The Real Value of China's Stock Market*

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Abstract

Counter to common perception, stock prices in China are strongly linked to firm fundamentals. Since the reforms of the early 2000s, stock prices are as informative about future profits as they are in the US. Moreover, although the market is segmented from international markets, Chinese investors price individual stock characteristics much like other global investors: they pay up for size, liquidity, and long shots. Chinese investors even discount for market risk. Post-crisis, SOEs have lower price informativeness and lower returns than privately-owned firms. For international investors who can access it, China's stock market has offered high returns and low correlation with other equity markets. We conclude that this market is functioning as efficiently as equity markets in other large economies and has the potential to play an important role in capital allocation.

JEL Codes: E44, F30, G12, G14, G15, O16, O53, P21, P34.

Keywords: capital allocation, price informativeness, market integration, global investing.

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Abstract

Counter to common perception, stock prices in China are strongly linked to firm fundamentals. Since the reforms of the early 2000s, stock prices are as informative about future profits as they are in the US. Moreover, although the market is segmented from international markets, Chinese investors price individual stock characteristics much like other global investors: they pay up for size, liquidity, and long shots. Chinese investors even discount for market risk. Post-crisis, SOEs have lower price informativeness and lower returns than privately-owned firms. For international investors who can access it, China's stock market has offered high returns and low correlation with other equity markets. We conclude that this market is functioning as efficiently as equity markets in other large economies and has the potential to play an important role in capital allocation.

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1 Introduction

Despite its rapid growth in listings and market capitalization, China's stock market retains its reputation as a casino, dominated by retail investors and subject to frequent regulatory interventions and significant restrictions on the tradability of shares.[1] Researchers and journalists emphasize the low correlation between China's stock market and its GDP.[2] The market's high volatility erodes buy-and-hold returns and further fuels the perception of dysfunction and poor performance. Repeated market interventions, trading halts, and IPO suspensions reflect low confidence in the market by regulators as well. Most recently, Deng and Wei (2018) report that regulators have "tightened standards on IPOs" reducing corporate financing by stock sales to only "5% of total new financing, compared with bank loans that made up 73% in 2017."

This paper analyzes the link between China's stock prices and firm fundamentals and shows that the perception of poor quality stock prices is no longer correct. We find that since the wave of market reforms that started almost two decades ago, stock prices in China have become as informative about future firm profits as they are in the US. In addition, although the market is still largely segmented from the rest of the global financial market, the pricing of these profits is consistent with that in other large economies. Like other global investors, Chinese investors pay up for large stocks, growth stocks, liquid stocks, and long shots. Chinese investors even discount for market risk. Thus, stock prices are linked to firm fundamentals through both cash flows and discount rates.

These results have important implications for the real economy. First, a large literature in economics links the informativeness of prices about future profits to managerial decision-making and corporate investment efficiency. The fact that stock prices in China contain as much information as those in the US suggests that China's stock market may be generating useful signals for managers and greater reliance on this market might improve capital allocation efficiency.

Second, our results suggest that global investors may be overly skeptical of China's stock market. China represents over 10% of the global stock market, but foreign participation has been very low, with foreign investor quotas unfilled. Although fears of repatriation risk, trading suspensions, and administrative costs have been clearly articulated, a quantitative assessment of the opportunity cost of underweighting China in portfolio allocation has been missing from the debate. We provide evidence that China's stock market has offered global investors both high average monthly returns and low correlation with other global stock

[1] The "casino theory" of China's stock market was first proposed by a well-known Chinese economist Wu Jinglian in 2001. More recently, The Economist (2015) dubbed China's stock market "a crazy casino."

[2] See, for example, Allen, Qian, Shan, and Zhu (2017) or the Wall Street Journal MoneyBeat (2015).

markets, yielding risk-adjusted excess returns of 1% per month. These high returns are plausible given the high market volatility that must be borne almost entirely by domestic Chinese who have little opportunity to diversify internationally. However, they represent an inflated cost of capital for Chinese firms and a potential drag on economic growth.

Until recently, China's stock market has been a side experiment in a financial system that is dominated by a $35-trillion banking sector which finances centrally planned investment and is supplemented by alternative financing channels which leverage China's relationship-based credit enforcement mechanisms (Allen, Qian, and Qian, 2005). Now with over 3500 firms listed and $7.5 trillion in market capitalization as of July 2018, and yet still extremely volatile, the stock market has become a focus of attention by international investors and regulators. Our results suggest that despite the underdevelopment of markets for equity mutual funds and derivatives, frequent government interventions, and a highly volatile economic environment, the stock market is successfully aggregating information about future corporate profits and pricing profits consistently, thus potentially improving the efficiency of capital allocation.

The implications of our results for the global economy are far reaching. China is the world's largest investor and greatest contributor to economic growth, so the efficiency of its investment and its role in sustaining global growth are of broad importance. Even in a political economy where the banking sector must remain dominant, the stock market has a critical complementary role to play, by aggregating diffuse information and generating signals that can be useful to regulators as well as to corporate managers and global investors. It is also a natural entry point and allocation channel for foreign capital. Finally, the stock market is an important exit point for private equity investment, and thus a key component of China's innovation strategy.

Figure 1 summarizes the history of listings, market capitalization, and ownership structure in the stock market.[3] The Main Boards were opened in Shanghai and Shenzhen in 1991 under the leadership of Deng Xiaoping as a platform for SOE privatization and reform. Privatization was gradual, with two-thirds of shares non-tradable until the Split-Share Structure Reform of 2005 established a market-based negotiation process to facilitate share unlock and compensate tradable shareholders for any adverse price effects. The SME and ChiNext Boards were opened in Shenzhen in 2004 and 2009 with more relaxed listing standards to accommodate small and medium enterprises, and even smaller entrepreneurial firms, with much less state ownership and control. As Figure 1 shows, the tradable fraction of the market grew steadily after these innovations, representing 76% of total market capitalization in

[3]See Carpenter and Whitelaw (2017) for a more detailed discussion of the development of China's stock market, the potential implications for the real economy, and a survey of the relevant literature.

2016. The mutual fund industry started in 1998 but is still small despite regulatory efforts to promote its growth. Equity and hybrid mutual funds still hold less than 10% of the tradable portion of China's stock market. The China Securities Regulatory Commission (CSRC) consistently reports that individual investors account for 80% of total trading volume or more (see SINA (2013)).

The stock market has a number of other distinctive features as well. The IPO process is tightly controlled by the CSRC, and IPOs were suspended altogether during 2005 and 2013. Delistings are rare. Instead firms go into regulatory "special treatment," but are then often taken over by private firms seeking a public listing. The market is held almost entirely by domestic Chinese investors. The CSRC ratified the Qualified Foreign Institutional Investors (QFII) program in 2002 and approved the Shanghai-Hong Kong Connect program in 2014 and the Shenzhen Hong-Kong Connect program in 2016. However quotas in these programs have never been filled. Total foreign ownership still amounts to less than $200 billion. Stock price movements are capped at 10% per day, after which trading in the affected stock is automatically suspended. Firms can also suspend the trading of their stock almost indefinitely. Short selling has been legal since 2006, but is often difficult to implement in practice. On the other hand, the market is a centralized, pure-order driven forum, with all orders visible, and no extended trading period for institutional investors, so institutional and retail investors have equal access to information from a microstructure point of view.

The paper begins by analyzing the informativeness of China's stock market about future corporate profits over the period 1995 to 2016, using stock price and accounting data on A shares for all firms in the China Stock Market and Accounting Research (CSMAR) database. This is augmented with holdings data from Wind Information Inc. (WIND). Following Bai, Philippon, and Savov (2016), we define the price informativeness of the stock market as the cross-sectional variation in future earnings predicted by equity market value. We find that the informativeness of prices has steadily improved since the establishment of market reforms around the time of China's entry into the WTO and is now the same as that in the US. We conduct several robustness checks and relate the trends in the price informativeness to China's legal, market, and accounting regimes since 1995.

We also study cross-sectional variation in price informativeness associated with three variables that are of particular interest in China: the extent of state-ownership, the existence of dual-listed H shares trading in Hong Kong, and the amount of holdings by foreign institutional investors under the QFII program. Firms with higher state ownership have lower stock price informativeness, but only after the post-crisis stimulus, consistent with the idea that the political risk associated with large state subsidies makes earnings harder to predict. We also find that firms with H shares dual-listed and priced in Hong Kong have lower stock price informativeness, perhaps because shocks to Hong Kong discount rates leak into the A-share prices of dual-listed stocks and create variation unrelated to earnings. Finally, the presence of QFII investors is weakly positively associated with stock price informativeness. This could be due to their stock selection processes rather than a causal effect.

Having established a strong link between current prices and future profits, we then study cross-sectional patterns in returns to show how investors account for firm-specific variables in the discounting of those profits. We find that, although the stock market is largely segmented from other international equity markets, Chinese investors price stocks remarkably like investors in other large economies. This evidence extends previous studies with shorter sample periods and further establishes a strong link between stock prices and firm fundamentals in China. There is also evidence that China-specific firm characteristics predict future returns in the cross-section. In the same post-crisis period in which state ownership is negatively correlated with stock price informativeness, state ownership also negatively predicts future returns, perhaps because state subsidies serve to insulate firms from negative shocks and hence reduce risk. QFII ownership positively predicts returns. The natural interpretation is that these foreign institutions have superior forecasting ability rather than that they generate risk for which investors must be compensated.

Finally, we look at China's stock market from the viewpoint of international equity investors. Our evidence on the quality of equity pricing in China suggests that international investors may be overly cautious about investing in China. We provide additional evidence in support of this view by summarizing the USD returns of China's stock market in terms of traditional performance measures. We show that China's stock market not only offers high average monthly returns compared with stock markets in other large economies, but also exhibits low correlation with these markets. In particular, this market delivered a four-factor alpha for USD investors of 1% per month during the period 1995-2016. We conclude with a brief discussion of the policy implications of our analysis.

2 Stock price informativeness about future profits

This section analyzes the quality of stock prices in China by examining their informativeness about future firm profits. Section 3 examines the cross-section of returns and shows that Chinese investors price stock characteristics much like investors in other large economies. Taken together, these results show that stock prices in China are strongly linked to firm fundamentals.

A long literature in economics, finance, and accounting going back to Hayek (1945) and Fama (1970) links good legal and market institutions to stock price informativeness about future profits, and further to the efficiency of capital allocation and corporate investment. Elements of this nexus include the benefits of effective listing, disclosure, and auditing policy (Amihud and Mendelson, 1988; Diamond and Verrecchia, 1991; Healy and Palepu, 2001; Hail and Leuz, 2009), aggregation of diffuse information across individuals, incentives to generate information, and its inference from prices (Grossman and Stiglitz, 1980; Glosten and Milgrom, 1985; Kyle, 1985), and managerial use of price signals in resource allocation and investment decisions (Wurgler, 2000; Baker, Stein, and Wurgler, 2003; Durnev, Morck, and Yeung, 2004; Chari and Henry, 2004; Chen, Goldstein, and Jiang, 2007; Bakke and Whited, 2010). Bond, Edmans, and Goldstein (2012) provide a detailed review.

Bai et al. (2016) develop a model in which stock price informativeness promotes efficient allocation of corporate investment and economic growth. They define price informativeness as the extent to which market valuations differentiate firms that will have high profits from those that will not. Empirically, they measure price informativeness in a given year t as the predicted variation, $b_t \times \sigma_t(\log(M/A))$, in the following cross-sectional regression of earnings k years ahead on current market equity value and current earnings, normalized by book asset value,

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k} \ , \tag{1}$$

where the $1_{i,t}^s$ are sector indicators to control for industry effects. They use this model to study the trend of stock price informativeness in the US.

Other authors have developed different measures of price informativeness. Morck, Yeung, and Yu (2000) inspired a strand of literature that uses the R^2 from a market model, and other measures of stock price synchronicity, as inverse measures of the degree of stock-specific information in prices. As these authors acknowledge, this measure is problematic for cross-country comparisons when market-level volatility differs across countries, making a stock's idiosyncratic variance a more robust measure than R^2. In addition, as originally emphasized by Roll (1988), even this idiosyncratic variance is generated by both news and noise, and thus, as Hou, Peng, and Xiong (2013) demonstrate, it is also problematic as a measure of price informativeness. More recently, working in a Grossman and Stiglitz (1980) framework, Dávila and Parlatore (2017) and Dávila and Parlatore (2018) define price informativeness as the precision of the unbiased signal of the asset payoff contained in the asset price from the perspective of an external observer. Distinguishing price variance attributable to news from that attributable to noise, Dávila and Parlatore (2018) address the question of whether equilibrium price informativeness is positively related to equilibrium price variance and find that under certain parameterizations it is.

Because of the potentially confounding effect of noise in idiosyncratic return variance and Morck R^2, we prefer the more direct measure of price informativeness proposed by Bai et al. (2016), which is the most relevant for the role of stock prices in capital allocation. Farboodi, Matray, and Veldkamp (2017) also adopt the Bai-Phillipon-Savov measure to study the effect of increased data availability and processing power on price informativeness, and Kacperczyk, Sundaresan, and Wang (2018) use it to study the impact of foreign investors on market efficiency.

