Understanding the Valuation Gap between State-Owned and Non-State-Owned Enterprises*

Yuanlan Cao[†], Avanidhar Subrahmanyam[‡], Xuewei Yang[§] and Peng Zhu[¶]

March 7, 2025

*We appreciate comments from Zhiguang Cao, Feng He, Steven Ho, Fuwei Jiang, Jie Li (Discussant), Jinyu Liu (Discussant), Yue Qi, Jiaqi Qin, Yong Qin, Honglin Ren, Stephen Satchell (Discussant), Chenyu Shan, Yuxi Wang (Discussant), Celim Yildizhan, Li Yu, Andrew Zhang, Xiaodi Zhang, Xiaoquan Zhu (Discussant), and seminar participants at Shanghai University of Finance and Economics, Wuhan University, Capital University of Economics and Business (Beijing, China), Peking University HSBC Business School, Renmin University of China, University of Nevada, Zhongnan University of Economics and Law, Nankai University, Tianjin University, the 2nd Xiangjiang River Forum in EFM for Young Scholars, the 4th Annual Meeting of Financial Econometrics and Financial Risk Management Branch of Management Science and Engineering Society of China, the 20th Chinese Finance Annual Meeting, the 2024 China International Risk Forum (CIRF) and China Finance Review International (CFRI) Joint Conference, the 2nd China Corporate Finance Summer Forum, the 3rd Nanchang Annual International Finance Conference, and the 2024 Sydney Banking and Financial Stability Conference. We appreciate the generous provision of individual stock ESG rating data by Sino-Securities Index Information Service (Shanghai) Co. Ltd for our research. We also appreciate Robert Stambaugh for making publicly available the CH-3 risk factors used in this study. This work was supported by National Natural Science Foundation of China (Nos. W2411065, 72122008, 72495151, 11961141009).

[†]School of Management and Engineering, Nanjing University, 22 Hankou Road, Gulou District, Nanjing, Jiangsu 210093, China. Email: ylcao@smail.nju.edu.cn

[‡]Anderson Graduate School of Management, University of California at Los Angeles. Phone: +1 310 825-5355; email: asubrahm@anderson.ucla.edu

[§]School of Management and Engineering, Nanjing University; Institute of New Finance, Nanjing University. Phone: +86 18915945150; email: xwyang@nju.edu.cn.

[¶]School of Management and Engineering, Nanjing University, 22 Hankou Road, Gulou District, Nanjing, Jiangsu 210093, China. Email: pengzhu@smail.nju.edu.cn

Understanding the Valuation Gap between State-Owned and Non-State-Owned Enterprises

Abstract

What explains valuation disparities between state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs)? We address this question using the Chinese stock market as our backdrop. Our study simultaneously considers a large number of economic hypotheses on why SOEs' and NSOEs' market valuations might differ. The findings suggest that differential distribution across industries only partially explains SOE/NSOE valuation differences. Profitability and its uncertainty emerge as the most significant influences on disparities, followed by liquidity and expected growth. After controlling for these influences, we find that valuation differences between SOEs and NSOEs become economically and statistically insignificant across industries. Our work provides evidence supporting the applicability of classical valuation theories in SOEs, which are often described as anomalously deviating from traditional models of value.

Keywords: State-owned enterprises; Valuation; Chinese stock market.

JEL Classification: G12

1 Introduction

In countries other than the U.S., it is not uncommon for the state to have majority ownerships in a significant fraction of publicly traded firms. Are such state-owned enterprises (SOEs) valued similarly to non-SOEs (NSOEs)? If not, what is the source of the discrepancies in valuations? Shleifer and Vishny (1994) indicate that SOEs often act in the interest of politicians, rather than customers, and also operate for the purposes of providing employment, rather than efficiency of production. However, these aspects should translate to impacts on risk, profitability, and growth in profits, all of which would affect valuations of publicly-traded SOEs relative to NSOEs. To what extent can valuation differences be explained by such traditional influences, as opposed to simply a difference in ownership structure per sé? More generally, what are the determinants of the SOE-NSOE value divergence? The goal of our paper is to perform a thorough empirical investigation of these questions, using the Chinese A-share market as the backdrop.

Over the past three decades, the Chinese stock market has emerged as the second-largest market globally, closely trailing the United States (Carpenter and Whitelaw 2017). SOEs are a large part of the Chinese economy, and China is oft-cited as a success story for the state ownership structure, as SOEs coexist and flourish side-by-side with NSOEs.[1] Anecdotally, however, SOEs are said to receive lower valuations compared to NSOEs.[2] This phenomenon has garnered significant attention from industry practitioners, particularly after a speech by Yi Huiman, who was then the chairman of the China Securities Regulatory Commission, in November 2022. During his talk, Yi expressed concerns about the lower valuation of SOEs and called for the development of a "valuation system with Chinese characteristics" that evaluates enterprises beyond traditional dimensions. The impact of his speech is evident in Figure 1, where it can be observed that within the week following Yi's remarks, the average stock price of SOEs increased by approximately 1.74%, while that of NSOEs decreased by about 2.54%. It is noteworthy that prior to the speech, price trends in SOEs and NSOEs were close to parallel.

While the market's response to the regulatory concerns is fleeting, it underscores the importance of delving deeper into the underlying sources of SOE valuations relative to NSOEs. Indeed, SOEs play a significant role in national economies which operate under socialist systems. Investigating their valuations contributes to a deeper understanding of the performance and

[1] In mid-2023, SOEs, on aggregate, formed about half of China's total equity market capitalization; viz. https://tinyurl.com/4ytkemdv.

[2] For example, see https://tinyurl.com/2jc7s77c.

efficiency of these firms, which are crucial for economic growth and development in managed economies. Additionally, to guide policy decisions on public and private sector development, it is vital to consider how SOEs and NSOEs are valued relative to each other. Furthermore, examining the applicability of conventional variables for valuation can help clarify the issue of whether a non-traditional valuation model for SOEs is in fact necessary.

We propose that our understanding of SOE/NSOE valuation can be advanced by considering how their relative value depends on a comprehensive set of economic drivers. This allows us to uncover the incremental contribution of each force in the presence of others, and to examine the collective importance of such forces. Accordingly, we develop and test a series of hypotheses on the SOE-NSOE valuation differential, with proxies for the forces that drive these hypotheses. To the best of our knowledge, such an analysis, which encompasses a range of determinants, has not been conducted prior. We start out by confirming that the lower valuations of SOEs relative to NSOEs persist over time. The Chinese government's control over the distribution of SOEs across industries motivate us to regard industry membership as a key determinant of these SOE-NSOE valuation differentials. A decomposition of the differential shows that heterogeneity in industry membership only partially explains the valuation difference between SOEs and NSOEs. To put it differently, even within the same industry, significant valuation differences persist between SOEs and NSOEs.

