standard errors. We indicate significance at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

	A-shares						U.S.					
Signal	Full sample		Years for $p < 0.05$	Recent sample		Years for $p < 0.05$	Short sample		Years for $p < 0.05$	Full sample		
	H-L (EW)	H-L (VW)		H-L (EW)	H-L (VW)		H-L (EW)	H-L (VW)		H-L (EW)	H-L (VW)	
−SIZE	15.8% ***	14.6% **	14	23.9% ***	24.9% ***	4	1.7%	2.5%	224	2.8%	3.7%	
	(3.18)	(2.47)		(3.24)	(2.76)		(0.27)	(0.41)		(1.26)	(1.56)	
B/P	11.5% **	10.3% *	24	3.3%	2.3%	493	9.3% *	3.9%	117	8.8% ***	3.5%	
	(2.25)	(1.86)		(0.46)	(0.26)		(1.83)	(0.57)		(3.84)	(1.26)	
E/P	7.4% *	7.8%	37	-2.4%	-3.8%	139	3.2%	3.7%	99	2.4%	3.3%	
	(1.67)	(1.50)		(-0.43)	(-0.49)		(1.03)	(0.62)		(0.98)	(1.26)	
S/P	10.0% ***	11.7% ***	9	2.6%	2.4%	243	11.3% **	8.4%	26	11.0% ***	8.4% ***	
	(3.48)	(3.12)		(0.51)	(0.37)		(2.01)	(1.22)		(4.04)	(2.89)	
D/P	7.8% **	5.7%	52	-2.4%	-8.7%	31	2.7%	1.6%	888	1.8%	0.7%	
	(2.01)	(1.27)		(-0.42)	(-1.03)		(0.51)	(0.21)		(0.86)	(0.26)	
GP	4.5%	1.2%	1,231	3.2%	3.2%	133	7.5% **	5.0%	35	7.3% ***	5.5% ***	
	(1.11)	(0.26)		(0.63)	(0.50)		(2.09)	(1.04)		(4.25)	(2.76)	
OP	1.6%	1.7%	547	-5.0%	-2.1%	180	6.1% *	2.1%	145	6.0% ***	2.0%	
	(0.39)	(0.39)		(-1.39)	(-0.43)		(1.91)	(0.51)		(2.98)	(0.78)	
−ΔASSET	1.5%	2.2%	296	3.7%	8.7% *	9	10.8% ***	8.1% *	11	10.5% ***	7.5% ***	
	(0.46)	(0.53)		(1.20)	(1.95)		(3.15)	(1.90)		(7.00)	(4.04)	
−ΔBOOK	-0.4%	-0.7%	2,880	4.5% *	8.9% **	8	7.1% **	8.4% *	10	6.9% ***	7.5% ***	
	(-0.13)	(-0.17)		(1.74)	(2.02)		(2.05)	(1.95)		(4.87)	(3.97)	
−ACC	4.3% **	5.1%	32	3.1%	4.2%	50	4.1%	4.9%	42	3.8% ***	4.4% **	
	(2.10)	(1.41)		(1.20)	(0.82)		(1.30)	(0.96)		(2.82)	(2.12)	
−NOA	4.9% *	5.3%	33	5.4% *	6.7%	13	9.7% **	7.8%	14	9.1% ***	7.2% ***	
	(1.88)	(1.58)		(1.86)	(1.59)		(2.47)	(1.64)		(4.48)	(3.78)	
−VOL	8.5% **	6.8%	44	2.8%	-0.6%	6,795	7.4%	9.8%	25	5.7%	8.3% *	
	(2.14)	(1.37)		(0.38)	(-0.07)		(1.03)	(1.25)		(1.46)	(1.96)	
−BETA	4.7%	3.3%	197	4.4%	3.2%	243	4.2%	2.1%	405	3.1%	0.9%	
	(1.18)	(0.65)		(0.64)	(0.37)		(0.52)	(0.31)		(0.91)	(0.27)	
−I-VOL	6.0%	5.6%	59	1.4%	-0.7%	5,202	6.9%	7.9%	31	5.2%	6.3%	
	(1.56)	(1.19)		(0.20)	(-0.08)		(1.00)	(1.12)		(1.36)	(1.60)	
MOM	-1.4%	-1.1%	1,720	-8.5%	-11.7%	16	21.6% ***	19.3% **	6	22.0% ***	20.2% ***	
	(-0.30)	(-0.22)		(-1.35)	(-1.46)		(3.70)	(2.52)		(6.50)	(5.29)	
−REV-ST	8.3% **	5.4%	69	21.9% ***	23.0% ***	4	14.8% ***	3.4%	93	15.2% ***	3.7%	
	(2.02)	(1.10)		(3.88)	(2.90)		(3.19)	(0.64)		(5.53)	(1.22)	
−REV-LT	8.5% *	12.1% **	17	5.9%	7.9%	18	6.2%	3.5%	149	6.4% ***	3.9%	
	(1.70)	(2.15)		(1.20)	(1.36)		(1.08)	(0.51)		(2.92)	(1.48)	
Years	1995-2016 (T = 22)			2008-2016 (T = 9)			Simulated (T = 10)			1965-2016 (T = 52)		