We take the model of Bai et al. (2016) to the data on earnings, equity market value, and asset book value from the China Stock Market and Accounting Research (CSMAR) database from 1995 to 2016. For the earnings variable $E_{i,t}$, we use the net profit reported for firm i earned over calendar year t. For equity market capitalization $M_{i,t}$, we multiply firm i's A-share price at the end of year t by the total number of shares outstanding, including tradable A, B, and H shares and nontradable shares. As in Bai et al. (2016), we deflate all nominal quantities by the GDP deflator. We winsorize all variables at the first and ninety-ninth percentiles. To control for industry effects, we construct a version of the 1-digit SIC classification from CSMAR's industrial code B. We also eliminate financial firms from the sample, although this makes little difference to the results. A few papers in the accounting literature document low quality of auditing and reported earnings in China (DeFond, Wong, and Li, 1999; Chen and Yuan, 2004; Wang, Wong, and Xia, 2008). Such errors should bias our results against finding price informativeness.

2.1 Baseline results

Figure 2 plots the estimates of the coefficient b_t from regression (1) with their 95% confidence bands, the predicted variation $|b_t| \times \sigma_t(\log(M/A))$, and the marginal R^2 for forecasting periods $k = 1, 3$, and 5, for each year $t = 1995$ to $2016 - k$. The confidence bands use White heteroskedasticity-consistent standard errors.[4] Marginal R^2 is the increment in the R^2 of regression (1) created by adding $\log(\frac{M_{i,t}}{A_{i,t}})$ as a regressor. The different price informativeness measures have broadly similar patterns. The coefficients and their corresponding t-statistics are also reported in the top panel of Table 1. From approximately 2003 onwards, the coefficients at all horizons are statistically significant, with t-statistics exceeding 4 in every year. Moreover, the patterns across forecasting horizons are similar, with a marked increase in the coefficient, particularly at the longer horizons, from the late 1990s to a relatively sustained level in the later years.

The bottom panel of Table 1 reports the time-series average of the price informativeness coefficient for forecasting horizons $k = 1$ to 5, and Figure 3 plots these averages vs. k. As

[4]We also calculated standard errors clustered by industry, with qualitatively similar results.

Bai et al. (2016) find for the US, the coefficient increases with forecasting horizon. This may be because more distant earnings realizations are better proxies for the earnings stream capitalized in market value, particularly in China where growth rates are high.

2.1.1 Robustness checks

There are two potentially related concerns about the results reported in Table 1 and Figures 2 and 3. The first is about composition effects over time. In the US market, Bai et al. (2016) report significant time-variation in price informativeness associated with a composition effect, which is why the vast majority of their analysis focuses only on firms in the S&P500 that do not exhibit this composition effect. As they document in Appendix C, in the full cross-section of listed firms, there is a dramatic increase in the cross-sectional dispersion in earnings, as measured by the cross-sectional standard deviation of $E_{i,t+k}/A_{i,t}$, and in the cross-sectional dispersion in valuations, as measured by the cross-sectional standard deviation of $\log(\frac{M_{i,t}}{A_{i,t}})$ (see Table C1 and Figure C1 in their paper). This increase in cross-sectional dispersion apparently causes a decrease in price informativeness over time. A natural question is whether composition effects underly the time-variation in price informativeness that we document, especially given that the number of firms in our sample increases dramatically over our sample period, as documented in Figure 1.

To address this question, Figure 4 plots the time series of the cross-sectional dispersion of earnings and valuations for our China sample. The top plot shows the cross-sectional median and the 10th and 90th percentiles of earnings, $E_{i,t+1}/A_{i,t}$. The bottom plot shows the same cross-sectional statistics for valuations, $\log(\frac{M_{i,t}}{A_{i,t}})$. There is some evidence of an increase in the cross-sectional dispersion of earnings, particularly in the lower tail of the distribution, in the early to mid 2000s. This time period also coincides with lower price informativeness, as shown in Figure 2, and a period when there were significant concerns about the quality of accounting reports, to be discussed in the next section. However, the period of significantly positive and relatively stable price informativeness that begins in 2003 coincides with a similarly stable period of earnings dispersion. In other words, there is no evidence that the more than doubling in the number of firms in our sample from 2003 onwards has any meaningful effect on either the dispersion of earnings or price informativeness. While there is dramatic variation in the level of valuations in China, which is hardly surprising given the volatility of prices at the market level and the stability of asset values, there is little evidence of large changes in the cross-sectional dispersion. In general, the median, and the 10th and 90th percentiles move together over time, with a slight indication of an increase in dispersion in the latter part of the sample. To summarize, there is no evidence that the post-2003 price informativeness measures are significantly influenced by a composition effect.

The second concern is that institutional features specific to China's stock market are somehow influencing our results and obscuring the interpretation of the measure of price informativeness. We conduct a number of robustness checks to allay these concerns, and turn to a more detailed analysis of how certain features of Chinese firms affect their stock price informativeness in Section 2.3. One key feature of China's stock markets is that the listing process is tightly controlled by the CSRC, with stringent listing requirements, and often a very long waiting list of firms that want to go public. The CSRC has also closed the IPO market, often for long periods of time, at various points in the past, partly in response to perceived weakness in the market (Cong, Howell, and Zhang (2017)). One result of this limitation on going public is that the value of a public listing itself may be substantial. This listing value could be a significant fraction of the market value of the smallest companies because these companies are potentially the targets of reverse mergers in which private companies merge with these listed firms in order to achieve publicly listed status without having to go through the IPO process (Lee, Qu, and Shen (2017)). If so, this value associated with the potential to be used as a shell in a reverse merger could increase the valuation ratio we use in our price informativeness regression, making these values less predictive of future earnings.

In their examination of the size and value effects in China, Liu, Stambaugh, and Yuan (2018) suggest excluding the smallest 30% of firms by market capitalization from the analysis because 83% of reverse mergers in their sample come from these three deciles, and we follow this suggestion. More than half of reverse mergers come from the bottom decile alone, so we also conduct an analysis with the only smallest 10% of stock excluded. For brevity, we do not report the full time series of coefficients at the various horizons for these robustness checks, but the bottom panel of Table 1 reports the average coefficients over time for all five horizons for subsamples with the smallest 10% and 30% of stocks removed. Comparing these averages to those for the full sample in Table 1 shows that eliminating these stocks has almost no effect whatsoever on the average coefficients. The year-by-year effects are also economically very small. This invariance to excluding small stocks may be surprising, but there are a number of mitigating factors. There are only 133 reverse mergers in the 10-year sample period, 2007-2016, used in Liu et al. (2018), an average of barely more than 11 per year. Perhaps shell value is not that important economically. However, one might speculate that the prices of small firms, in general, would be less informative. Our results suggest that this is not the case in China, but this result needs to be considered in light of the fact that the tight regulation of IPOs has the effect of truncating the left tail of the size distribution of Chinese firms, a point we will return to later when we look at the cross-section of expected returns. Regardless, the absence of a small-firm effect in price informativeness lends additional support to the argument that composition effects, especially those associated with the opening of the Shenzhen SME and ChiNext boards are not driving our results.

A second feature of China's stock market is the existence of so-called "special treatment" firms. In general, these are firms that are in danger of delisting due to periods of negative earnings, although delistings for this reason are extremely rare, in part due to the shell value of a public listing discussed above. There are several different categories of special treatment, but in addition to poor performance, these firms all have in common the fact that their daily price moves are restricted to a maximum of 5% in each direction relative to the standard price move limit of 10%. For various reasons, it is possible that these special treatment firms are unusual and have differential price informativeness. We exclude all special treatment firms and run the same price informativeness regression, with the results reported in the bottom panel of Table 1. As with our size screens, special treatment firms do not appear to be having an economically significant effect on our overall results. Given the robustness of the baseline full sample results, we continue to use the full sample of nonfinancial firms in the rest of our analysis.

2.1.2 Historical context

Finally, we consider the time-series pattern of the baseline stock price informativeness in the context of the progression of regulatory reforms that took place in China during our sample period. Figure 5 plots the time series of price informativeness as measured by predicted variation for $k = 3$ in the context of the regulatory reforms and relevant stock market news events taking place in China over the sample period. The early years were a time of market construction and transition from a decentralized and disorganized stock market to a centralized modern market. In 1996, Dow Jones began to publish the China, Shanghai 30, and Shenzhen indices, which attracted a significant following by equity analysts. In addition, the exchanges unified limit-order books and greatly reduced trading commissions, which increased liquidity. Chordia, Roll, and Subrahmanyam (2008) show theoretically that increasing liquidity improves market efficiency and informativeness, which suggests that these developments contributed to the rise of informativeness in China's stock market over this period. The adoption of a price change limit of 10% and a one-day minimum holding period in 1996 may also have deterred stock price manipulation, as suggested by Kim and Park (2010). In 1997, the CSRC became the official regulator of China's stock market.

The years from 1998 to 2002 were a low point in price informativeness. By many accounts, this was a period of rampant speculation, accounting fraud, and stock price manipulation. In 1998, prices of firms in special treatment for financial distress began to soar and the CSRC reported widespread market manipulation. Pump-and-dump schemes were also common during this period. This may be consistent with theory in Goldstein, Ozdenoren, and Yuan (2013) showing that undesirable coordination across speculators makes the market less informative, decreases real investment, and increases stock market volatility. In early 2000, the first stock traded above 100 RMB, an important cognitive benchmark, and this sparked an investigation by the CSRC, which revealed serious accounting fraud. Later that year several other major accounting scandals came to light. In 2001, a well-known Chinese financial economist Wu Jinglian proposed the "casino theory" of China's stock market, suggesting that China's equity market had failed to fulfill its capital allocation function, and merely provided a platform for insiders and speculators to profit illegally at the expense of retail investors and minority shareholders whose interests were unprotected.

But the turn of the century ushered in a wave of significant reforms, lead by China's entry into the World Trade Organization (WTO) and marked by improvements in regulatory protection of minority shareholders, increases in accounting transparency and audit quality, privatization of state-owned enterprises, and the increase of foreign investors' direct investment in the A-share market. Gul, Kim, and Qiu (2010) show that stock price synchronicity in China significantly declined with the increase in foreign shareholding, audit quality, and the decrease of ownership concentration. At the end of year 2001, the CSRC enforced new and stricter delisting regulations to protect retail investor interests. In 2002, the CSRC ratified the QFII program, enabling qualified foreign institutional investors to invest in A shares directly. The first two foreign institutional investors were the Nomura and UBS open-end mutual funds. In 2004, the CSRC established the National Nine Rules to protect minority shareholder interests, deter stock price manipulation, and deter accounting and audit fraud.

In 2005, the CSRC introduced the Split Share Structure Reform to unlock nontradable shares gradually and privatize them through a firm-by-firm negotiation process that compensated the holders of tradable shares. The results plotted in Figure 5 suggest that this expansion and diversification of the base of market participants may have further boosted the informativeness of stock prices. Liao, Liu, and Wang (2011) and Li, Wang, Cheung, and Jiang (2011) study this reform in depth and document the improvements in information discovery and risk sharing it enabled. In 2006, the Shanghai and Shenzhen Stock Exchanges introduced margin trading and short selling pilot programs, which expanded gradually in the subsequent years. In a study of 46 countries, Bris, Goetzmann, and Zhu (2007) find evidence that allowing short sales permits prices to incorporate negative information more quickly. More recently, Ljungqvist and Qian (2014) document a direct mechanism through which the possibility of short sales gives arbitrageurs an incentive to incorporate negative information into prices. The combination of regulatory reforms, capital market development, an expanding investor base, improving accounting and auditing quality, and foreign investors' direct participation in the market may all have helped to boost price informativeness in China's stock market during this period. The final years, from 2007, are those of the financial crisis and subsequent reconstruction, during which price informativeness declined somewhat. The crisis could have depressed realized price informativeness for at least two reasons, one, because it precipitated extreme realizations from the distribution of earnings, and two, because it lead to some dislocation and mistrust of capital markets, which did in fact undermine the informativeness of prices.

2.2 Comparison to stock price informativeness in the US

Table 2 and Figure 6 compare stock price informativeness coefficients in China with those in the US over the same period for forecasting horizons $k = 3$ and 5 years.[5] We test formally for differences in the coefficients using the estimates of their standard errors from the cross-sectional regressions in each country and assuming independence of the coefficients across the two countries. The columns labeled "p-value" report the probability level in percent at which the null hypothesis that the coefficients in the US and China are equal can be rejected in favor of the alternative hypothesis that the US coefficient is greater. In other words, a p-value of 50% corresponds to a year in which the US and China price informativeness coefficients are equal, and p-values greater than 50% are in years in which the China coefficient is greater than the US coefficient. Counter to conventional wisdom, stock prices in China have become as informative about future profits as they are in the US. From 2004 onwards, all 14 of the p-values exceed the conservative threshold level of 10%, and there are 6 times in which the p-value exceeds 90%, i.e., observations for which the null hypothesis of equality can be rejected in favor of the alternative that price informativeness in China is greater than in the US at the 10% level.

Figure 6 provides visual confirmation of this result. The dotted line shows the highest China price informativeness level for which the hypothesis that price informativeness in China is as high as in the US can be rejected at the 10% level in a one-sided test. Stock price informativeness in China easily clears this conservatively high hurdle, i.e., we cannot reject the hypothesis that China's informativeness is as high as that in the US, in all years since 2003 for horizons $k = 3$ and $k = 5$. In many years China's stock price informativeness coefficient even exceeds that of the US.