Next, we construct several portfolios based on industry and other characteristics of SOEs and NSOEs. We treat these portfolios as observations for subsequent analysis, which reduces estimation noise and isolates the effects of firm characteristics on valuation. In addition to traditional measures of systematic and total risk, our proposed determinants from traditional valuation models include proxies for market openness, liquidity, growth, and profit uncertainty, all of which relate to classical stock valuation theory. We expect the first three to be positively related to valuation, and last to be negatively so. The results of panel regressions show that differentials in these attributes between SOEs and NSOEs, except market openness, are associated with valuation differences in the hypothesized direction. This finding is significant as it supports the view that the traditional valuation framework plays an important role in explaining valuation differences between SOEs and NSOEs.

We then examine the explanatory power of these determinants of interest in accounting for the valuation differences within each industry.[3] The bulk of the regressions produce

[3]This approach is similar to the GRS test (Gibbons, Ross, and Shanken 1989) in empirical asset pricing. The GRS test

insignificant intercepts, indicating that the proposed determinants effectively account for the valuation differences between SOEs and NSOEs within these industries. The average value of the 34 intercepts is 0.123, while the average valuation difference (based on the logarithm of the market-to-book ratio, Ln MB) is 0.315, which implies that about 60% of the intercept is captured by the determinants. The average adjusted R^2 of these time-series regressions is about 60%.

To assess the relative significance of each determinant, we conduct a dominance analysis. Our findings indicate that age since first listing (a proxy for uncertainty) makes the highest contribution in explaining valuation differences. It explains 17% of the variation in valuation differences on average across industries. This result aligns closely with the evolution of the Chinese capital market. When this market was established, a key objective was to provide financial support to SOEs facing operational challenges during the economic transition period from a planned to a partial market economy. However, this market has gradually shifted its focus wholly towards serving the real economy, which predominantly comprises private enterprises (accounting for 90% of it), and supporting their growth. Prior to 2003, the initial period of our empirical analysis, there were a total of 917 SOE initial public offerings (IPOs) in the market, whereas NSOEs only accounted for 313 IPOs. However, after 2003, the trend reversed significantly, with 458 SOE IPOs and 2,841 NSOE IPOs. In addition to the listing age, we find that other characteristics such as profitability and stock liquidity also play a role in explaining valuation differences.

Do non-fundamental characteristics have any influence on valuation? For example, in the Chinese stock market, the implementation of an approval-based IPO system makes it challenging for companies seeking to go public to enter the market through IPOs (see Allen et al. 2024). As a result, these firms often resort to acquiring underperforming publicly listed companies through reverse mergers to obtain substantial listing status. These underperforming listed companies thus possess shell value (see, e.g., Liu, Stambaugh, and Yuan 2019 and Lee, Qu, and Shen 2023). We examine whether shell value contributes to the valuation gap between SOEs and NSOEs. We employ the exogenous regulatory event of IPO suspensions, which led to a surge in shell value, to examine whether there were significant changes in the valuation difference. The results, however, do not support the notion that shell value is a factor influencing the valuation differential.

is used to examine whether the proposed factors can explain the returns of assets without leaving significant alphas that represent abnormal returns. Our regressions examine whether the proposed determinants can explain valuation differences without leaving significant intercept estimates that represent unexplained valuation differences. Rather than using common factors on the right-hand side of the regression, we use the characteristics as explanatory variables.

Another characteristic we consider is social responsibility. Unlike private firms, SOEs have operational objectives that go beyond pursuing economic interests. These objectives typically encompass national interests and social responsibilities, a particularly emphasized aspect in socialist China. We investigate the explanatory power of social responsibility (S), along with environmental responsibility (E) and governance (G), on valuation differentials using ESG rating data from Sino-Securities, one of the most popular ESG rating institutions in China.[4] The disparities in social responsibility activities undertaken by SOEs and NSOEs are associated with differences in their valuations. However, a similar result is not found for environmental responsibility and governance. Further, the incremental contribution of social responsibility in explaining variations in valuation differentials is limited. For instance, in a multiple regression analysis, the R^2 value marginally increases by less than 2%, and dominance analysis shows that its contribution to the R^2 value is below 5%. In short, social responsibility is statistically significant but appears to have a limited importance compared to the previously-discussed, more traditional, determinants.

To illustrate that valuation differences primarily stem from differences in valuation determinants rather than ownership disparities, we further employ event study methodology to analyze the impact of ownership changes, specifically, the mixed-ownership reform (MOR), on valuation of SOEs. MOR refers to the introduction of non-state capital to achieve a mixed ownership structure.[5] Estimates from stacked Difference-in-Differences (DID) that control for our traditional determinants of the SOE-NSOE spread indicate that valuations do not exhibit a significant change following MORs. We conclude that the relationship between ownership and valuation is indeed absorbed by the attributes we consider.

Our work contributes to the literature on the performance of SOEs. SOEs have often been associated with inefficiency. Theoretically, there are different perspectives that provide explanations for the inefficiency of SOEs. For example, De Alessi (1969) emphasizes that SOEs which restrict individuals from engaging in specialized ownership functions weaken the incentive to monitor performance. Tirole (1994) analyzes the problem of insufficient incentives for government agents and identifies the diversity and non-measurability of government objectives as factors leading to low-powered incentives. Shleifer and Vishny (1994) characterize state-owned enterprises as institutions through which politicians fulfill their personal objectives, such

[4] We are grateful to Sino-Securities Index Information Service (Shanghai) Co.Ltd for generously providing us with the dataset.

[5] See Section 6 for a detailed discussion on MOR.

as instructing them to hire more supporters or providing financing to firms that support them. Shleifer (1998) highlights that politicians' resource transfers to their supporters through policies have led to inefficiencies in SOEs.[6] Empirically, extensive research comparing the performance of SOEs and NSOEs generally finds that SOEs tend to exhibit lower efficiency. Boardman and Vining (1989) review 55 empirical studies on the relative performance of SOEs and NSOEs and find that only six of them claim that SOEs financially outperform NSOEs. They also provide evidence on 500 largest non-U.S. firms that after controlling for a wide variety of factors, the accounting performance of SOEs in competitive industries is substantially worse than that of similar NSOEs. Megginson and Netter (2001) review empirical studies that evaluate the efficiency of SOEs and NSOEs and indicates that seven of ten support that private firms perform better than SOEs. Megginson, Nash, and Van Randenborgh (1994) compares the pre- and post-privatization financial and operating performance of companies from 18 countries and find strong performance improvements. Our work indicates that the performance of SOEs is lower than that of NSOEs, whether it be in terms of profitability or growth, although traditional determinants such as liquidity and volatility also play a role in explaining the SOE-NSOE valuation spread.