Table 2: Summary statistics for Chinese and U.S. equity markets.

We report summary statistics as of the end of each year for A-shares and U.S. stocks, since after the inception of Chinese equity markets in 1990. For ease of comparison, we convert RMB to U.S. dollars at prevailing exchange rates obtained from the U.S. Federal Reserve. SOE data are only available beginning in 2004.

Year	A-shares						U.S.		
	Number of listed firms	Market cap, US$B	Avg. firm size, US$B	SOEs as % of listed firms	SOEs as % of market cap	Non-tradable shares as % of market cap	Number of listed firms	Market cap, US$B	Avg. firm size, US$B
1991	12	1.21	0.10	-	-	61.82%	5,843	3,345.91	0.57
1992	31	17.07	0.55	-	-	74.17%	5,997	3,851.52	0.64
1993	99	43.33	0.44	-	-	83.32%	6,258	4,371.42	0.70
1994	270	24.14	0.09	-	-	79.88%	6,808	4,595.84	0.68
1995	297	52.69	0.18	-	-	80.20%	6,948	5,711.27	0.82
1996	367	87.36	0.24	-	-	76.31%	7,382	6,654.42	0.90
1997	656	200.77	0.31	-	-	73.97%	7,612	9,664.60	1.27
1998	785	271.72	0.35	-	-	73.59%	7,495	11,435.16	1.53
1999	873	359.43	0.41	-	-	71.97%	6,991	13,429.94	1.92
2000	974	540.78	0.56	-	-	69.82%	6,764	15,687.67	2.32
2001	1,113	581.90	0.52	-	-	68.46%	6,143	13,215.73	2.15
2002	1,164	585.00	0.50	-	-	70.88%	5,610	10,186.59	1.82
2003	1,227	530.00	0.43	-	-	71.30%	5,200	11,306.23	2.17
2004	1,323	520.03	0.39	70.14%	84.14%	72.19%	5,058	12,802.13	2.53
2005	1,367	412.94	0.30	68.69%	83.36%	72.53%	4,966	14,679.88	2.96
2006	1,353	551.16	0.41	68.07%	82.17%	65.87%	4,871	14,933.88	3.07
2007	1,455	2,998.01	2.06	63.23%	69.99%	71.55%	4,793	16,690.90	3.48
2008	1,585	3,246.37	2.05	59.75%	85.31%	72.67%	4,600	14,230.74	3.09
2009	1,601	4,118.59	2.57	60.02%	85.38%	59.18%	4,264	11,039.35	2.59
2010	1,869	3,742.18	2.00	52.27%	77.52%	44.46%	4,129	12,515.34	3.03
2011	2,207	4,663.99	2.11	46.04%	74.15%	34.12%	3,937	14,792.45	3.76
2012	2,422	3,870.04	1.60	41.95%	73.54%	33.46%	3,820	15,154.64	3.97
2013	2,468	4,048.98	1.64	41.25%	64.61%	28.82%	3,719	18,736.93	5.04
2014	2,519	4,794.07	1.90	40.10%	61.05%	26.57%	3,812	21,277.23	5.58
2015	2,775	9,186.75	3.31	36.40%	56.48%	28.46%	3,849	22,785.40	5.92
2016	2,868	7,706.06	2.69	35.32%	51.86%	29.01%	3,715	22,372.68	6.02