Table 2 and Figure 6 compare the magnitudes of the coefficients from equation (1) in China and the US over time. A potential concern is that if the cross-sectional standard

[5] Many thanks to Alexi Savov for providing us with the US results. The US results shown here are slightly different from those reported in Bai et al. (2016) because of small methodological differences, such as the use of net income instead of EBIT, which is more comparable across the two countries.

deviation of the market value regressor, $\sigma_t(\log(M/A))$, is different in the US than in China, then a comparison of the predicted variations, $b_t \times \sigma_t(\log(M/A))$ in the US and China could yield different implications than a comparison of the regression coefficients, b_t. However, the plot of the cross-sectional dispersion of market valuations in Figure 4 is very similar to the corresponding plot in Panel A of Figure 1 in Bai et al. (2016) for the US from 2003 onwards. In particular, in this latest period, the average difference between the 10th and 90th percentiles of valuations in China is 2.0, which is very close to the corresponding value over the same period for the US. We conclude that comparing price informativeness regression coefficients across between China and the US is a reasonable approach.

2.3 Cross-sectional variation in stock price informativeness

This section examines China-specific firm characteristics that might explain cross-sectional variation in price informativeness. Given the importance of China's economy and markets, understanding more about the efficiency of China's stock market is of interest in its own right. In addition, given that increasing price informativeness might improve capital allocation and economic growth, this examination may have important policy implications. We focus on three variables that are of particular interest in China: the extent of state ownership, whether the firm is dual-listed in Hong Kong, and the extent of foreign ownership under the QFII program.

As illustrated in Panel B of Figure 1, prior to the Split Share Structure Reform of 2005, state ownership was large and heavily concentrated in non-tradable shares. Subsequent to the 2005 reform, large numbers of these shares became tradable. However, the effect of the reform on the extent of state ownership depends on whether state entities sold or retained their shares, which the data from CSMAR do not indicate. To measure state ownership after the 2005 reform, we turn to holdings data from the WIND database and aggregate the number of shares held by the top ten holders that are state entities. These data include holdings of both tradable and non-tradable shares, and WIND records whether a specific holder is a state-owned entity. For years prior to the 2005 reform, we use the non-tradable state-owned share data from CSMAR, which we believe is a good proxy for total state ownership.

Figure 7 plots some descriptive statistics for our state ownership variable. Specifically, we plot the mean, median, and 10th percentile of state ownership in the cross-section at the beginning of each year. Through 2005, mean and median state ownership are stable at between 30% and 40%. These numbers are lower than the state ownership of closer to 75% shown in Figure 1 because these latter numbers are computed on a value-weighted basis.

Pursuant to Deng Xiaoping's privatization guideline to "grasp the large and let go of the small," state ownership is much higher in large firms than in small firms. These large firms are reflected better by the 90th percentile of state ownership which hovers below 70%.

After the 2005 reform, there is a dramatic change in state ownership. Mean ownership falls to less than 20% by the end of the sample, and median ownership falls close to zero. Clearly, the state is selling its stakes in the smallest firms and the distribution is becoming much more right skewed. This skewness is evident in the 90th percentile, which drops much less than the median and remains above 50%. In other words, the state is holding on to its ownership and control in the small number of large companies that it thinks are most strategically and economically important, such as the large banks and energy companies.

State ownership could affect price informativeness in any number of ways. State support of state-owned firms, either direct or in the form of access to cheap capital through state-owned banks, could be unpredictable and thus lead to unpredictable profits. Alternatively, state support might serve to smooth out profit fluctuations associated with broader economic fluctuations. Additional considerations are the structural break in the distribution of state ownership around the Split Share Structure Reform, and the possible structural break in state support associated with the unprecedented economic stimulus following the financial crisis.

The second firm characteristic is a dummy variable that indicates whether a stock that is traded as an A share on the Shanghai or Shenzhen exchange also has a twin H share with identical cash flow and voting rights dual-listed in Hong Kong and traded in HKD. Dual listing of Chinese firms is only allowed in Hong Kong and there are now close to 100 such firms. In some cases the firms listed in China first, in some cases in Hong Kong first, and in some cases the listings were almost simultaneous. Dual listings are of particular interest in the case of Chinese stocks because, due to the effective legal segmentation between the Chinese and Hong Kong markets for much of our sample, these stocks are traded and owned by very different investor clienteles. This segmentation is evidenced by violations of the law of one price across the two markets, wherein the shares in China trade at a substantial average premium relative to their Hong Kong counterparts.[6] In terms of price informativeness, one might hypothesize that sophisticated international investors who can trade in Hong Kong might cause these prices to reveal incremental information about future profitability, thus making the prices in China also more informative.

The third firm characteristic we introduce is the extent of ownership by foreign institutional investors under the QFII program. This program was initiated in 2002, and ownership numbers are small throughout the sample, with the cross-sectional average ownership never

[6]Carpenter and Whitelaw (2017) report a median ratio of A share price to H share of over 1.5 in 2016.

exceeding 0.2%. Not surprisingly, this ownership is concentrated in a relatively small number of stocks, with even the 75th percentile of the cross-sectional distribution equal to zero in every year. These data are also from the WIND database, which records the QFII ownership for every stock. Given that the level of QFII ownership is very small, it is unlikely that the trading of these investors directly affects prices. However, it could be that these investors identify and hold stocks whose prices are more informative, perhaps because these same stocks have other attractive characteristics such as higher transparency or better governance.

To study the cross-sectional variation in stock price informativeness in China, we estimate interaction effects of the firm characteristic of interest with the stock price regressor $\log(\frac{M_{i,t}}{A_{i,t}})$ in two different specifications. The first specification is a simple extension of regression (1):

$$\frac{E_{i,t+k}}{A_{i,t}} = a_{0t} + a_{1t}X_{i,t} + (b_{0t} + b_{1t}X_{i,t})\log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k} \ , \tag{2}$$

for $k = 1$ to 5, where $X_{i,t}$ is the firm characteristic, e.g., the percentage of state ownership, and b_{1t} is the coefficient on the interaction term, e.g., the extent to which state ownership affects price informativeness.

The challenge with this specification is that it estimates a different effect each year, and there is likely not enough cross-sectional variation in dual-listing or QFII ownership to identify this effect well. Consequently, we also estimate a panel regression version of regression (1), with a constant interaction coefficient across years, but with year dummies to allow the coefficients in the basic regression to continue to vary across years. Specifically, we estimate panel regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_{0t} + a_{1t}X_{i,t} + (b_{0t} + b_1 X_{i,t})\log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k} \ , \tag{3}$$

for $k = 1$ to 5, where the time subscripts on the basic coefficients $a_{0t}, a_{1t}, b_{0t}, c_t$, and d_t^s are a shorthand to indicate that year dummies are incorporated to allow these coefficients to vary across time. We estimate only a constant average dual-listing or QFII effect across time to increase power.

Table 3 reports the estimates of the interaction coefficient b_{1t} and their t-statistics for each year and horizons $k = 1$, 3 and 5 for the state ownership variable. Through the year 2008, there is no clear pattern, with sporadically significant t-statistics and coefficients of differing sign both across horizons and over time. These patterns are consistent with sampling variation, and they show no systematic effect of state ownership on price informativeness. In contrast, starting in 2009, 13 of the 15 coefficients are negative, and 11 of the 15 are significant at conventional significance levels, with t-statistics exceeding 3 in magnitude in 8 cases. At the more informative horizons of 3 and 5 years, all the coefficients are negative and statistically significant. From 2009 onwards, the results strongly suggest a negative effect of state ownership on price informativeness. In terms of economic significance, the coefficient at the 5-year horizon is in the range -0.1 to -0.2, implying that state ownership of 50% decreases the price informativeness coefficient by 0.05 to 0.10 relative to a firm that is completely privately owned. These changes are relative to a baseline coefficient of 0.07 to 0.11 in the same years, as reported in Table 1. Taking into account the slope coefficient on the valuation ratio, b_{0t}, private firms have a total price informativeness coefficient of 0.161 at the 5-year horizon in 2011, relative to 0.064 for a firm with 50% state ownership. In other words, the prices of these state-owned firms are 60% less informative about future profits. Given that this negative effect of state ownership emerges in prices primarily in 2009 and later, it is natural to attribute it to the massive stimulus program that the Chinese government undertook after the financial crisis. As documented by Chen, He, and Liu (2017), four trillion yuan was initially funneled through the state-owned banks, often to other state-owned firms, to stimulate investment. It is easy to imagine that the effects on the profits of these firms was difficult to anticipate. This negative effect of state ownership on price informativeness may explain the overall decline in price informativeness documented in Figure 5. It would be interesting to see if the effect of state ownership on price informativeness disappears as the stimulus and its effects wane in the coming years.

For the panel regressions, the coefficients b_1 and their t-statistics for forecasting horizons $k = 1$ to 5 are reported in the Table 4. The top panel shows the results for dual listing of H shares, while the bottom panel shows the results for QFII ownership. In both cases, three sets of coefficients are reported. The top set is for the panel regression with only the firm characteristic of interest included. The second set includes additional controls for the other two firm characteristics, i.e., state ownership and QFII ownership in the case of dual listing and state ownership and dual listing in the case of QFII ownership. Finally, the last set reports the average coefficient from a sequence of yearly cross-sectional regressions. No t-statistic is reported for this average, and the individual year-by-year coefficients are generally statistically insignificant due to the lack of power associated with insufficient cross-sectional variation in the firm characteristic. The reason to report this average is to illustrate the extent to which the panel coefficients above it are driven primarily by cross-sectional variation. If they are, then the average cross-sectional coefficient will be close to the panel regression coefficient.

As the table shows, the presence of dual-listed H shares is associated with lower levels of A-share price informativeness. Although this runs counter to the theory in Foucault and

Gehrig (2008), it is consistent with the evidence in Fernandes and Ferreira (2008) that cross-listing on US exchanges improves price informativeness for firms from developed markets, but reduces it for firms from emerging markets. It may be that because the A- and H-share markets are partially segmented, with well-documented differences in pricing, discount rate shocks in Hong Kong leak into A-share prices and create variation unrelated to expectations about future earnings. Including the control variables reduces the magnitude of the effect somewhat due to the relatively small but positive correlation between dual listing and the degree of state ownership. The similarity in magnitudes of the average of the cross-sectional coefficients to those from the panel regression suggests that the effect is coming from cross-sectional rather than time-series variation, which is hardly surprising given that the dual-listing dummy changes only once for firms as they become dual listed. In terms of economic magnitude, the effect is smaller than that of state ownership, but dual-listed firms have price informativeness coefficients that are on the order of 30% smaller than their non-dual listed counterparts.

To illustrate the effect of QFII ownership on stock price informativeness, the second panel of Table 4 presents estimates of the coefficient on the interaction of the fraction of firm i's shares that are QFII owned with the stock price regressor $\log(\frac{M_{i,t}}{A_{i,t}})$. The effect is weak and economically insignificant, but QFII ownership is generally associated with higher levels of price informativeness, particularly at short horizons. This result is consistent with that in Kacperczyk et al. (2018), who report that foreign institutional ownership generates increased price informativeness. The effect of QFII ownership is strengthened somewhat by including the other variables as controls, since QFII ownership is positively correlated with both state ownership and dual listing. The average of the cross-sectional coefficients is slightly larger still, but they remain economically insignificant. Regardless, given the very small magnitude of QFII holdings, this is unlikely to be a causal effect but rather a result of the method by which foreign investors in China select stocks.

3 The cross-section of expected returns

Section 2 documents an increasingly strong link between stock prices and expected future earnings. This section presents new evidence on how Chinese investors discount those expected earnings and which stock characteristics they pay up for. First, we conduct a direct comparison of cross-sectional pricing in China and the US over the 1995–2016 sample period, using a set of standard variables. The results suggest that Chinese investors price stocks much like other global investors: they pay up for size, liquidity, and long shots. They also discount for market risk, an effect that is much harder to find in developed markets.

These findings provide further evidence that stock prices in China are strongly linked to firm fundamentals.

Second, we examine the cross-sectional predictability in China associated with three China-specific variables: the degree of state ownership, the existence of dual-listed H shares, and the amount of QFII ownership. Our results suggest that after the 2009 economic stimulus, investors paid a premium for firms with greater state ownership, perhaps in anticipation of risk reduction through state support. In addition, after the 2003 introduction of the QFII program, stocks with greater QFII ownership earned higher returns, which we attribute to QFII stock selection ability rather than to investors discounting those stocks more heavily.

3.1 Cross-sectional pricing in China and the US

Our analysis updates and extends earlier studies of the cross-section of A-share returns in China and how they relate to patterns documented in other markets. Chen, Kim, Yao, and Yu (2010) examine cross-sectional stock return predictability in China over the period July 1995 to June 2007 using data from the PACAP-CCER China database. They consider 18 firm-specific variables found to predict returns in the US. They find that all 18 have signs consistent with US evidence, and five are significant in their sample, compared with eight variables that are significant in the US data over the same period. Cakici, Chan, and Topyan (2011) analyze stock return predictability in China from January 1994 to March 2011 using data from Datastream and find strong predictive power for size, book-to-market, cash-flow-to-price, and earnings-to-price, but not momentum. More recently, Hu, Chen, Shao, and Wang (2018), using data from the Chinese Capital Market Database, and Liu et al. (2018), using data from WIND, estimate size and value premiums in China and get somewhat contradictory results. Both find a significant size premium, but Hu et al. (2018) argue that there is no value premium except in the very early years of the market, while Liu et al. (2018) document an economically and statistically significant value premium in the 2007-2016 period, especially when using the earnings-price ratio to proxy for value. Our results on China A-share returns are based on data from CSMAR and WIND over the period January 1995 to December 2016. To provide a direct comparison to the signs and magnitudes of the coefficients in the US, we also present corresponding results for the US over this same period using identical methodology and variable definitions. Liu et al. (2018) drop the smallest 30% of stocks to remove the premium associated with the shell value of being a reverse merger target. We keep these stocks for the sake of comparability with the US and other studies, and because we view any premium associated with shell value as an aspect of the China size effect.