This paper is closely related to research on stock valuation in the Chinese market. Bailey (1994) finds that Chinese foreign class B-shares trade at a discount relative to A-shares available to Chinese citizens, and Bailey, Chung, and Kang (1999) document that among the 11 markets where both domestic and foreign shares are issued, only the Chinese domestic stock prices are higher than those of foreign markets. This phenomenon is also known as 'Chinese A-B share premium'. Chan, Menkveld, and Yang (2008) attribute the A-B premium to information asymmetry, and Mei, Scheinkman, and Xiong (2009) emphasize the role of speculative trading on the A-B premium. Wang and Jiang (2004) document a discount of H-shares traded on the Hong Kong Stock Exchange relative to A-shares, and suggest that the A-H premium is correlated with relative market liquidity. These studies on price disparities of cross-listed stocks in China only cover a small portion of stocks in the Chinese stock market. Bekaert et al. (2022) analyze the valuation differentials between the Chinese and the U.S. market, and focus more on a cross-country comparison. Our work differs from all of theirs as we focus on studying the valuation differences between two types of companies, namely state-owned and private-owned, within the same market.[7] Our contribution

[6] One can refer to literature reviews by Lawson (1994) and Peng et al. (2016) on theories of SOEs.

[7] There are also studies that discuss the relationship between government ownership and firm value. For instance, Boubakri et al. (2018) document the non-linear impact of government ownership on firm market valuation across nine East Asian economies. Beuselinck et al. (2017) find that government ownership mitigates the decline in firm value during financial crises, based on a sample of 28 European countries. However, these two studies do not include China.

is to do a deep-dive into the determinants of valuation differences between SOEs and NSOEs, in the Chinese stock market, the largest emerging market.

A large literature documents that the Chinese listed firm's performance is negatively correlated with the proportion of state ownership (see, e.g., Lin and Su 2008; Xu and Wang 1999; Chen, Firth, and Xu 2009). The lower performance of Chinese SOEs is commonly attributed to their engagement in policy burdens or multiple tasks, which become more pronounced during China's economic transition period. (see, e.g., Lin, Cai, and Li 1998; Lin and Tan 1999; Bai et al. 2000; Bai, Lu, and Tao 2006). Existing work suggests that privatization reform in the stock market, such as the share issue privatization and the split-share structure reform that converts non-tradable shares into tradable ones, have lead to increased output, profitability, and innovation in SOEs (see, e.g., Sun and Tong 2003; Liao, Liu, and Wang 2014; Harrison et al. 2019; Tan et al. 2020). Additionally, some studies document special patterns in real investment by SOEs or lending by state-owned banks during specific periods, such as election years or periods when economic stimulus plans are implemented, to provide a micro-level perspective on understanding the inefficiencies associated with SOEs (see, e.g., Ru 2018; Cong et al. 2019; Li, Lin, and Xu 2020; Alok and Ayyagari 2020). Our research documents patterns in the valuation differences between SOEs and NSOEs over time and across industry structures, and suggests that these differences can be attributed to not only profitability but also to the environment for trading stock, which has been overlooked in existing studies.

Finally, there is a growing body of research focusing on various issues in the Chinese stock market. Liu, Stambaugh, and Yuan (2019) suggest that shell values resulting from listing system deficiencies contaminate stock prices, and an adjusted Fama-French factor model that removes shell values explains cross-sectional returns well in the Chinese stock market. Carpenter, Lu, and Whitelaw (2021) highlight that the informational efficiency of the Chinese stock market is comparable to that of the U.S. market. Leippold, Wang, and Zhou (2022) apply machine learning methods to empirical asset pricing in the Chinese stock market and identify key predictors that differ from those in the U.S. market. Li et al. (2023) consider more than 400 anomaly variables and seven factor models using Chinese A-share data. They show that the NSOE subsample generates a much higher number of significant anomaly variables than SOE subsample. Allen

Chen, Firth, and Xu (2009) and Wei, Xie, and Zhang (2005) document that the firm value (measured as Tobin's Q) is associated with ownership types. However, they only explain this relationship from the perspective of operational performance. Furthermore, their sample periods are from the early part of the 2000s when there are fewer listed companies in the Chinese stock market, with a significant proportion being state-owned enterprises.

et al. (2024) examine the long-term underperformance of the Chinese stock market and attribute it to deficiencies in the listing and delisting systems, investor sentiment, and poor corporate governance. Different from Allen et al. (2024), our focus is to investigate the extent to which valuation disparities can be explained by traditional determinants of value. We take into account both fundamentals (such as profitability, growth, uncertainty and leverage) and stock trading attributes (such as liquidity and turnover). We add to existing research about finance by demonstrating that these classical determinants play a significant role in explaining valuation differences between SOEs and NSOEs.

It is worth reiterating what our Chinese context adds to existing research about finance in general. China possesses not only the world's second-largest stock market but also a large SOE sector, which is a component absent in the U.S. economy. This unique reality provides an ideal setting for understanding how government ownership affects valuations.[8] Although researchers have shown that valuation disparities between Chinese SOEs and NSOEs are related to accounting performance differences, we show that other determinants matter as well. Specifically, our findings confirm the additional roles of liquidity, turnover, and uncertainty on valuation differentials.

Overall, the detailed analysis of SOE-NSOE valuation differences using accounting and financial market determinants, as well as regulatory policy shifts, forms our contribution to the literature. We note that our main goal is to pin down determinants of the valuation differentials in a comprehensive empirical analysis. An in-depth investigation of the precise reasons for *why* these determinants differ across SOEs and NSOEs is something we leave for further research. Instead, we simply put across the idea that SOEs are just firms like any other, and the determinants of their valuations largely correspond to intuitive economic determinants already considered in earlier literature. In other words, the SOE-NSOE valuation disparity is not an "anomaly" but arises in large part simply because SOEs differ along intuitive economic dimensions.

The paper is organized as follows. In Section 2, we provide a description of the data and valuation variables, and we document stylized facts on the valuation gap between SOEs and NSOEs. In Section 3, we introduce hypotheses that aim to explain the differences in valuation and discuss the model settings used to test these hypotheses. Section 4 reports the main results. Section 5 analyzes some alternative explanations for valuation differentials. Section 6 provides

[8] In fact, this institutional feature has also caught the attention of scholars at large. According to Bruton et al. (2015), among the 39 papers on SOEs published in the journals of the Financial Times' top 45 between 2000 and 2014, 30 of them specifically examined Chinese SOEs as a research sample.

supportive evidence for the preceding findings through event studies on MORs of SOEs. Section 7 concludes this work.