Table 3: List of anomalies and corresponding stock characteristics.

The table provides a list of anomalies described in the text, along with one or more cross-sectional variables associated with each anomaly. Predictors preceded by a minus sign are those variables hypothesized to have an inverse relationship with future stock returns. The last column lists rebalancing frequencies for factor strategies corrsponding to each predictor.

Type	Predictor	Description	Frequency
Size	−SIZE	Market capitalization	Annual
Valuation	B/P	Book-to-price ratio	Annual
	E/P	Earnings-to-price ratio	Annual
	S/P	Sales-to-price ratio	Annual
	D/P	Dividend yield	Annual
Profitability	GP	Gross profitability	Annual
	OP	Operating profitability	Annual
Investments	−ΔASSET	Change in total assets	Annual
	−ΔBOOK	Change in book value	Annual
Accounting conservatism	−ACC	Accruals	Annual
	−NOA	Net operating assets	Annual
Risk	−VOL	Total risk	Annual
	−BETA	Systematic risk	Annual
	−I-VOL	Idiosyncratic risk	Annual
Returns-based	MOM	Momentum	Monthly
	−REV-ST	Short-term reversal	Monthly
	−REV-LT	Long-term reversal	Monthly

Table 4: Summary statistics for stock characteristics.

The table presents summary statistics for the predictors listed in Table 2 and described in the text, for our sample of A-shares stocks, pooling observations over the period 1995-2016. SIZE is given in units of log RMB. The data necessary to construct ACC are only available as of 2000; REV-LT begins in 1996. We list the number of stock-date observations for each variable in the last column.

Predictor	Mean	St. Dev.	25%	Median	75%	Skewness	Kurtosis	N
SIZE	22.328	1.054	21.600	22.195	22.904	0.712	3.659	24,378
B/P	0.371	0.251	0.194	0.304	0.478	1.463	5.244	24,207
E/P	0.025	0.035	0.010	0.022	0.038	-0.682	8.871	24,206
S/P	0.531	0.681	0.142	0.300	0.622	2.977	13.498	24,206
D/P	0.008	0.011	0.000	0.004	0.012	1.976	7.218	24,193
GP	0.137	0.093	0.075	0.116	0.175	1.384	5.326	24,072
OP	0.094	0.119	0.032	0.087	0.152	-0.031	5.243	24,072
ΔASSET	0.204	0.360	0.023	0.118	0.260	3.467	18.948	22,825
ΔBOOK	0.189	0.425	0.019	0.075	0.183	3.974	22.337	22,825
ACC	-0.007	0.094	-0.058	-0.013	0.035	0.717	5.602	20,217
NOA	0.699	0.302	0.540	0.698	0.842	0.837	6.878	21,827
VOL	0.030	0.010	0.023	0.028	0.036	0.844	3.120	23,752
BETA	1.089	0.232	0.946	1.099	1.244	-0.245	3.070	23,752
I-VOL	0.001	0.000	0.000	0.000	0.001	1.326	4.835	23,752
MOM	0.088	0.471	-0.229	0.036	0.368	0.406	3.202	277,168
REV-ST	0.006	0.133	-0.067	0.003	0.081	-0.038	3.944	283,536
REV-LT	0.347	0.803	-0.225	0.313	0.891	0.204	2.653	193,684

Table 5: Correlations across value-weighted A-shares factor strategies.