Using the methodology of Fama and MacBeth (1973), we average the coefficients from firm-level cross-sectional regressions of returns on seven predictor variables: BETA, SIZE, BM, MOM, ILLIQ, MAX, and REV. Following Scholes and Williams (1977) and Dimson (1979) to account for nonsynchronous trading, BETA is obtained from regressing daily firm returns on daily current, lead, and lagged market returns over the previous month and summing the three coefficients. Following a long literature going back to Banz (1981), SIZE is the natural logarithm of the total market value of firm equity at the end of the previous month. For comparability of summary statistics across countries, SIZE is calculated in US dollars by converting the Chinese yuan values at the prevailing exchange rate. This conversion has no effect on the cross-sectional coefficient estimate because the exchange rate is the same for every firm in the cross-section in a particular month, and the log transformation converts this multiplicative scaling into an additive constant. However, the currency conversion does affect the summary statistics.

As in Fama and French (1992), BM is the ratio of book value of equity to market value of equity at the end of the previous calendar year. This ratio is used from the end of June for 12 months to ensure that the relevant accounting data is available to investors when we include it in the regressions. Following Jegadeesh and Titman (1993), momentum, MOM, is defined as the cumulative stock return over the previous eleven-month period, lagged one month.

We measure illiquidity, ILLIQ, as the average over the previous month of the daily ratio of the absolute value of the stock return to the total value of shares traded, as in Amihud (2002). For comparability with the US results, we measure trading volume in US dollars, again converting at the prevailing exchange rate. In contrast to SIZE discussed above, this conversion does change the cross-sectional coefficient estimate in each month, because here there is no log transformation. Effectively, the currency conversion scales the ILLIQ coefficient by the same exchange rate used to convert the trading volume in the denominator of ILLIQ. Due to China's management of the exchange rate over the period, which results in a stable series, this conversion has no qualitative effect on the results. Following Bali, Cakici, and Whitelaw (2011), MAX is the maximum daily stock return over the previous month and, following Jegadeesh (1990) and Lehmann (1990), short-term reversal, REV, is the return on the stock over the previous month.

The top panel of Table 5 presents descriptive statistics for each predictor variable. The middle panel presents results of simple regressions for each of these predictors, multiple regressions with BETA, SIZE, BM, and MOM as predictors, multiple regressions with these four variables together with each additional predictor variable included in turn, and multiple regressions with all variables included simultaneously. The middle panel contains equal-weighted time-series averages of the monthly regression coefficient estimates. The bottom panel contains time-series averages of the monthly coefficient estimates weighted by the square root of the number of firms in the monthly cross-section, which Figure 1 shows has been steadily increasing over time. In parentheses below each coefficient estimate is its associated Newey-West-adjusted t-statistic.

Table 6 reports the same descriptive statistics and cross-sectional regression coefficient estimates for stock returns in the US over the same 1995-2016 sample period. Again, the bottom panel presents average coefficients weighted by the square root of the number of firms in the cross-sectional regressions. For the US this number has been declining for much of the sample period.

Before examining the regression results, it is worth taking a brief look at the summary statistics in the top panels of Tables 5 and 6, which are time-series averages of the cross-sectional statistics within each month. The most notable feature of the data is that the cross-sectional standard deviations of all the US variables exceed those of their counterparts in China. This result is especially surprising for the return measures MOM and REV because it is well known that volatility at the market level in China greatly exceeds that in China. One explanation is that while market level variability is larger, the higher synchronicity of firms in China in the form, for example, of higher R^2's in market model regressions, reduces the ratio of total risk to systematic risk in China. It is total risk that is reflected in the cross-sectional standard deviation of MOM and REV.

With regard to SIZE, mean and median firm market capitalizations are similar across the two countries, but the US has both significantly larger and significantly smaller firms. The range of the 5th to 95th percentiles in China is very similar to the inter-quartile range in the US. The truncation of the left tail of the size distribution in China is partly a function of the tightly regulated IPO process. For many years only larger, more profitable firms were allowed to go public. This same selection mechanism may account for the fact that the US has both more high growth and deep value stocks as measured by BM. Finally, the most striking contrast between the two markets is in the distributions of ILLIQ. Median ILLIQ is almost seven times higher in the US than in China, and the mean is 150 times higher. The distribution of ILLIQ in the US is highly skewed. Again, the existence of many very small capitalization firms in the US may, in part, explain this phenomenon. The main point is that the magnitudes of the coefficients discussed below must be interpreted in the context of the distribution of the predictor variables.

The estimates of the regression coeffcients in the middle and bottom panels of Tables 5 and 6 show that the cross-sectional return patterns associated with the Fama-French-Carhart factors in China are surprisingly similar to those for US stocks. In China, the coefficient on SIZE is generally strongly significantly negative, though it loses some magnitude and significance in the presence of ILLIQ. The same is true for the US, although the coefficient is much smaller in magnitude, which is partly compensated for by the fact that the predictor is more than twice as volatile. In other words, while the effect on expected returns of a doubling in SIZE is 4 to 5 times larger in China, a one-standard deviation increase is associated with only about twice as large an effect in China.

The coefficients on BM are positive, albeit generally statistically insignificant, in both China and the US. The decline in the estimated magnitude of the value premium in the US in recent times is well known.[7] Liu et al. (2018) find a more significant value premium in China using the earnings-price ratio to proxy for value. The momentum effect is positive but statistically weak in both markets. In the US this is due, in part, to the momentum crash in 2009. Whether or not the premiums attributable to size, book-to-market, and momentum should be interpreted as evidence of market inefficiency, the predictive power of these variables for stock returns in China is in line with the cross-sectional return patterns in the US over the same period and also consistent in direction with those documented for developed economies in earlier samples, such as in Fama and French (1998) and Fama and French (2012).

As for our additional predictors, the coefficient on ILLIQ is consistently significantly positive in both countries, with greater statistical significance evident in China. As in the US, Chinese investors charge a premium for bearing illiquidity, whether to compensate for direct trading costs or the risk of trading against more informed market participants. Information asymmetry between corporate insiders and outsiders, government insiders and outsiders, and domestic and foreign investors is regarded as a major concern in China. This information asymmetry could partially explain why the magnitude of the coefficient is so much larger in China. This result suggests that legal, accounting, and market reforms that increase transparency and level the playing field might not only attract more market participants, but also lower firms' cost of capital. Alternatively, the different market structure and the dominance of retail relative to institutional investors might mean that trading volume affects liquidity to a very different degree in China. It is certainly notable that the mean and standard deviation of ILLIQ are on the order of 200 times larger in the US.

The coefficient on MAX is highly significantly negative in China, as in the US data, although again the magnitude is larger. This result is particularly striking given that this variable is effectively truncated at 10% due to the regulatory price move limits, and that

[7]For example, the average monthly return on the Fama-French HML value portfolio is -0.08% over the last decade of our sample period January 2007 to December 2016, compared to 0.47% over the full prior sample period July 1926 to December 2006.

in the US this effect is heavily concentrated in firms with the most extreme returns. The truncation has two offsetting effects. On one hand, it potentially degrades the information in MAX in China, which intuition suggests should lower the coefficient, but on the other hand, it also reduces the measured magnitude of the extreme returns, which should boost the coefficient. In any case, we interpret the large magnitudes of the coefficient estimates as strong evidence that, like US investors, Chinese investors pay up for lottery-like payoffs. Moreover, the fact that investors in China know that future returns will also be subject to this cap apparently does not diminish their appetite for high MAX stocks. This similarity in investor preferences is especially noteworthy considering potentially strong cultural differences between the two groups, and it raises the possibility that many of the behavioral biases documented for US investors may also hold more universally. The coefficient on REV is also significantly negative, as in the US.

In contrast to the results using US data, the average coefficient on BETA is economically large and significantly positive in the multiple regressions, although not when used by itself. Weighting with the square root of the number of firms in the cross-section increases both the magnitude and significance of the BETA coefficient. This is intuitive for a couple of reasons. First, as more diverse firms are added to the sample, the increased cross-sectional dispersion in the BETA covariate increases the precision of the cross-sectional coefficient estimate. In addition, given likely measurement error in the BETAs and associated attenuation bias in its coefficient estimate, an increase in the ratio of the cross-sectional variance of the true betas to that of the measurement error would reduce the attenuation bias and increase the coefficient estimate. Finally, the high measured equity premium in China, 40 basis points per month in the bottom panel, compared with a very small and negative premium in the US, is well justified theoretically. As we document in Section 4 and Table 8, China's equity market portfolio has very high volatility, twice that of the US, and this high market volatility is not diversifiable for domestic Chinese investors, who lack access to international capital markets.

3.2 The pricing of China-specific firm characteristics

The stock market in China has certain unusual features, which suggests that other firm characteristics might be priced in the cross-section of expected returns. We focus on the three variables introduced and discussed in our analysis of cross-sectional variation of price informativeness: the extent of state ownership, the existence of dual-listed H shares, and the amount of QFII ownership. The fraction of shares owned by the state might proxy for the political risk inherent in the firm's returns. Given the frequent direct involvement of the

Chinese government in managing the economy through direct intervention in the operations of primarily state-controlled banks and industrial firms, it is an empirical question as to what effect the probability of future interventions might have on investors' perception of risk. Since the nature and extent of interventions is uncertain, risk could be greater and require additional compensation in terms of expected returns. Alternatively, government intervention might smooth out returns of state-controlled firms, thus reducing risk and required returns. For firms with dual-listed H shares, the question is whether the evidence of lower price informativeness for these shares also implies a higher risk premium. Finally, while the presence of a small holding by international institutional investors is unlikely to affect the risk premium, it is possible that these investors have the ability to forecast returns better than the rest of the market. Thus, the scale of QFII holdings might predict future returns in the cross-section.

The top panel of Table 7 presents the results from an examination of the predictability associated with these variables in a format similar to that of Table 5. We present the average cross-sectional coefficients and their associated Newey-West-adjusted t-statistics from monthly return regressions over the full sample and report results for both simple regressions and multiple regressions with the new variable added to a standard Fama-French-Carhart four-factor model. For the state-ownership and H-share variables, the sample spans the full period 1995-2016. However, the QFII program was only initiated in 2002, so the sample period for this variable is 2003-2016.

For state ownership, the simple regression coefficient is negative and of borderline statistical significance, but even this effect disappears when controlling for size. State ownership tends to be higher in larger firms, and state ownership picks up the size effect due to this positive correlation. A similar phenomenon occurs with H-share dual listing, whose coefficient appears negative in the simple regression but is essentially zero after controlling for size, due again to the positive correlation. For QFII holdings, the control for correlation with size is also important. The simple regression specification shows little or no QFII effect, but after controlling for the size premium, the effect of QFII holdings is large and positive. In terms of economic magnitude, a 1% holding implies a return premium of more than 20 basis points a month, or approximately 2.5% on an annualized basis. It is difficult, although perhaps not impossible, to believe that this effect is causal, i.e., that small holdings of foreign institutional investors increase risk and required return. Rather, the evidence suggests that these investors have some ability to identify stocks that will subsequently perform well. One important takeaway from this analysis, is that the magnitude of the size premium in China makes it imperative to control for this effect when examining other potential risk premiums in the cross-sections of stock returns.

Our final analysis, in the bottom panel of Table 7, takes into account the phenomenon uncovered in our investigation of price informativeness that the effects of state ownership on stock prices underwent a fundamental shift after the financial crisis. Therefore, we re-examine the risk premium associated with state ownership for the post-crisis subperiod 2009-2016. This subperiod is admittedly short in the context of standard cross-sectional pricing tests, but the strength of the price informativeness results suggest that it is worth examining. Given the shortness of the subperiod, the results are quite striking. In the simple regression specification, the magnitude of the average coefficient is more than three times as large in this 8-year sample as in the full 22-year period, and, even after controlling for size, the average coefficient is negative, economically significant, and of borderline statistical significance. It appears that in this period associated with heavy government intervention in state-owned firms, investors demand lower returns for these firms, i.e., they are willing to pay up to own firms in which government support presumably reduces risk. Of course, an alternative or additional explanation would be that these firms performed unexpectedly poorly over this period.

4 Opportunities for global investors

The strong link between stock prices and firm fundamentals established in Sections 2 and 3 has important implications for investors. The consistency of pricing suggests that global investors may be overly skeptical about investing in China's stock market. In this section we quantify the opportunity cost to global investors and Chinese firms of China's continued market segmentation. These results re-emphasize the value of a larger role for China's stock market in the global economy.

China's stock market accounts for almost 10% of the $80-trillion global equity market, but foreign investment in China's stock market remains extremely low. Although China ratified the QFII program in 2002, the RQFII program in 2011, the Shanghai-Hong Kong Connect program in 2014, and the Shenzhen-Hong Connect program in 2016, the quotas approved across these programs total only about $200 billion and the quotas themselves are not filled. These limited holdings imply a significant underweighting by foreign investors, even relative to documented home biases in international investing, such as those reported by Cooper, Sercu, and Vanpee (2013) and other authors cited therein.

The recent negotiations surrounding the decision by MSCI to include China A-shares in its emerging market index clarified many of the issues. Although the CSRC signaled a willingness to work out the necessary market reforms early on, MSCI postponed A-share inclusion in both 2015 and 2016, citing investor concerns about repatriation risk associated with limits on foreign withdrawals, liquidity risks associated with trading suspensions and one-day minimum holding periods, and other administrative issues. Bank analysts also cited broad skepticism of China's markets among global investors. In June 2017, MSCI announced that it would include 222 A shares with a weight of less than 1% in its emerging market index, with future increases in A-share representation contingent on the success of negotiations with CSRC about further stock market reforms.