2 Data, Concept, and Stylized Facts

In this section, we describe our data, and present some preliminary analyses of the SOE-NSOE valuation differential.

2.1 Data

We start with SOEs and NSOEs listed on the Chinese stock market from 2003 to 2021. Our sample includes all listed A-share firms.[9] We select the year 2003 as the sample starting point for two reasons: First, some of the current important regulations in the Chinese stock market were not prevalent in the 1990s.[10] Second, most variables employed in this study, such as ownership types and quarterly financial reports, are only accessible or obtainable from the year 2003.

The data used in this work can be classified into five categories. 1) Basic information on listed companies, including the listing date, shareholder structure, actual controller information, capital structure, industry classification, etc., 2) stock trading data, including daily closing prices and trading volumes of stocks, 3) firms' periodic financial reports on a quarterly basis. 4) Analyst forecast data, which involves forecasts of net profit and operating income from research reports of security analysts, and 5) other data, including factor returns in the Chinese stock market, the consumer price index, IPO prospectus files, and firms' ESG rating scores. We collect much of our data from the CSMAR database. The ESG ratings are provided by Sino-Securities, a Chinese

[9] The stocks listed on the exchanges in mainland China can be classified into A-shares and B-shares based on the investor composition. A-shares are stocks issued and traded by domestic residents within the mainland. B-shares are stocks issued within the mainland while traded by foreign investors. Due to the strict foreign exchange controls imposed on domestic residents and market access restrictions imposed on foreign residents in China, the A-share and B-share markets were effectively segregated (see Chan, Menkveld, and Yang 2008 and Mei, Scheinkman, and Xiong 2009 for more institutional information). Apart from listing on the mainland, some Chinese companies also choose to list on China Hong Kong stock market and foreign stock markets such as the U.S. The stocks discussed in this work focus on those in A-share market.

[10] Although the government introduced principles for fair disclosure of financial information for listed companies as early as 1993, there were no specific guidelines on how these principles should be implemented by the companies. Each company formulated its own standards, which limited the comparability of accounting data across companies. It was not until 1998 and 1999 that comprehensive regulations regarding financial reporting were designed and implemented. In December 1998, the legislative body passed China's first *Securities Law*, which came into effect in July 1999. In December 1998, the China Securities Regulatory Commission (CSRC) issued detailed guidelines for the disclosure of operating revenues by companies, which were implemented in January 1999. In April 2001, the CSRC issued guidelines for the content and format of quarterly reports for listed companies, which were implemented in January 2002.

company engaged in this endeavor. The factor returns used in this work are obtained from the personal homepage of Rob Stambaugh, one of the authors of Liu, Stambaugh, and Yuan (2019).

Following Bekaert et al. (2022), we apply the following filters to the sample: 1) Exclude firms listed for less than one year; 2) drop stocks with less than 45 daily observations during the most recent quarter; 3) drop stocks with less than 120 daily observations during the most recent year; 4) remove observations of firms with negative total assets or equity or total revenue in the most recent quarter; and 5) exclude observations of firms with missing ownership structure or industrial classification.

We use the market-to-book ratio (MB) to measure the valuation of listed firms; this is a simplified version of Tobin's q (Baker and Wurgler 2002). MB is calculated as the market value of the equity divided by its book value. Compared to profit-based valuation ratios such as price-to-earnings ratio, MB is likely to be less affected by earnings management.

The CSMAR database provides ownership information which classifies a firm as an SOE if it is controlled by state-owned enterprises, government agencies and institutions, central government and its departments, or local government and its departments. All investors in the market can trade the floating shares of listed companies, regardless of whether they are classified as SOEs or NSOEs. Additionally, each share, whether held by an individual or state-owned shareholders, carries exactly the same dividend rights and voting rights.[11]

2.2 Preliminary Analyses

We first compute MB for SOEs and NSOEs on a quarterly basis from 2003 to 2021. Figure 2 displays the time series of MB for SOEs and NSOEs, which are obtained by averaging the valuations within each sector on a quarterly basis.[12] Throughout the sample period, the average valuation of SOEs has consistently been lower than that of NSOEs. The time-series average valuations for NSOEs and SOEs are 2.876 and 1.869, respectively. That is, compared to SOEs, for a book value of 1 yuan, investors on average assign a market value that is 1.007 yuan higher to NSOEs relative to SOEs. Another relevant fact is that the valuation difference between NSOEs and SOEs (represented by the bars in the figure) is positive but exhibits a fluctuating trend. The former phenomenon has led to a popular narrative in the market that SOEs are undervalued.

However, the undervaluation of stocks might suggest that holding these stocks can potentially

[11]See IA.1 for further information about CSMAR and additional institutional details on share transactions in SOEs.

[12]We calculate weighted average valuations using the book value of company equity as weights. Similar patterns can be observed when using equal weights for the average valuation, as shown in Figure IA.1 in the appendix.

lead to higher returns, particularly in the long run, as the undervaluation is corrected. To test this assertion, we compare the returns of portfolios consisting of SOEs and NSOEs at the beginning of the first day of each quarter throughout the sample period, specifically in January, April, July, and October. We hold these portfolios for durations of 1, 3, and 5 years, respectively, and calculate the corresponding returns for each duration. Table 1 reports the equal-weighted average returns as well as value-weighted average returns of the portfolios formed at different time. We observe that there is either no significant difference in the returns between SOEs and NSOEs, or NSOEs tend to have higher holding-period returns. Further, NSOEs exhibit higher volatility, ultimately resulting in an insignificant difference in the Sharpe ratios between portfolios of SOEs and NSOEs. To sum up, despite the lower valuation of SOEs, they have not demonstrated significantly higher returns. We therefore conclude that the lower valuations of SOEs do not translate to higher holding-period returns, indicating a stable valuation discrepancy, rather than an "anomaly" rising from behavioral biases.[13]

It is conceivable that the lower valuation of SOEs compared to NSOEs might arise from the larger market share of low-expected-valuation industries within the SOEs. In fact, the operational choices of China's SOEs, particularly in terms of industry layout, are influenced by the government. As early as 1999, in a policy document issued by the Chinese government, explicit objectives were set regarding the industry layout of SOEs: "(SOEs) should adhere to a balanced approach of expansion and contraction. . . The industries and sectors that the SOEs should focus on include those related to national security, natural monopolies, providing important public goods and services, as well as pillar industries and high-tech industries. In other industries and sectors, the development of individual, private, and other non-public ownership economies is encouraged."[14] Figure 3 displays the time-series average of industry valuations along with the proportion (measured as total assets) of SOEs within each industry.[15] It is evident that in

[13]One might note that the reported returns here are different from the holding returns reported in Figure 1 of Allen et al. (2024). We mention two aspects that might possibly lead to the differences. The first is that Allen et al. (2024)'s returns are inflation-adjusted, while our Table 1 reports nominal returns. Table IA.1 in the appendix of our paper provides the results for real returns (i.e., after adjusting nominal returns for inflation); the results change little. The second is that the sample period in Allen et al. (2024) differs from ours; see Figure IA.2 for an illustration.