The table presents correlations among value-weighted factor returns associated with A-shares strategies given in Table 1, over the full sample period covering 1995-2016. The data necessary to construct ACC are only available as of 2000; REV-LT is available beginning in 1996.

	−SIZE	B/P	E/P	S/P	D/P	GP	OP	−ΔASSET	−ΔBOOK	−ACC	−NOA	−VOL	−BETA	−I-VOL	MOM	−REV-ST	−REV-LT
−SIZE	1.00	0.04	-0.86	-0.15	-0.52	0.13	-0.71	0.67	0.64	-0.67	-0.53	-0.10	-0.69	-0.25	-0.13	0.30	0.26
B/P		1.00	-0.01	0.46	0.54	-0.52	-0.33	0.41	0.41	0.39	0.39	0.06	0.41	-0.10	-0.44	-0.05	0.43
E/P			1.00	0.31	0.60	-0.03	0.74	-0.67	-0.67	0.71	0.54	0.15	0.65	0.29	0.15	-0.34	-0.12
S/P				1.00	0.47	0.07	0.14	0.02	0.06	0.24	0.15	-0.15	0.29	0.14	-0.20	-0.12	0.28
D/P					1.00	-0.23	0.21	-0.20	-0.23	0.73	0.57	0.11	0.70	0.04	-0.10	-0.21	0.16
GP						1.00	0.27	-0.15	-0.21	-0.28	-0.36	-0.07	-0.39	-0.03	0.42	0.03	-0.33
OP							1.00	-0.68	-0.66	0.44	0.28	0.11	0.37	0.27	0.30	-0.19	-0.38
−ΔASSET								1.00	0.82	-0.21	-0.15	0.02	-0.28	-0.25	-0.26	0.20	0.29
−ΔBOOK									1.00	-0.36	-0.23	-0.09	-0.31	-0.14	-0.35	0.27	0.42
−ACC										1.00	0.64	0.92	0.31	0.24	0.04	-0.26	0.05
−NOA											1.00	0.69	0.84	0.25	-0.03	-0.20	0.10
−VOL												1.00	0.35	0.17	0.11	-0.10	-0.01
−BETA													1.00	0.23	-0.15	-0.23	0.05
−I-VOL														1.00	-0.06	-0.15	0.30
MOM															1.00	-0.17	-0.24
−REV-ST																1.00	0.00
−REV-LT																	1.00

Table 6: Turnover for value-weighted A-shares factor strategies.

The table provides average annual two-way turnover for the long and short portfolios employed in the value-weighted factor strategies described in the text, over the full sample period covering 1995-2016, along with combined turnover associated with long-short factor strategies. The universe is made up of the largest 80% of stocks, by market capitalization. Due to data limitations, trading of ACC begins in 2000; REV-LT begins trading in 1996.

Predictor	Long Portfolio Turnover	Short Portfolio Turnover	Overall Turnover
−SIZE	41.8%	55.9%	97.7%
B/P	61.7%	58.3%	119.9%
E/P	73.1%	53.7%	126.9%
S/P	55.9%	44.7%	100.7%
D/P	75.9%	67.1%	143.0%
GP	44.9%	48.2%	93.0%
OP	62.6%	56.0%	118.6%
−ΔASSET	82.1%	84.0%	166.1%
−ΔBOOK	84.8%	84.8%	169.7%
−ACC	72.8%	79.0%	151.8%
−NOA	73.8%	45.8%	119.6%
−VOL	82.7%	73.5%	156.2%
−BETA	82.9%	74.2%	157.1%
−I-VOL	82.1%	70.2%	152.3%
MOM	554.2%	411.9%	966.1%
−REV-ST	1031.0%	1096.7%	2127.6%
−REV-LT	254.2%	368.0%	622.2%

Table 7: Momentum strategy returns for A-shares and U.S. equities over various formation and holding periods.