An important omission from the debate has been an assessment of the opportunity cost to global investors of underweighting China in their portfolio allocation. Table 8 summarizes the menu of risks and returns available to global USD equity investors, based on value-weighted stock market performance from 1995 to 2016. For China, the weighting uses tradable market value rather than total market value in the weighting. As the table shows, mean monthly excess returns in China have been almost double those of the US and Europe over the period. Stock market volatility in China has also been double that of the western markets. However, from the viewpoint of a well-diversified investor, asset volatility is not the relevant measure of an asset's contribution to portfolio risk. Instead, an asset's contribution to portfolio risk is measured by its covariance with the portfolio return. By this measure, China's stock market looks very attractive. Whereas the stock market returns across the developed economies are highly correlated, likely reflecting a high degree of financial market and economic integration, China's stock returns have very low correlation with the other markets. China's stock market offers global investors the opportunity for diversification as well as high average returns.

To quantify the extra return China's stock market offers global USD investors given its high mean and low correlation, Table 9 presents its Jensen's alphas with respect to the US and global Fama-French-Carhart factors over the period 1995–2016. The table presents alphas and their t-statistics for four different China portfolios: the broad market, small stocks minus big stocks, value stocks minus growth stocks, and winners minus losers. These market, size, value, and momentum portfolios are constructed according to the methodology of Fama and French (1993), Carhart (1997), and the Ken French Data Library. We form the six 2×3 value-weighted size-book-to-market portfolios and the six 2×3 value-weighted size-momentum portfolios and construct the zero-cost size, book-to-market, and momentum factor portfolios for China. We use tradable rather than total market value for portfolio weights. As the table shows, China's stock market delivered an alpha of approximately 1% per month to USD investors over the period. The alphas on the size and value portfolios are more statistically significant. Given the difficulty of short selling in China, the size and value portfolio returns are hypothetical, but they still point the way to potentially profitable trading strategies.

The high stock returns available in China suggest that investor skepticism may be overblown, especially in light of the quality of pricing documented in Sections 2 and 3. Such high returns are not surprising given the current equilibrium in which the stock market is almost entirely held and discounted by domestic Chinese investors who are effectively prohibited by capital controls from diversifying into international markets and thus bear the full brunt of China's stock market volatility. But these high potential returns for global investors also amount to a high cost of capital for Chinese firms. A large literature provides both theory and evidence on the positive effects of liberalization and integration on emerging markets' cost of capital, investment, growth, and investment opportunities for foreign investors through improvements in risk sharing across countries. In samples of up to 25 countries, Henry (2000a,b, 2003) and Chari, Henry, and Sasson (2012) find that stock market liberalizations reduce cost of capital and boost investment, growth, and wages. Chari and Henry (2004, 2008) study the effect of market liberalization at the firm level and show how stock prices and corporate investment respond to reductions in cost of capital that occur after liberalization. Our evidence suggests that China has much to gain from opening its stock market to the international investment community.

To illustrate the cost that constraints on international diversification impose on domestic Chinese equity investors, and further justify their high required returns, Table 10 shows the real annualized buy-and-hold CNY returns that would be earned by an investor holding 100% of their wealth in China's stock market over our sample period. The exchange rate data are from Datastream and the CNY inflation data are from the World Bank. In contrast to the nominal average annualized monthly USD return of 17.17%, the real CNY annualized buy-and-hold return over 1995-2016 is only 9.01%. As the table shows, much of the difference is attributable to the toll that high volatility takes on buy-and-hold returns relative to average per period returns, about one-half the variance of returns. This further helps to explain why undiversified Chinese investors would discount so heavily for the stock market's high variance. The table also includes US returns over the period. China's outperformance is somewhat less when measured in buy-and-hold-returns because the US stock market has much lower variance.

The table also shows returns over the period 2001-2014, which matches the sample period of Allen et al. (2017). They find that over the period 2001-2014, the cumulative real CNY buy-and-hold return on the equity of listed firms is -6%, for an annualized buy-and-hold return of -0.44%. The difference between this result and our 4.02% shown in Table 10 is at least partly attributable to the difference in the weighting scheme. Allen et al. (2017) weight stock returns by total market capitalization, which relates to the market valuation of China's macroeconomy, while we weight by tradable market value, reflecting our focus on investment opportunities. Weighting by total market capitalization gives more weight to the large state-owned enterprises, which did less well than the smaller private firms over the period.

5 Conclusions

This paper shows that, counter to common perception, stock prices in China are strongly linked to firm fundamentals. Since the reforms of the early 2000s, stock prices in China are as informative about future profits as they are in the US. Furthermore, although the market is largely segmented from international equity markets, Chinese investors price individual stock characteristics remarkably like investors in other large economies: they pay up for size, liquidity, and long shots. Chinese investors also discount for market risk, a theoretically well-motivated effect that has been difficult to find in developed markets.

We introduce three new China-specific firm characteristics: the extent of state ownership, the amount of QFII holdings, and the existence of dual-listed H shares. We find that after the crisis, firms with greater state ownership have lower price informativeness and lower average returns, which we interpret as a negative return premium for state guarantees. Stocks with greater QFII ownership have greater stock price informativeness and higher returns, which we attribute to QFIIs' stock selection ability. Stocks with twin H shares listed in Hong Kong have lower price informativeness, which we attribute to discount rate shocks of global investors trading H shares creating noise in the corresponding A share prices. Finally. we show that from the viewpoint of international investors, China's stock market offers high average returns and low correlation with other equity markets, yielding a four-factor alpha of over 1% per month.

The policy implications of our results are clear. Despite the challenge of developing in the shadow of a massive state-subsidized banking sector, with only a fledgling institutional investor base, numerous constraints on its capacity for price discovery, and a highly uncertain economic environment, China's stock market appears to be pricing capital remarkably well, and seems ready for a greater role in domestic and international capital allocation. Additional regulatory reforms could increase incentives to produce information and facilitate information transmission, such as enabling better incorporation of negative information into prices by facilitating short-selling, relaxing the 10% collar on price movements, and minimizing trading suspensions. Limiting government interventions would also increase the firm-specific information content of prices and improve incentives to generate information about corporate profits, as opposed to government policy changes, further supporting investment efficiency. Liberalizing the flow of capital by opening up the IPO window to a broader and more heterogeneous set of firms and removing barriers to international investment, such as constraints on liquidity and the repatriation of profits, would further empower the market to attract capital, allocate it efficiently, and support economic growth.

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Table 1: Stock price informativeness in China 1995-2016

The top panel presents coefficient estimates and White-heteroscedasticity-consistent t-statistics (in parentheses) for the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$ in annual cross-sectional regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k}$$

for China for forecasting horizons $k = 1$, 3 and 5 over the period 1995 to $2016 - k$. The variables are winsorized at the 1st and 99th percentiles. The bottom panel presents the average across years of the coefficient estimates for the full sample, samples excluding the 10% and 30% smallest stocks, and a sample excluding stocks with special treatment status for each horizon $h = 1$ to 5.

Full Sample, Year-by-Year Coefficients and t-Statistics						
	$k=1$		$k=3$		$k=5$	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
1995	0.004	(0.89)	0.037	(2.82)	0.063	(3.98)
1996	0.029	(3.96)	0.077	(5.43)	0.064	(2.65)
1997	0.049	(4.36)	0.069	(6.01)	0.040	(2.69)
1998	0.032	(6.64)	0.040	(4.44)	0.001	(0.12)
1999	0.020	(4.69)	0.011	(1.43)	-0.004	(-0.41)
2000	0.011	(2.06)	0.002	(0.37)	-0.019	(-2.12)
2001	0.010	(2.04)	0.021	(2.98)	0.012	(1.27)
2002	0.013	(2.88)	0.010	(1.59)	0.030	(2.28)
2003	0.027	(5.19)	0.037	(6.04)	0.063	(4.58)
2004	0.033	(6.59)	0.067	(6.71)	0.093	(5.97)
2005	0.030	(6.81)	0.072	(6.12)	0.073	(4.53)
2006	0.054	(7.78)	0.075	(7.08)	0.142	(4.45)
2007	0.046	(5.60)	0.071	(5.97)	0.098	(4.65)
2008	0.036	(7.14)	0.082	(6.71)	0.108	(6.73)
2009	0.029	(6.07)	0.080	(5.48)	0.069	(6.21)
2010	0.023	(6.94)	0.066	(7.22)	0.104	(7.16)
2011	0.033	(8.50)	0.043	(8.38)	0.108	(7.59)
2012	0.019	(5.64)	0.047	(7.70)		
2013	0.016	(8.93)	0.055	(8.26)		
2014	0.020	(7.77)				
2015	0.015	(8.10)				

Time-Series Average Coefficients					
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
Full sample	0.026	0.040	0.051	0.058	0.061
Ex. smallest 10%	0.025	0.040	0.051	0.058	0.063
Ex. smallest 30%	0.025	0.040	0.050	0.056	0.059
Ex. spec. treat.	0.023	0.039	0.052	0.061	0.068

Table 2: Stock price informativeness in the US 1995-2014 and comparison with China

Coefficient estimates for the US and China and t-statistics for the US (in parentheses) for the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$ in annual cross-sectional regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k}$$

for forecasting horizons $k = 3$ and 5 over the period 1995 to $2014 - k$. The columns labeled p-value report the probability level in percent at which the null hypothesis that the coefficients in the US and China are equal can be rejected in favor of the alternative hypothesis that the US coefficient is greater, under the assumption that the coefficient estimates are uncorrelated across countries.

	$k = 3$				$k = 5$			
	US		China		US		China	
	Coeff.	t-stat	Coeff.	p-value	Coeff.	t-stat	Coeff.	p-value
1995	0.066	(8.85)	0.037	3.2	0.067	(5.57)	0.063	40.8
1996	0.047	(5.82)	0.077	96.9	0.101	(9.16)	0.064	8.6
1997	0.059	(8.29)	0.069	77.6	0.026	(1.72)	0.040	74.6
1998	0.062	(12.07)	0.040	1.7	0.025	(2.14)	0.001	7.9
1999	-0.004	(-0.52)	0.011	91.2	0.026	(3.55)	-0.004	0.9
2000	-0.022	(-2.21)	0.002	98.1	0.037	(6.84)	-0.019	0.0
2001	0.041	(6.88)	0.021	1.6	0.056	(8.09)	0.012	0.0
2002	0.056	(14.79)	0.010	0.0	0.059	(9.84)	0.030	2.3
2003	0.060	(14.64)	0.037	0.1	0.058	(6.99)	0.063	60.5
2004	0.041	(6.02)	0.067	98.7	0.080	(7.20)	0.093	74.5
2005	0.048	(5.50)	0.072	95.3	0.053	(4.57)	0.073	83.4
2006	0.049	(3.60)	0.075	93.8	0.084	(8.97)	0.142	95.9
2007	0.072	(10.35)	0.071	47.0	0.075	(8.99)	0.098	85.0
2008	0.049	(12.29)	0.082	99.5	0.057	(9.53)	0.108	99.8
2009	0.080	(15.23)	0.080	50.1	0.078	(12.23)	0.069	23.5
2010	0.069	(12.06)	0.066	40.0				
2011	0.052	(10.41)	0.043	10.5				

Table 3: State ownership and stock price informativeness in China 1995-2016

Coefficient estimates and White-heteroscedasticity-consistent t-statistics (in parentheses) for the coefficient on the interaction term $X_{i,t} \log(\frac{M_{i,t}}{A_{i,t}})$ in annual cross-sectional regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + (b_{0t} + b_{1t} X_{i,t}) \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k},$$

where $X_{i,t}$ is the fraction of state-owned shares, for China for forecasting horizons $k = 1$, 3 and 5 over the period 1995 to $2016 - k$. The variables are winsorized at the 1st and 99th percentiles.

	$k = 1$		$k = 3$		$k = 5$	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
1995	0.050	(2.86)	0.093	(2.10)	0.002	(0.03)
1996	-0.029	(-0.92)	-0.082	(-1.59)	-0.221	(-2.40)
1997	-0.018	(-0.67)	0.034	(0.86)	0.050	(0.94)
1998	0.012	(0.64)	0.004	(0.12)	-0.005	(-0.13)
1999	-0.003	(-0.23)	0.038	(1.36)	0.029	(0.72)
2000	-0.018	(-1.00)	-0.026	(-1.19)	0.002	(0.05)
2001	0.017	(1.00)	-0.012	(-0.46)	-0.006	(-0.19)
2002	0.022	(1.53)	0.003	(0.15)	0.053	(1.39)
2003	0.025	(1.42)	0.047	(2.35)	0.084	(2.14)
2004	0.023	(1.49)	0.039	(1.52)	0.086	(2.36)
2005	0.037	(2.89)	0.018	(0.63)	-0.026	(-0.62)
2006	-0.042	(-2.36)	0.024	(0.92)	0.008	(0.12)
2007	0.012	(0.63)	0.007	(0.25)	-0.067	(-1.41)
2008	0.002	(0.14)	0.006	(0.23)	-0.066	(-1.92)
2009	0.008	(0.64)	-0.074	(-2.53)	-0.107	(-3.80)
2010	0.007	(0.84)	-0.085	(-4.78)	-0.153	(-5.34)
2011	-0.007	(-0.85)	-0.054	(-4.25)	-0.193	(-5.92)
2012	-0.018	(-2.55)	-0.057	(-3.85)		
2013	-0.012	(-2.38)	-0.068	(-3.69)		
2014	-0.024	(-3.48)				
2015	-0.005	(-0.80)				

Table 4: Cross-sectional variation in stock price informativeness 1995-2016

Coefficient estimates and White-heteroscedasticity-consistent t-statistics (in parentheses) for the coefficient on the interaction term $X_{i,t} \log(\frac{M_{i,t}}{A_{i,t}})$ in panel regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_{0t} + a_{1t}X_{i,t} + (b_{0t} + b_1 X_{i,t}) \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k}$$

for forecasting horizon $k = 1$ to 5 over the period 1995 to 2016-k. In the first panel, $X_{i,t}$ indicates whether firm i has dual-listed H shares in year t. In the second panel, $X_{i,t}$ is the fraction of firm i's shares that are owned by qualified foreign institutional investors at year t. The last line in each panel reports the average of cross-sectional interaction coefficients estimated on a year-by-year basis. "Controls" indicates the inclusion of the dual-listing indicator, QFII ownership, and state ownership in the specification.