[14]The expression originates from the "Decision of the Central Committee of the Communist Party of China on Several Major Issues Regarding the Reform and Development of State-Owned Enterprises." This document was approved during the 4th Plenary Session of the 15th Central Committee of the Communist Party of China and was issued by the 15th Central Committee of the Communist Party of China.

[15]In this and other relevant sections, we employ the industry classification standard established by the CSRC. This classification includes a total of 19 primary industries. Due to the vast scale and various range of China's manufacturing sector, we further subdivided it into 30 secondary industries within manufacturing (industry codes starting with 'C'). For other 18 primary industries, we kept the classification at the primary level. Therefore, there are 48 industries in total: 18 non-manufacturing primary industries and 30 secondary manufacturing industries.

certain industries with lower valuations, such as construction, ferrous metals, and energy, the proportion of SOEs is close to 100%. In contrast, NSOEs have a larger proportion in industries with higher valuations, such as cultural & educational production and instrumentation production. Consequently, we propose the following hypothesis as an explanation for the overall valuation difference between SOEs and NSOEs:

H0: *SOEs are concentrated in industries with lower valuations, resulting in their lower valuation.*

We perform the following decomposition of the valuation differential (DV) between NSOEs and SOEs to examine the role of industry structure:

$$\begin{aligned} DV = V^{NSOE} - V^{SOE} &= \sum_{j=1}^{N} w_{jt}^{NSOE} V_{jt}^{NSOE} - \sum_{j=1}^{N} w_{jt}^{SOE} V_{jt}^{SOE} \\ &= \sum_{j=1}^{N} w_{jt}^{NSOE} \left(V_{jt}^{NSOE} - V_{jt}^{SOE} \right) + \sum_{j=1}^{N} \left(w_{jt}^{NSOE} - w_{jt}^{SOE} \right) V_{jt}^{SOE} \\ &= DI + DS. \end{aligned} \tag{1}$$

Here, w_{jt}^{NSOE} and w_{jt}^{SOE} are the equity weights of industry j in all NSOEs and all SOEs respectively. The first component, DI, represents the valuation differential within the same industry between NSOEs and SOEs, and thus it constitutes an industry-neutralized valuation difference. The second component, DS, captures industry weight differences between NSOEs and SOEs and represents the valuation effect of a different industry structure across these categories. By computing the mean of both sides of Eq. (1) and the covariance between them and DV, we derive the following two equations:

$$mean(DV) = mean(DI) + mean(DS), \tag{2}$$

and

$$Cov(DV, DV) = Cov(DI, DV) + Cov(DS, DV). \tag{3}$$

Eq. (2) breaks down the average value of DV into the average values of DI and DS. On the other hand, Eq. (3) decomposes the variance of DV into the covariances between DI and DV, and between DS and DV. These two equations provide a decomposition of the level of and the variation in valuation differences.

We compute the DV, DI and DS each quarter and then conduct the above decompositions. First, the time-series average of the DV is 1.002, which is very close to the value shown in Figure

2.[16] Following Eq. (2), we decompose the MB differential of 1.002 into DI and DS. We find that the DI has a time-series average of 0.631 and the DS an average of 0.371. That is, the structural component, DS, contributes to less than half of the overall valuation difference. We also evaluate how much the structural component contributes to the total variance of the overall differential as in Eq. (3). The variance of DV is 0.349. The covariance between DS and DV is 0.181 and it accounts for 51.8% of the variation of total valuation differentials. Thus, an explanation based on differences in industry structure (**H0**) leaves a significant portion of the valuation difference unexplained.

Figure 4 further depicts the valuation differences between SOEs and NSOEs across industries. Out of the 33 industries examined, NSOEs have higher valuations than SOEs in 29 industries. The largest valuation difference is observed in the IT industry, with a valuation of 2.049 for SOEs and a valuation of 4.710 for NSOEs, representing a difference of 2.661. On the other hand, in a few industries, SOEs are valued higher than NSOEs. For instance, in the Alcohol, Drink, & Tea industry, SOEs have a valuation of 5.509, while NSOEs have a valuation of 4.854, indicating a difference of 0.6 higher for the former.

Another important stylized fact we mention here (and analyze later) is the average difference in time since listing between SOEs and NSOEs. The early development of the Chinese stock market is closely intertwined with China's SOE reforms. The reconstruction of the Chinese stock market took place in the 1990s, a crucial period in China's economic system reform, during which the country first proposed the goal of building a socialist market economy. In the transition from a centrally planned economic system to a market-oriented system, a large number of SOEs suffered significant losses due to the lack of modern corporate governance and management expertise.[17] The listing of an SOE not only enables it to raise a significant amount of capital to offset losses but also facilitates improvement in governance and information disclosure. At that time, Chinese leaders put forward several significant measures to support the revitalization of SOEs, one of which was to promote the financing of SOEs through their listing on the stock market. As a result, in the early stages of the Chinese stock market, SOEs had a dominant presence.

Figure 5 presents the listing trajectory of SOEs and NSOEs in the early and later stages of the Chinese stock market. Prior to 2003, SOEs accounted for 75% of the total number of listed companies, with 917 out of 1,230 companies listed on the A-share market being SOEs. After 2003,

[16] The discrepancy arises from the calculation of Eq. (1), where only industries with more than 5 companies are retained.

[17] For example, during the mid-1990s, more than 40% of SOEs were loss making (Lin, Cai, and Li 1998).

there is a reversal in the number of SOEs and NSOEs in the market. Since the establishment of the SME board in 2004, there has been a slight increase in the number of new NSOEs entering the stock market compared to SOEs on an annual basis. The establishment of the ChiNext in 2009 further opened the gates for a significant influx of NSOEs into the stock market.[18] In 2017, the number of newly listed NSOEs was thirteen times higher than that of SOEs. Thus, NSOEs have entered the market intensively more in later years relative to SOEs, resulting in a younger listing age.