The table presents annualized mean returns to a momentum factor applied to Chinese and U.S. stocks, with *t*-statistics in parentheses. Specifically, we sort stocks according to past returns evaluated over various formation periods (ranging from J=1 month to J=12 months), long the top decile (past winners) and short the bottom decile (past losers) based on value weighting, and assess the performance of these long-short portfolios over various holding periods (from K=1 month to K=12 months). Positive returns indicate success for momentum, while negative returns imply that reversal is the correct strategy. In China, for each year during the 2008-2016 sample, we trade the 450 largest firms with listed A-shares; in the U.S., we evaluate strategy performance from 1965-2016, trading all stocks in CRSP. We indicate significance at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

J		A-shares					U.S.				
	K =	1	3	6	9	12	1	3	6	9	12
1	W-L	-19.7% **	-13.1% *	-22.2% ***	-8.4%	-12.0% *	-6.2% *	1.6%	2.2%	9.5% ***	2.2%
		(-2.10)	(-1.87)	(-2.98)	(-1.26)	(-1.79)	(-1.86)	(0.52)	(0.76)	(3.26)	(0.81)
3	W-L	-15.8%	-5.6%	-12.3%	-1.9%	-9.9%	3.6%	10.0% ***	10.4% ***	12.4% ***	9.0% ***
		(-1.62)	(-0.64)	(-1.54)	(-0.27)	(-1.40)	(0.97)	(2.82)	(3.02)	(3.58)	(2.61)
6	W-L	-19.3% **	-12.2%	-11.5%	-5.0%	-15.1% *	7.0% *	12.6% ***	13.8% ***	13.3% ***	10.7% ***
		(-2.00)	(-1.39)	(-1.32)	(-0.65)	(-1.85)	(1.69)	(3.22)	(3.80)	(3.64)	(3.07)
9	W-L	-15.4%	-13.8%	-16.5% *	-6.5%	-21.0% **	11.2% **	14.9% ***	16.1% ***	13.7% ***	9.9% ***
		(-1.53)	(-1.49)	(-1.84)	(-0.80)	(-2.34)	(2.55)	(3.57)	(4.07)	(3.65)	(2.62)
12	W-L	-18.4% *	-15.8% *	-25.2% ***	-9.3%	-20.9% **	16.0% ***	17.7% ***	15.5% ***	12.9% ***	10.1% ***
		(-1.93)	(-1.75)	(-2.84)	(-1.15)	(-2.30)	(3.59)	(4.34)	(4.03)	(3.31)	(2.75)
Years		2008-2016					1965-2016				

Table 8: A-shares accounting conservatism strategies over various samples around accounting reforms.

We report annualized equal-weighted (EW) and value-weighted (VW) mean returns for accounting conservatism factors in A-shares, as described in the text, with *t*-statistics in parentheses. Our universe consists of the largest 80% of stocks, by market capitalization. We provide results for the full sample over which we may calculate accruals, beginning in 2000, as well as before and after major Chinese accounting changes that took effect in 2007. We rebalance A-shares portfolios annually in May. We indicate significance at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

Factor	A-shares, before		A-shares, after		A-shares, full	
	H-L (EW)	H-L (VW)	H-L (EW)	H-L (VW)	H-L (EW)	H-L (VW)
Total accruals	5.6% *	5.9%	3.1%	4.2%	4.3% **	5.1%
	(1.72)	(1.19)	(1.20)	(0.82)	(2.10)	(1.41)
Total accruals, excluding loss firms	7.5% **	6.9%	3.4%	3.1%	5.4% **	4.9%
	(2.13)	(1.32)	(1.40)	(0.61)	(2.55)	(1.36)
Net operating assets	1.5%	2.9%	5.4% *	6.7%	3.7% **	4.9% *
	(0.74)	(1.03)	(1.86)	(1.59)	(2.02)	(1.92)
Years	2000-2007		2008-2016		2000-2016	

Table 9: Factor returns for A-shares under industry-neutral and SOE-neutral portfolio construction.