H shares listed						
	Horizon					
Specification	k=1	k=2	k=3	k=4	k=5	Controls
Panel	-0.008	-0.013	-0.018	-0.027	-0.043	No
	(-2.55)	(-3.82)	(-3.85)	(-4.12)	(-5.02)	
Panel	-0.007	-0.010	-0.013	-0.019	-0.030	Yes
	(-2.43)	(-2.98)	(-2.63)	(-2.81)	(-3.31)	
Cross-sectional	-0.003	-0.009	-0.009	-0.025	-0.033	Yes
QFII ownership						
	Horizon					
Specification	k=1	k=2	k=3	k=4	k=5	Controls
Panel	0.005	0.005	0.006	0.009	0.002	No
	(2.52)	(1.30)	(0.93)	(1.14)	(0.18)	
Panel	0.006	0.007	0.008	0.013	0.007	Yes
	(2.90)	(1.75)	(1.35)	(1.55)	(0.68)	
Cross-sectional	0.009	0.024	0.025	0.033	0.027	Yes

Table 5: Summary statistics and cross-sectional return regressions for China 1995–2016

The top panel reports time series averages of summary statistics in the monthly cross-section for the predictor variables. The second and third panels report time-series averages of slope coefficients and associated Newey-West adjusted t-statistics (in parentheses) from monthly cross-sectional regressions of firm returns on firm-specific predictor variables 1995–2016. The second panel shows ordinary time-series averages of coefficient estimates. The bottom panel shows average monthly coefficient estimates weighted by the square root of the number of firms in the monthly cross-section. BETA is the Scholes-Williams-Dimson beta obtained from regressing daily firm return on daily current, lead, and lagged market returns over the previous month. SIZE is the log of total market value of equity at the end of the previous month in USD. BM is the Fama-French book-to-market ratio of book value of equity to market value of equity at the end of the previous calendar year. MOM is Jegadeesh-Titman momentum defined as the cumulative stock return over months $t-12$ to $t-1$. ILLIQ is Amihud illiquidity measured as the average over the previous month of the daily ratio of the absolute value of the stock return to the total USD value of shares traded. MAX is the Bali-Cakici-Whitelaw maximum daily stock return over the previous month. REV is Jegadeesh-Lehmann short-term reversal defined as the return on the stock over the previous month.

	BETA	SIZE	BM	MOM	ILLIQ	MAX	REV
Mean	1.05	19.74	0.40	0.222	0.0073	0.059	0.020
Std. deviation	0.71	0.81	0.24	0.386	0.0179	0.031	0.108
Skewness	-0.57	0.99	0.24	1.86	9.76	2.95	1.77
5th percentile	0.11	18.67	0.13	-0.259	0.0005	0.029	-0.117
25th	0.73	19.16	0.26	-0.022	0.0020	0.042	-0.044
50th	1.07	19.62	0.37	0.163	0.0045	0.055	0.005
75th	1.39	20.17	0.52	0.400	0.0089	0.072	0.068
95th	1.96	21.25	0.81	0.884	0.0209	0.100	0.203
Coefficient	0.10						
(t-statistic)	(0.48)						
		-0.86					
		(-4.46)					
			0.61				
			(1.21)				
				0.01			
				(0.03)			
					266.0		
					(2.73)		
						-17.60	
						(-5.99)	
							-3.22
							(-3.45)
	0.27	-0.88	0.58	0.25			
	(1.85)	(-4.97)	(1.19)	(1.00)			
	0.29	-0.70	0.71	0.24	224.7		
	(1.94)	(-3.96)	(1.55)	(0.97)	(2.37)		
	0.35	-0.88	0.51	0.31		-19.33	
	(2.39)	(-4.96)	(1.08)	(1.32)		(-8.16)	
	0.18	-0.85	0.59	0.14			-3.31
	(1.32)	(-4.76)	(1.23)	(0.58)			(-3.77)
	0.32	-0.67	0.70	0.20	256.6	-16.38	-2.38
	(2.31)	(-3.74)	(1.64)	(0.82)	(2.46)	(-7.01)	(-2.29)
WLS	0.41	-0.73	0.37	0.17	294.6	-14.42	-3.94
	(4.41)	(-3.60)	(1.08)	(0.65)	(2.74)	(-6.72)	(-4.26)

Table 6: Summary statistics and cross-sectional return regressions for the US 1995–2016

The top panel reports time series averages of summary statistics in the monthly cross-section for the predictor variables. The second and third panels report time-series averages of slope coefficients and associated Newey-West adjusted t-statistics (in parentheses) from monthly cross-sectional regressions of firm returns on firm-specific predictor variables 1995–2016. The second panel shows ordinary time-series averages of coefficient estimates. The bottom panel shows average monthly coefficient estimates weighted by the square root of the number of firms in the monthly cross-section. BETA is the Scholes-Williams-Dimson beta obtained from regressing daily firm return on daily current, lead, and lagged market returns over the previous month. SIZE is the log of total market value of equity at the end of the previous month in USD. BM is the Fama-French book-to-market ratio of book value of equity to market value of equity at the end of the previous calendar year. MOM is Jegadeesh-Titman momentum defined as the cumulative stock return over months $t-12$ to $t-1$. ILLIQ is Amihud illiquidity measured as the average over the previous month of the daily ratio of the absolute value of the stock return to the total USD value of shares traded. MAX is the Bali-Cakici-Whitelaw maximum daily stock return over the previous month. REV is Jegadeesh-Lehmann short-term reversal defined as the return on the stock over the previous month.

	BETA	SIZE	BM	MOM	ILLIQ	MAX	REV
Mean	0.91	19.75	0.61	0.124	1.1398	0.070	0.010
Std. deviation	1.36	1.89	0.46	0.483	4.2608	0.049	0.125
Skewness	0.22	0.15	1.52	1.20	6.85	2.18	3.44
5th percentile	-1.24	16.71	0.10	-0.497	0.0003	0.021	-0.184
25th	0.12	18.37	0.29	-0.181	0.0034	0.037	-0.063
50th	0.83	19.70	0.50	0.049	0.0292	0.057	0.003
75th	1.65	21.05	0.81	0.320	0.3174	0.087	0.073
95th	3.29	23.03	1.51	1.035	5.7526	0.167	0.227
Coefficient	-0.05						
(t-statistic)	(-0.46)						
		-0.17					
		(-2.55)					
			0.42				
			(2.33)				
				-0.05			
				(-0.12)			
					0.073		
					(1.63)		
						-2.56	
						(-1.05)	
							-1.86
							(-2.93)
	-0.06	-0.16	0.22	0.12			
	(-0.80)	(-2.25)	(1.16)	(0.34)			
	-0.06	-0.15	0.22	0.13	0.051		
	(-0.84)	(-2.21)	(1.17)	(0.35)	(1.50)		
	0.00	-0.20	0.19	0.07		-5.39	
	(0.00)	(-3.65)	(1.06)	(0.19)		(-3.17)	
	-0.07	-0.13	0.25	0.09			-2.39
	(-0.96)	(-1.84)	(1.33)	(0.23)			(-4.09)
	-0.03	-0.15	0.23	0.09	0.057	-3.77	-2.09
	(-0.42)	(-2.80)	(1.29)	(0.25)	(1.71)	(-1.98)	(-3.36)
WLS	-0.02	-0.16	0.23	0.19	0.056	-3.48	-2.30
	(-0.36)	(-2.70)	(1.19)	(0.54)	(1.92)	(-1.72)	(-3.65)

Table 7: Cross-sectional return regression for China 1995-2016: China-specific variables

Time-series averages of slope coefficients and associated Newey-West adjusted t-statistics (in parentheses) from monthly cross-sectional regressions of firm returns on firm-specific predictor variables 1995–2016. BETA is the Scholes-Williams-Dimson beta obtained from regressing daily firm return on daily current, lead, and lagged market returns over the previous month. SIZE is the log of total market value of equity at the end of the previous month in USD. BM is the Fama-French book-to-market ratio of book value of equity to market value of equity at the end of the previous calendar year. MOM is Jegadeesh-Titman momentum defined as the cumulative stock return over months $t-12$ to $t-1$. SOE is the percentage of state ownership. H indicates whether the stock is dual-listed as an H share in Hong Kong. QFII is the percentage of ownership by QFIIs.

	BETA	SIZE	BM	MOM	SOE	H	QFII
1995-2016					-0.54		
					(-1.72)		
1995-2016						-0.51	
						(-1.95)	
2003-2016							-1.10
							(-0.10)
1995-2016	0.26	-0.88	0.60	0.23	0.00		
	(1.75)	(-5.14)	(1.24)	(0.95)	(-0.01)		
1995-2016	0.30	-0.81	0.64	0.21		0.09	
	(2.08)	(-4.56)	(1.33)	(0.85)		(0.29)	
2003-2016	0.58	-1.00	-0.31	0.09			22.78
	(4.83)	(-4.79)	(-0.88)	(0.26)			(2.25)
2009-2016					-1.65		
					(-2.75)		
2009-2016	0.48	-1.23	-0.14	-0.15	-0.86		
	(2.98)	(-4.80)	(-0.33)	(-0.45)	(-1.78)		

Table 8: Stock market returns in large economies 1995–2016

Annualized means and volatilities (in %) of monthly USD excess returns in stock markets in four large economies and their correlations over the period January 1995 to December 2016.

	China	US	Europe	Japan
Mean	14.77	7.83	6.44	0.24
Volatility	31.63	15.32	17.51	17.95
Corr. with US	0.19			
Corr. with Europe	0.23	0.80		
Corr. with Japan	0.13	0.45	0.50	

Table 9: Alphas of China portfolios with respect to US and global factors 1995–2016

Monthly alphas (in %) of USD returns on the China market, size, value, and momentum factor portfolios with respect to the US and global Fama-French-Carhart factors, and their Newey-West adjusted t-statistics (in parentheses) over the period January 1995 to December 2016.

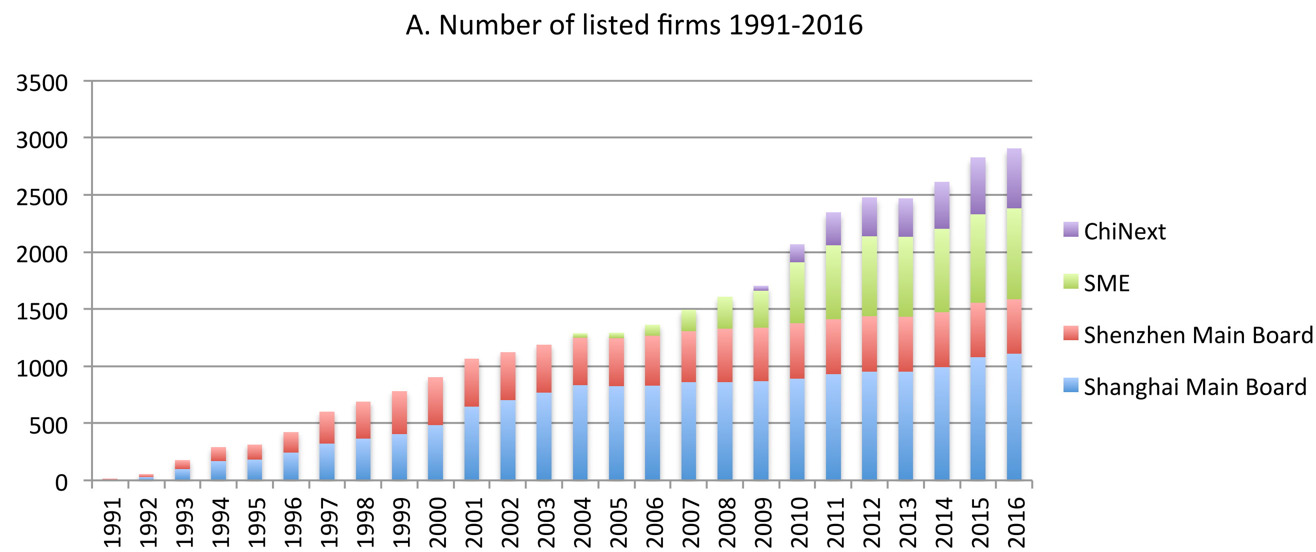
China portfolio		US factors		Global factors	
		1-factor	4-factor	1-factor	4-factor
RMRF	Alpha	0.97	0.97	0.99	0.91
	t-stat	(1.39)	(1.34)	(1.47)	(1.27)
SMB	Alpha	1.25	1.26	1.25	1.29
	t-stat	(4.63)	(4.56)	(4.64)	(4.63)
HML	Alpha	0.73	0.72	0.74	0.71
	t-stat	(2.26)	(2.38)	(2.28)	(2.24)
WML	Alpha	0.10	0.06	0.10	-0.01
	t-stat	(0.38)	(0.23)	(0.37)	(-0.02)