3 Hypothesis and Methodology

In this section, we first discuss our economic hypotheses, and then discuss the variety of methods we use to test these.

3.1 Hypothesis Development

Our analysis builds upon simple existing asset pricing models. The price of a stock is determined by the present value of the future cash flows provided by the corresponding firm, and we assume that, in analogy to Gordon's Growth Formula, it can be expressed using a constant growth rate g and discount rate r as follows:

$$P = \frac{E}{r-g}, \tag{4}$$

where E and P are the expected earnings and the stock price, respectively.[19] Dividing both sides of Eq. (4) by the book value of equity (B) yields an expression for the valuation metric, Market-to-Book ratio (MB), as

$$MB = \frac{P}{B} = \frac{E}{B} \cdot \frac{1}{r-g} = \frac{ROE}{r-g}, \tag{5}$$

where ROE denotes the return-on-equity. Eq. (5) implies that there are three determinants of stock valuation: profitability, discount rate, and growth. Motivated by Eq. (5), we propose the following hypothesis to examine the role of profitability in explaining the differences in valuation.

[18] The SME Board and ChiNext are two separate stock market segments in China. The SME Board, a market segment specifically designed for small and medium-sized enterprises, was established on the Shenzhen Stock Exchange in 2004. ChiNext, formally known as the Growth Enterprise Market (GEM), was launched by the Shenzhen Stock Exchange in 2009. It is a stock market segment aimed at supporting innovative and high-growth potential enterprises, particularly in the technology and emerging industries. Both the SME Board and ChiNext play important roles in facilitating the financing and growth of small and medium-sized enterprises as well as promoting innovation and entrepreneurship in China's capital market.

[19] Our use of the Gordon model here does not imply that it is a predominant source for understanding stock valuation. Nonetheless, its insights about the determinants of valuation remain valid under more general settings.

Hypothesis H1. *Higher profitability of NSOEs compared to SOEs leads to their higher valuation.*

While most research on SOEs focuses on the higher profitability of NSOEs and the subsequent positive impact on their valuation relative to SOEs, we go beyond this pathway and consider the effects of differences in discount rates and growth prospects as determinants of differences in valuation. When considering the characteristics which affect the discount rate, three crucial pieces of economic reasoning emerge. First, according to classical asset pricing theory, the required rate of return is determined by a stock's exposure to systematic risk. If SOEs and NSOEs have different risk exposures, these differences may contribute to variations in their stock valuations. Second, the overall risk level (measured by return volatility) of stocks influences the required rate of return if diversification is imperfect; higher volatility should correspond to a higher expected return, leading to a lower stock valuation. Third, increased financial leverage amplifies equity risk, which in turn elevates the required rate of return. Therefore, we propose the following hypotheses:

Hypothesis H2a. *Differences in systematic risk exposure between SOEs and NSOEs contribute to their valuation disparities.*

Hypothesis H2b. *Differences in overall risk levels between SOEs and NSOEs lead to differences in their valuations.*

Hypothesis H2c. *Differences in leverage levels between SOEs and NSOEs translate into differences in their valuations.*

Comparative studies on the valuation differences between A-shares (Chinese domestic shares) and other share classes (such as B-shares, H-shares, or U.S. -listed shares) have identified sources of discount rate discrepancies beyond systematic and total risk measures. The first determinant we consider is market openness (Bekaert et al. 2022, Fernald and Rogers 2002). This literature indicates that, compared to domestic investors, foreign investors may assign lower valuations to the same stocks, possibly because of increased information uncertainty they face relative to domestic investors, which implies a higher discount rate. Thus, when there are differences in the accessibility of foreign investment across stocks of Chinese SOEs and NSOEs, it leads to disparities in their valuations. Another possible channel is liquidity (also mentioned by Bekaert et al. 2022). Many studies indicate that liquidity plays an important role in the cross-section of discount rates (Amihud 2002; Carpenter, Lu, and Whitelaw 2021). Investors generally demand lower discount rates for stocks with higher liquidity. As a result, differences in stock liquidity can lead to variations in valuation. We leverage these explanations suggested by existing research.[20] We thus have the following two hypotheses:

Hypothesis H2d. *Valuations differ for stocks with varying levels of accessibility to foreign investment. The greater the openness of SOEs relative to NSOEs, the lower the valuation.*

Hypothesis H2e. *Valuations differ for stocks with varying liquidity. The lower the liquidity of SOEs relative to NSOEs, the lower the valuation.*

Growth (g) is another important determinant of asset prices. However, characterizing growth is more challenging as it is difficult to measure accurately in advance. Assessing growth involves predicting future cash flows. Numerous attributes, such as market conditions, competitive landscape, and innovation, contribute to growth potential. But these influences are subject to uncertainties and can be challenging to quantify. Despite the challenges, we consider multiple measures of growth to capture a company's growth potential from different perspectives.

The first set of indicators is based on the company's historical financial performance, specifically the growth rates of total assets and operating revenue. These indicators reflect the company's past growth trajectory. It is common to assume that historical performance can be extrapolated to some extent into the future. Even though this extrapolation may not always be accurate, this assumption can provide insights into a company's growth momentum which is important in order to capture a firm's ability to generate and expand its business over time. If there is a substantial disparity in the historical growth rates between SOEs and NSOEs, it is reasonable to expect divergent valuation levels between the two. Thus, we have the following hypothesis:

Hypothesis H3a. *The lower the recent business growth rate of SOEs relative to NSOEs, the lower the valuation.*

The second set of growth measures comes from analysts' expectations. This is a more comprehensive indicator as analysts consider various factors, including industry trends, company performance, and market conditions, in order to form forecasts of a company's future growth. Following Bekaert et al. (2022), we utilize the median of expectations from multiple analysts to balance extreme forecast values. We propose the following hypothesis:

[20]While the real (risk-free) interest rate is a component of the discount rate, we focus on the valuation of two types of stocks within the same market. Their investors share the same interest rates, and therefore, we should not expect the interest rate level to have an impact on the valuation difference.