We report annualized equal-weighted (EW) and value-weighted (VW) mean returns for the A-shares factor strategies previously tested, including implementations under industry- and SOE-neutral portfolio construction, as described in the text, with t-statistics in parentheses. Our universe consists of the top 80% of stocks by market capitalization. We rebalance A-shares portfolios annually in May. We indicate significance at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

	Baseline results		Industry-neutral		SOE-neutral	
	H-L (EW)	H-L (VW)	H-L (EW)	H-L (VW)	H-L (EW)	H-L (VW)
−SIZE	23.9% ***	24.9% ***	23.0% ***	23.0% ***	23.0% ***	24.2% ***
	(3.24)	(2.76)	(3.04)	(2.82)	(3.30)	(2.92)
B/P	3.3%	2.3%	3.6%	3.5%	4.2%	4.1%
	(0.46)	(0.26)	(0.59)	(0.52)	(0.67)	(0.49)
E/P	-2.4%	-3.8%	-8.4%	-5.7%	-1.6%	-3.2%
	(-0.43)	(-0.49)	(-1.21)	(-0.72)	(-0.33)	(-0.45)
S/P	2.6%	2.4%	3.4%	6.2%	5.7%	3.9%
	(0.51)	(0.37)	(0.63)	(1.00)	(1.46)	(0.69)
D/P	-2.4%	-8.7%	-2.0%	-3.4%	-1.9%	-6.8%
	(-0.42)	(-1.03)	(-0.40)	(-0.55)	(-0.37)	(-0.98)
GP	3.2%	3.2%	3.3%	4.7%	1.6%	2.6%
	(0.63)	(0.50)	(0.75)	(0.99)	(0.35)	(0.45)
OP	-5.0%	-2.1%	-6.6% *	-3.2%	-5.0%	-2.5%
	(-1.39)	(-0.43)	(-1.72)	(-0.78)	(-1.34)	(-0.60)
−ΔASSET	3.7%	8.7% *	2.1%	4.5%	5.6% *	8.9% **
	(1.20)	(1.95)	(0.53)	(1.04)	(1.83)	(2.01)
−ΔBOOK	4.5% *	8.9% **	3.5%	4.1%	5.5% **	9.1% **
	(1.74)	(2.02)	(0.94)	(0.88)	(2.29)	(2.16)
−ACC	3.1%	4.2%	0.0%	0.8%	2.7%	4.9%
	(1.20)	(0.82)	(0.00)	(0.17)	(0.96)	(1.05)
−NOA	5.4% *	6.7%	3.1%	5.6%	7.0% **	7.4% **
	(1.86)	(1.59)	(0.95)	(1.36)	(2.45)	(2.00)
−VOL	2.8%	-0.6%	3.5%	3.1%	5.3%	2.3%
	(0.38)	(-0.07)	(0.49)	(0.39)	(0.78)	(0.27)
−BETA	4.4%	3.2%	-0.1%	2.9%	3.9%	3.2%
	(0.64)	(0.37)	(-0.01)	(0.39)	(0.58)	(0.40)
−I-VOL	1.4%	-0.7%	4.1%	4.3%	4.9%	2.6%
	(0.20)	(-0.08)	(0.58)	(0.53)	(0.78)	(0.30)
MOM	-8.5%	-11.7%	-11.6% *	-11.9%	-10.5% *	-11.4%
	(-1.35)	(-1.46)	(-1.94)	(-1.64)	(-1.77)	(-1.51)
−REV-ST	21.9% ***	23.0% ***	21.8% ***	26.7% ***	23.1% ***	26.0% ***
	(3.88)	(2.90)	(3.60)	(4.10)	(4.30)	(3.67)
−REV-LT	5.9%	7.9%	8.3% *	9.3% *	6.8%	9.4% *
	(1.20)	(1.36)	(1.67)	(1.69)	(1.52)	(1.76)
Years	2008-2016		2008-2016		2008-2016	