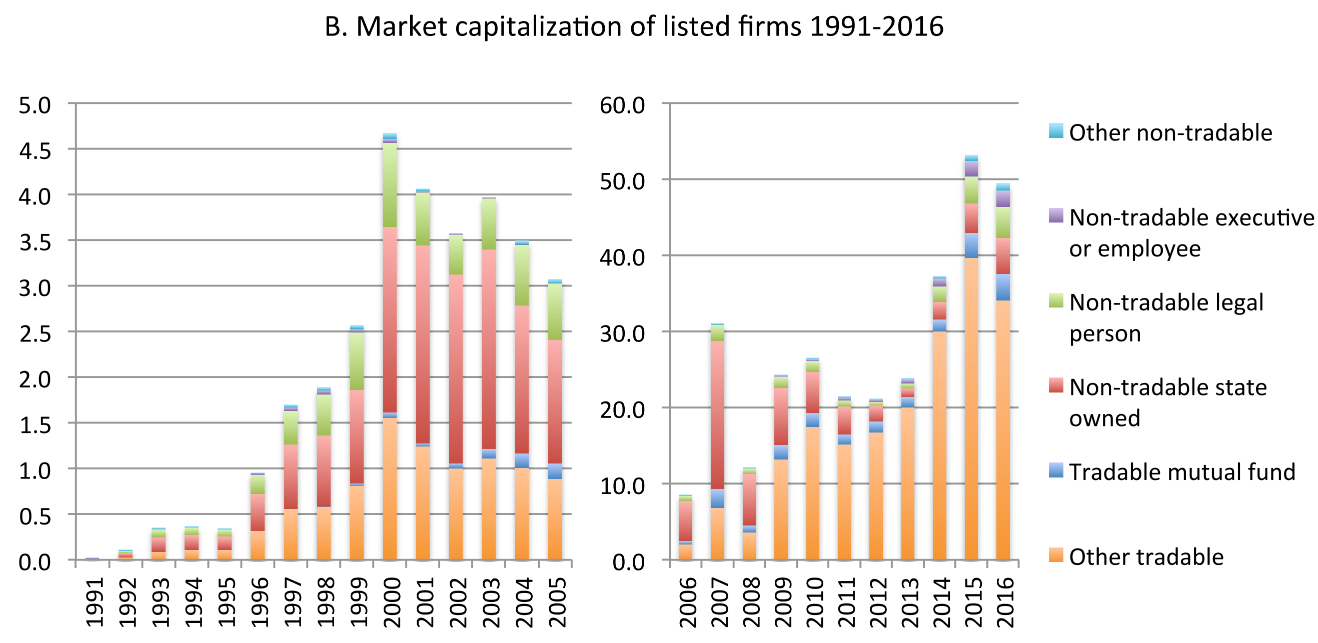
Table 10: Average monthly vs. buy-and-hold returns 1995–2016

Average monthly nominal USD returns in the top row, real CNY buy-and-hold returns in the bottom row, and the volatility, currency, and inflation effects that explain the difference, in the middle rows, for the China and US stock markets over two sample periods. All quantities are annualized and in percent.

	1995-2016		2001-2014	
	China	US	China	US
Avg monthly nom USD return	17.17	10.46	12.74	7.02
0.5*Var of monthly nom USD return	5.03	1.17	4.36	1.20
Avg monthly USD return on CNY	0.90	0.90	2.07	2.07
Avg CNY inflation	2.37	2.37	2.34	2.34
Approx real CNY BHR return	8.88	6.02	3.98	1.40
Actual real CNY BHR return	9.01	6.04	4.02	1.41

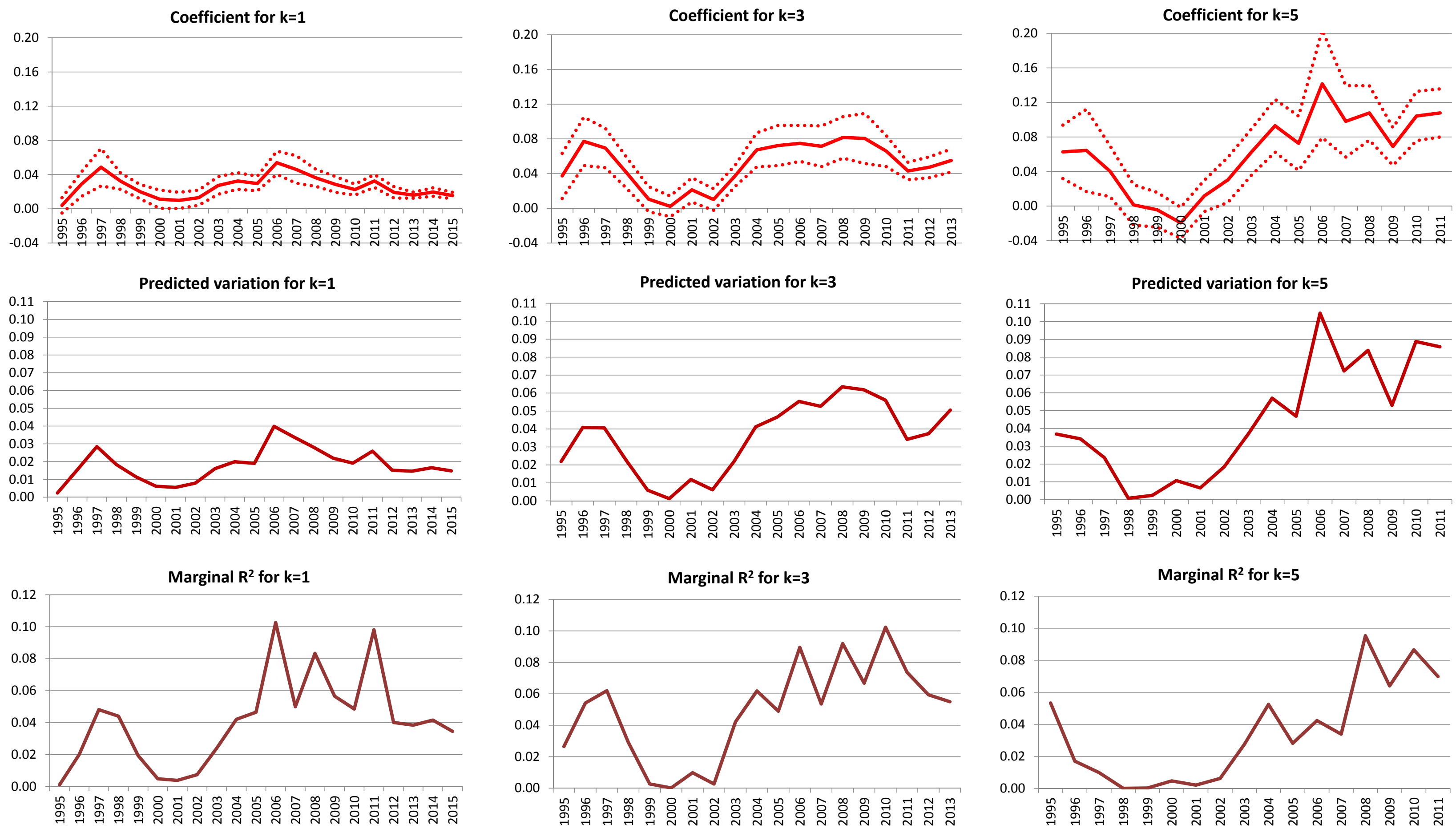
Figure 1: Number of firms and market capitalization on China's stock market 1991-2016





Panel A shows the number of firms listed on the Shanghai and Shenzhen main boards and the Shenzhen SME and ChiNext boards. Panel B shows the total market capitalization of these listed firms in trillions of RMB, split at year 2006 to accommodate the significant increase in scale, categorized by the type of share and holder.

Figure 2: Stock price informativeness in China 1995-2016

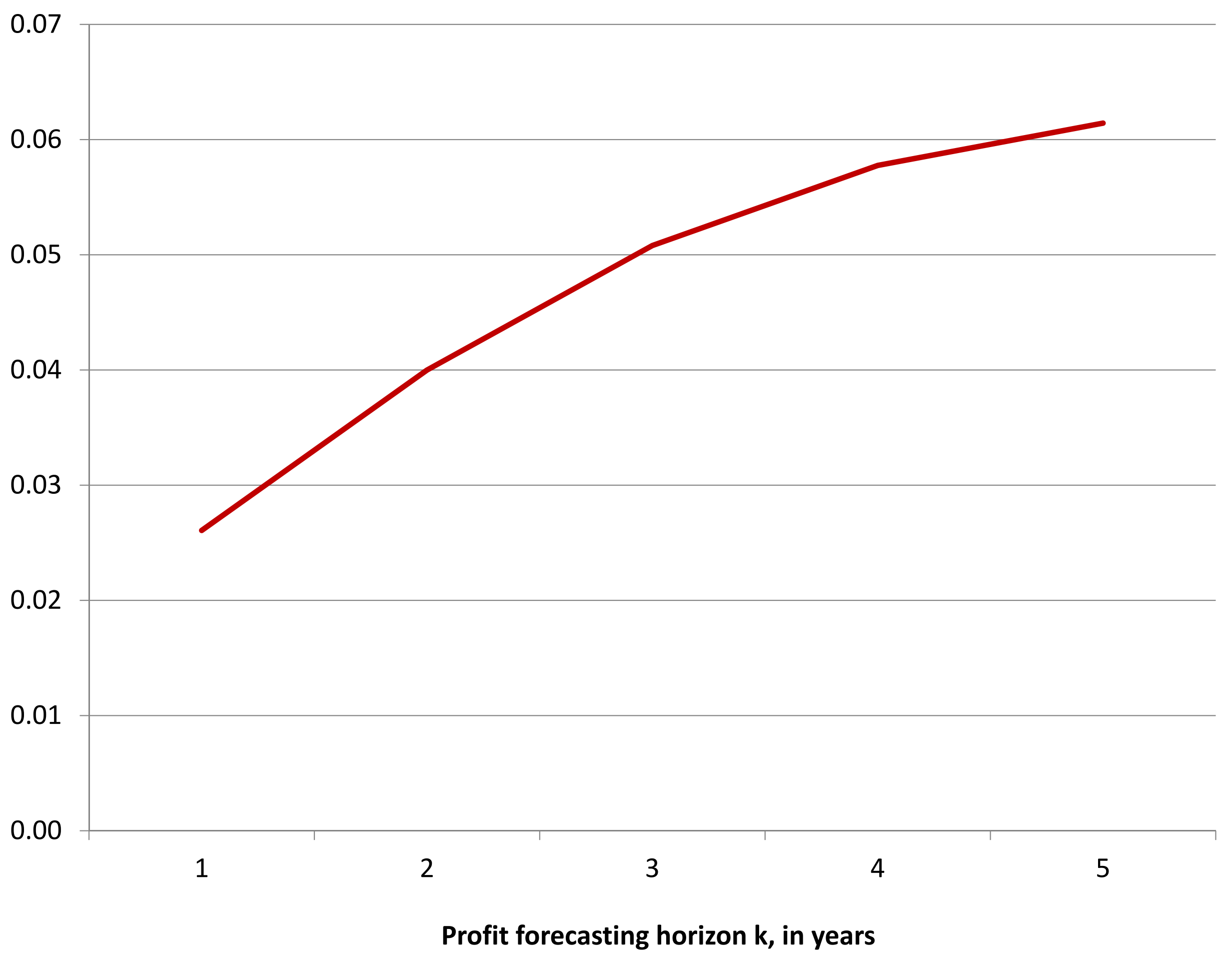


Results from annual cross-sectional regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k}$$

for forecasting horizons $k = 1$, 3, and 5 over the period 1995 to $2016 - k$. The top plots show the coefficients on $\log(\frac{M_{i,t}}{A_{i,t}})$ and their 95% confidence bands, the middle plots show the predicted variation, which is the coefficient times the standard deviation of the regressor, and the bottom plots show the marginal R^2 of this regressor.