Hypothesis H3b. *The lower the analysts' expected growth rate of SOEs relative to NSOEs, the lower the valuation.*

The last set of growth measures we employed is derived from patent data. A company's innovative originality strongly predicts higher profitability and future growth (Hirshleifer, Hsu, and Li 2018). Innovation activities can be measured from both inputs and outputs. On the input side, research and development (R&D) expenses can be used as a measure. On the output side, outcomes such as patents serve as a metric. Since the implementation of mandatory disclosure of research and development (R&D) expenses in financial statements for all listed companies in China began in 2018, we cannot measure a company's innovation from the input side for the predominant part of our sample. Therefore, we evaluate a company's innovation activities on the output side. We extract the number of innovation patents and utility model patents from the patent application documents of all listed companies.[21] The hypothesis is:

Hypothesis H3c. *The lower the level of innovation of SOEs relative to NSOEs, the lower the valuation.*

We next develop some hypotheses that go beyond the simple baseline of Eq. (5). We first note that speculative trading (based on belief divergence) has been extensively considered in the literature (see Scheinkman and Xiong 2003; Li, Subrahmanyam, and Yang 2021; Pearson, Yang, and Zhang 2021; DeFusco, Nathanson, and Zwick 2022). As demonstrated by Scheinkman and Xiong (2003), the price of an asset constitutes of two components: the fundamental valuation derived from future cash flows, and the speculative component generated by the asset owner's option to sell the share for a speculative profit. They show that the resale option, with the difference in investors' beliefs serving as the underlying asset, is valuable to the asset owner. According to the principles of option pricing, the resale option becomes more valuable as the divergence in investors' beliefs increases, so that investors trade more frequently with each other. If there are differences in the level of belief divergence across SOEs and NSOEs, their stock turnover rates will differ, as will the speculative component of value. Hence we propose the following hypotheses:

Hypothesis H4a. *The valuation difference between SOEs and NSOEs is positively correlated with the difference in their stock turnover.*

[21] In China, apart from invention patents and utility model patents, there is another type of patent known as design patents. However, design patents are less relevant for measuring innovative originality, and therefore, we do not take design patents into account.

Hypothesis H4b. *The valuation difference between SOEs and NSOEs is positively correlated with the degree to which investors' beliefs diverge within each of the two asset classes.*

Hypothesis H4c. *The correlation between turnover difference and valuation difference weakens after controlling for the difference in belief divergence between SOEs and NSOEs.*

In our empirical work, we use idiosyncratic volatility as a proxy for belief divergence within a security, which follows Jiang, Xu, and Yao (2009) and Mei, Scheinkman, and Xiong (2009).[22]

Finally, we develop two hypotheses that are related to time since listing (or listing age). The shorter the listing duration of a company, the less information investors have about its profitability, leading to greater earnings uncertainty. Pástor and Veronesi (2003) build a model that incorporating this uncertainty into stock valuations. They show that market-to-book ratios are positively related to growth rate uncertainty, owing to the convexity of values in the growth rate. Their model suggests that as listing age increases, investors' learning about future profitability strengthens, leading to a gradual reduction in uncertainty about the firm's operational cash flows, ultimately resulting in a decrease in valuation. Further, their model implies that, in addition to current profitability, the unknown average profitability in the future also has a positive influence on valuation, as shown in their Eq. (27). Consequently, we suppose that differences in firms' historical average profitability (a proxy for future expected profitability)[23] may help to explain valuation disparities. Based on this valuation model, we propose the following hypotheses:

Hypothesis H5a. *SOEs with lower historical average profitability have lower valuations.*

Hypothesis H5b. *SOEs with a longer listing history have lower valuations.*

3.2 The Basic Empirical Setting

To begin, we form several stock portfolios for SOEs and NSOEs based on industry or stock characteristics and use these portfolios as observations in the empirical analysis. Using portfolios as empirical observations in the analysis offers two advantages: First, by grouping stocks into portfolios based on industry or specific characteristics, we can isolate the impact of these

[22] We also attempt to use dispersion in analyst forecasts (Diether, Malloy, and Scherbina 2002) as a proxy for belief divergence. This measure, however, is only weakly related to differences in valuation and turnover; results are available upon request. Further, using dispersion in analyst forecasts results in significant sample loss. Therefore, we refrain from using this measure as a proxy for belief divergence.

[23] In unreported analyses, we find that, for every quarter during our sample period, the correlations (across all listed companies) between our proxy for future average profits (the 3-year historical average ROE) and future realized ROEs are significantly positive.

characteristics on valuation. Second, aggregating stocks into portfolios helps mitigate estimation errors that may arise from analyzing individual stocks.

Specifically, we construct 48 industry portfolios separately for SOEs and NSOEs using the industry classification of listed companies issued by the China Securities Regulatory Commission (CSRC). Additionally, we construct several characteristic-based portfolios to account for the impact of certain characteristics on valuations. Specifically, we sort SOEs and NSOEs separately based on size, liquidity, turnover, and ownership concentration.[24] Then, we select the top 30% and bottom 30% of companies from each category, forming portfolios with high and low characteristic values, respectively. We also consider the influence of high-tech attributes and the listing board (exchange). We form TMT (Technology, Media, and Telecommunications) and non-TMT portfolios for both SOEs and NSOEs.[25] Finally, we construct three board (or exchange-based) portfolios for both SOEs and NSOEs: Main board portfolios, Small and Medium-sized Enterprises (SME) board portfolios, and the combination of ChiNext board and the Science and Technology innovAtion boaRd (STAR) portfolios.[26] We end up with a total of 61 portfolios for both SOEs and NSOEs. However, not all periods have a complete set of 61 portfolios. If a portfolio in a specific period consists of fewer than 5 companies, the observation for that portfolio in that period is excluded. The portfolio formation process is repeated for each quarter throughout the sample period (2003-2021), which spans 19 years or 76 quarters. The filtered panel consists of 3,074 portfolio-quarter observations.

Following Bekaert et al. (2022), we set our empirical specification as follows:

$$DV_{j,t+1} = \beta\, DX_{j,t} + \gamma\, DControl_{j,t} + \mu_j + \epsilon_{j,t}. \tag{6}$$

In Eq. (6), the indices j and t represent portfolio and quarter respectively, DV represents the difference in valuation between NSOE and SOE, while DX and $DControl$ represent the differences in the explanatory variables and any control variable(s), respectively. The selection of independent

[24]The proxy variables for these four dimensions are as follows: the number of shares issued by the company recorded in the most recent quarter's balance sheet, the proportion of trading days with zero returns over the past quarter (Zero), the average daily turnover over the past quarter, and the number of shares issued divided by the total number of shareholders as of the end of the most recent quarter.

[25]TMT sectors include the following categories as per the classification of the CSRC: C39, Manufacture of Computers, Communications Equipment, and Other Electronic Equipment; I63, Telecommunications, Broadcasting, and Satellite Transmission Services; I64, Internet and Related Services; I65, Software and Information Technology Services; R87, Cultural and Artistic Industries.