Figure 3: Stock price informativeness in China by forecasting horizon k

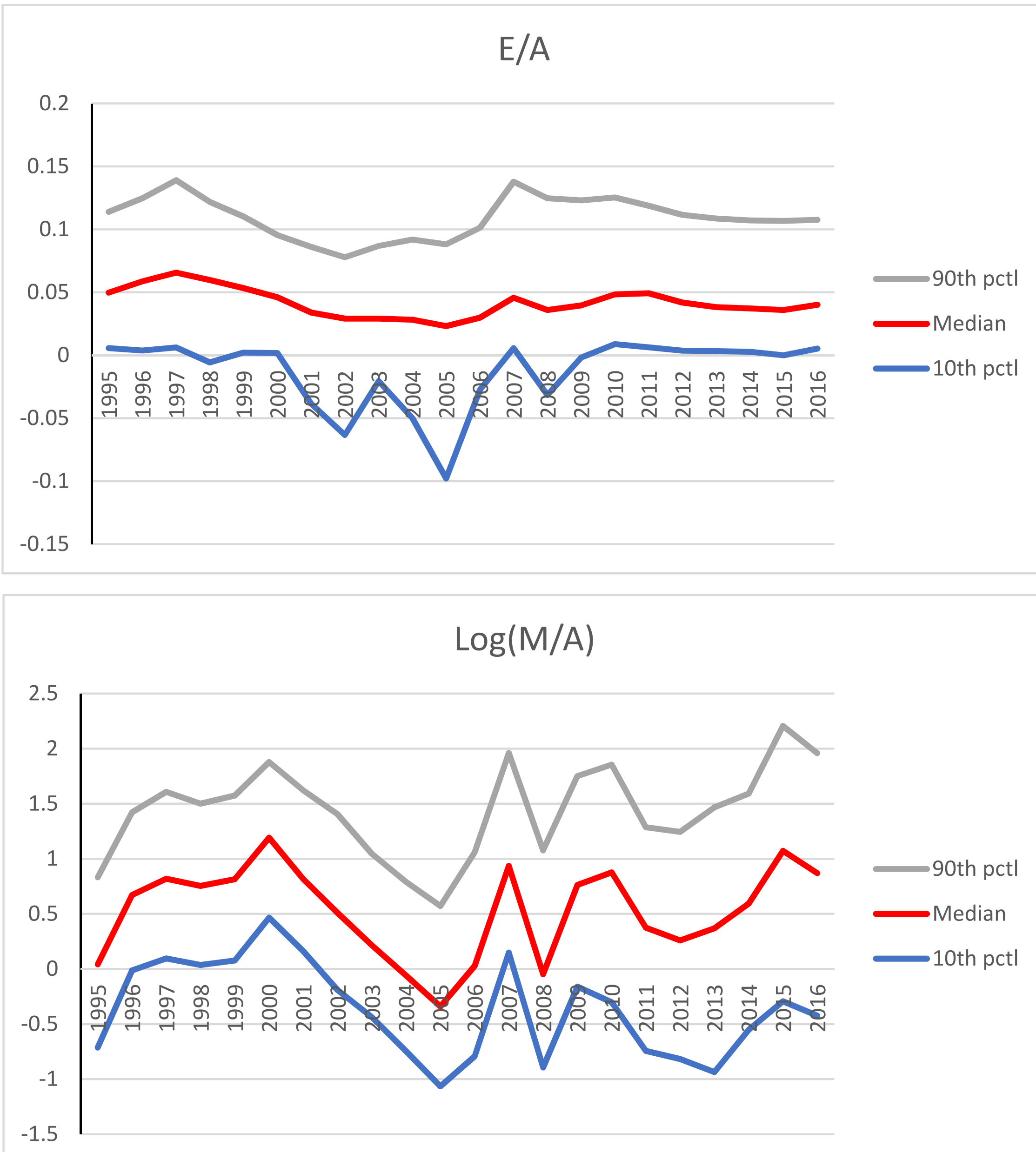


Time series average of the coefficient b_t from annual cross-sectional regressions of the form

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k}$$

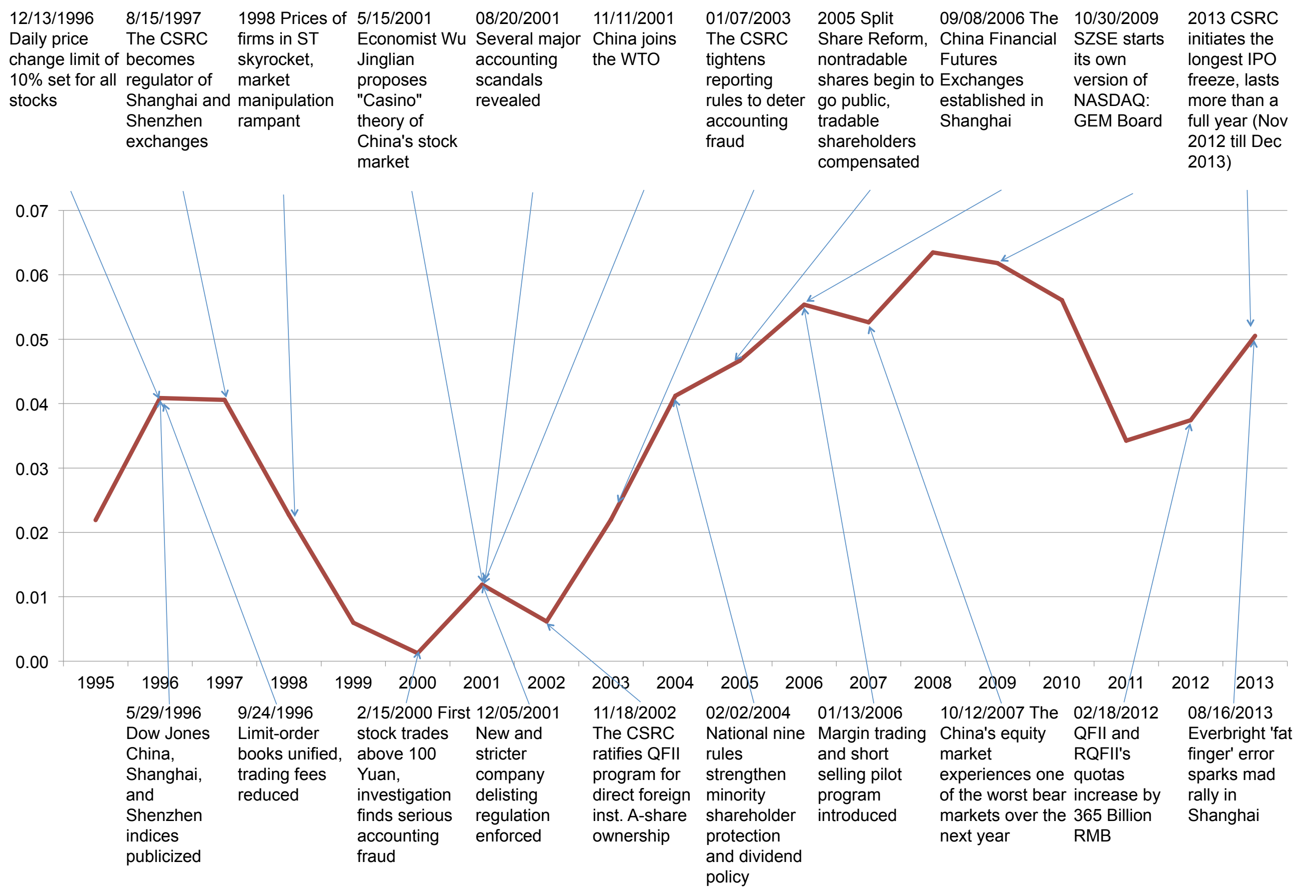
for forecasting horizons $k = 1$ to 5 over the period 1995 to $2016 - k$.

Figure 4: Descriptive statistics for profit and price ratios.



Annual, cross-sectional medians and the 10th and 90th percentiles of the profit ratio E/A and the valuation ratio $\log(M/A)$ in China for the period 1995-2016.

Figure 5: Stock price informativeness, regulatory reforms, and news events

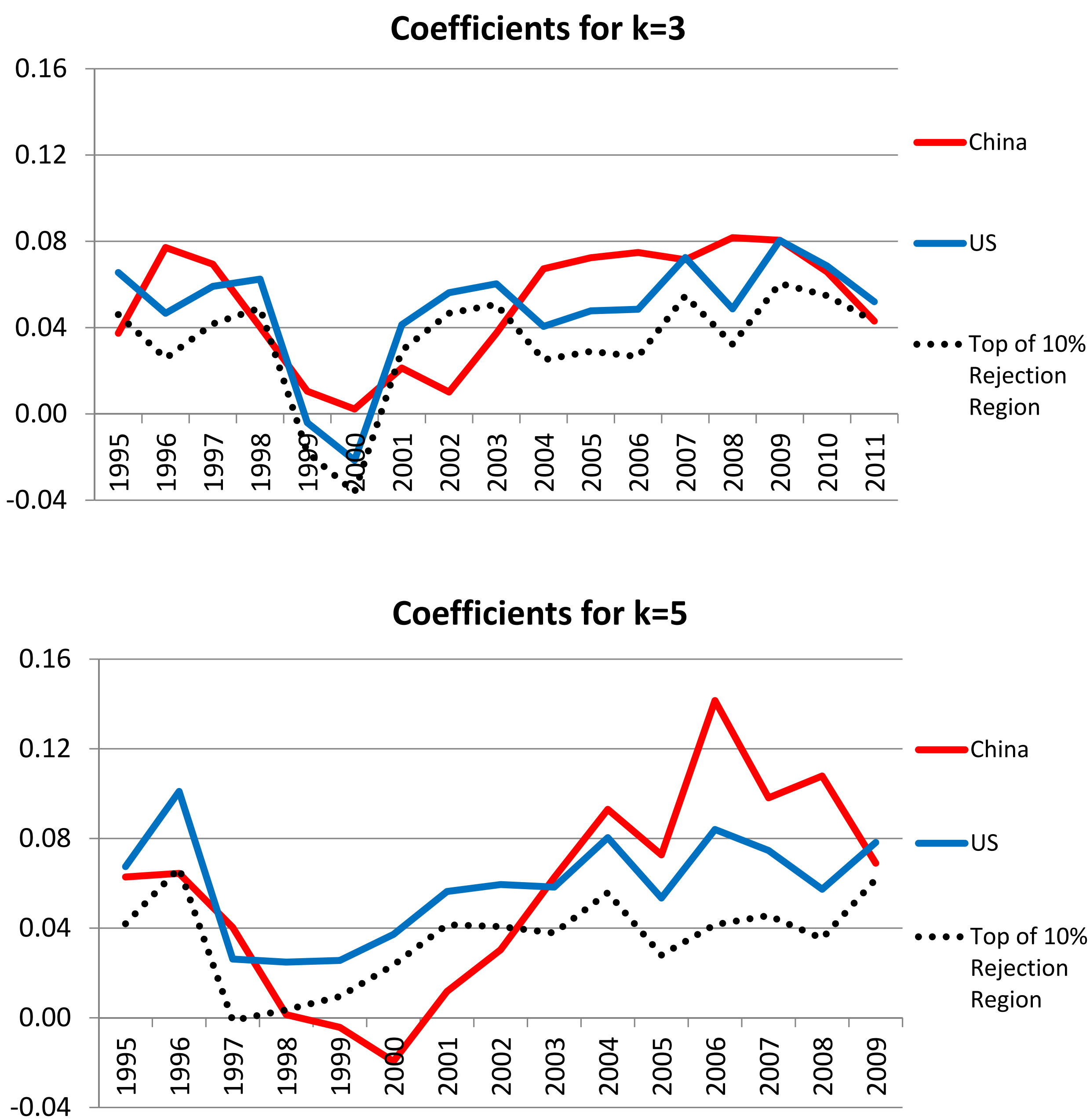


Predicted variation for the regressor $\log(\frac{M_{i,t}}{A_{i,t}})$ in annual cross-sectional regressions

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k}$$

for forecasting horizon $k = 3$, and the timing of various reforms and events that plausibly affected this predicted variation.

Figure 6: Stock price informativeness: China vs. US

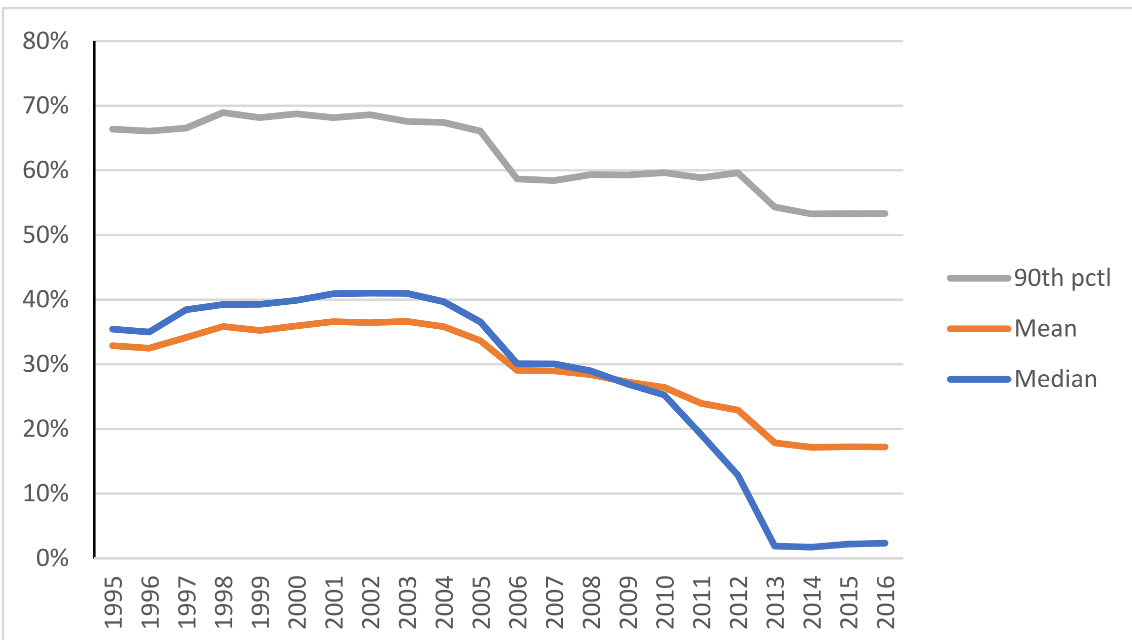


Coefficients b_t for China and the US from annual cross-sectional regressions

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t + b_t \log(\frac{M_{i,t}}{A_{i,t}}) + c_t(\frac{E_{i,t}}{A_{i,t}}) + d_t^s 1_{i,t}^s + \varepsilon_{i,t+k} \ .$$

The dotted line shows the highest China price informativeness level for which the hypothesis that prices in China are as informative as in the US can be rejected at the 10% level in a one-sided test.

Figure 7: Descriptive statistics for state ownership



The annual, cross-sectional mean, median and 90th percentile of the percentage of state ownership across firms in China for the period 1995-2016.