[26]We merge the ChiNext Board and STAR samples because the latter was established in 2019 and has a limited sample. Additionally, companies listed on the STAR Market and the ChiNext board are similar in that they both consist of entrepreneurial companies.

variables is determined by the hypotheses developed in Section 3.1. We control for size (calculated as the logarithm of a firm's total assets) in all regressions for valuation differences as the dependent variable. The rationale for this control is that while size looms large in valuation, the pathway is less certain. For example, large firms may be more visible, which implies less uncertainty and implies higher valuations (Merton 1987), or they might be complex and inefficient, which leads to lower growth and lower valuations (Lang and Stulz 1994). Since the mechanism by which size might operate is unclear, we use separate proxies for uncertainty and growth, and let size soak up any imperfections in our proxies. The definition and calculation methods for all dependent and independent variables are summarized in Table IA.2. For each portfolio, we calculate the average valuation, as well as the average values of other explanatory and control variables, using book value of equity as weights. To account for aspects that influence valuation but are not explicitly included, we include portfolio fixed effects.

For each hypothesis developed in Section 3.1, we run a regression with corresponding explanatory variable(s) as in Eq. (6). Subsequently, we perform a multivariate panel regression to investigate whether there are redundant hypotheses (or redundant explanatory variables) that do not provide additional explanatory power relative to others.

3.3 Explanatory Power for Valuation Differentials

Eq. (6) is specifically designed to test the validity of the hypotheses presented in Section 3.1, both individually and collectively. However, it does not provide information on whether these hypotheses completely capture the valuation differences between SOEs and NSOEs. To address this concern, we perform further analysis to evaluate the extent to which these hypotheses effectively explain the observed valuation differences.

We decompose the panel model of Eq. (6) into a series of time series regressions. Specifically, we run the following three time-series regressions for each portfolio:

$$DV_{t+1} \sim \mathbf{1}, \tag{7a}$$

$$DV_{t+1} \sim \mathbf{1} + DControl_t, \tag{7b}$$

$$DV_{t+1} \sim \mathbf{1} + DControl_t + DX_t. \tag{7c}$$

Here $\mathbf{1}$ denotes the unit vector, the prefix D represents the difference between NSOEs and SOEs, *Control* denotes the control variable *Size*, which is the same as in Eq. (6), and X_t are the explanatory variables with statistically significant coefficients and expected signs in the multivariate regression as in Eq. (6). The estimated intercepts from the regression, as in Model (7a), represent the valuation difference between NSOEs and SOEs within each industry (or characteristic) portfolio. Similarly, the intercepts estimated in Model (7b) capture the remaining mean valuation difference after controlling for differences in size. Likewise, in Model (7c), the estimated intercepts account for the mean valuation difference after considering the differences in valuation determinants proposed in Section 3.1. To assess the adequacy of explanatory variables in explaining valuation differences, we examine the distributional characteristics of the estimated intercepts and their corresponding t-stats for each industry (or characteristic) portfolio. The proximity of the intercepts to zero indicates the extent to which the components of valuation differences are captured by the explanatory variables.

Given that the right-hand side of the setting in Eq. (7c) includes many explanatory variables, we employ principal component analysis (PCA) to provide insights into how the intercept estimate decreases with an increase in the number of explanatory variables. Specifically, we arrange the characteristics of N industries over L variables in T periods into a matrix $Z_{NT\times L}$ with $N \times T$ rows and L columns. Here, N represents the number of industries, T represents the number of periods, and L represents the number of explanatory variables on the right-hand side of Eq. (7c). Subsequently, we apply PCA to the matrix $Z_{NT\times L}$, recording the factor loadings $B_{L\times L}$ of the principal components on each original variable, as well as the principal component score matrix $S_{NT\times L}$. Finally, we split the score matrix S into a series of industry matrices S_i (with T rows and L columns), where $i = 1, 2, ..., N$, and then conduct the following time series regressions:

$$DV_{i,t+1} \sim \mathbf{1} + S_{i,t}^{K}, \tag{8}$$

where $S_{i,t}^{K}$ represents the elements of the t-th row of matrix S_i, considering the first K columns, and the other symbols remain the same as in Eq. (7c).

3.4 Dominance Analysis

In addition to evaluating the extent to which the explanatory variables adequately explain valuation differences, we further investigate the relative importance of these variables. Specifically, we conduct a dominance analysis, which determines the relative importance of independent variables based on contributions to an overall model fit statistic. This statistic represents the average incremental contribution to R^2 made by an independent variable across all models in which it is included.[27] Assume that there are p variables in a multivariate regression (main regression) as:

$$y = a + \sum_{i=1}^{p} b_i x_i + \epsilon, \tag{9}$$

where y and x_i denote the dependent variable and the i-th independent variables respectively, a represents the intercept, and ϵ denotes the error term. A measure of $x_i's$ importance, marginal increment, is given as $R^2_{x_S,x_i} - R^2_{x_S}$, where x_S is any subset of k predictors, x_i excluded, and R^2 is calculated as the ratio of RSS (regression sum of squares) to TSS (total sum of squares). Since there are $\binom{p-1}{k}$ combinations of x_S, the contribution of x_i to the model fit with k variables can be measured by its average, that is,

$$C^k_{(i)} = \sum_{l=1}^{\binom{p-1}{k}} \frac{R^2_{x_{S_l},x_i} - R^2_{x_{S_l}}}{\binom{p-1}{k}}. \tag{10}$$

By averaging $C^k_{(i)}$ across all orders ($k = 0, 1, 2, ..., p-1$), one obtains C_{x_i}, the variable's average importance as:

$$C_{x_i} = \sum_{k=0}^{p-1} \frac{C^k_{(i)}}{p}. \tag{11}$$

It can be shown that the C_{x_i} is related to the total R^2 of Eq. (9) as follows:

$$R^2_{Eq.\ (9)} = R^2_{x_{1,2,...p}} = \sum_{i=1}^{p} C_{x_i}. \tag{12}$$

Therefore, a measure to assess the importance of variable x_i is via calculation of the DA_{x_i} as:

$$DA_{x_i} = \frac{C_{x_i}}{R^2_{Eq.\ (9)}}. \tag{13}$$

For each industry, we conduct dominance analysis by using Eq. (7c) as our main regression, and then calculating the average incremental contribution (C_{x_i}) and the relative importance (DA_{x_i}) of each explanatory variable (x_i) as above. We then compare the values of each of these variables across different industries.

[27] For more information about dominance analysis, see Budescu (1993) or Grömping (2007).

4 Summary Statistics and Results

We present the descriptive statistics for valuation and other variables in Table 2, categorized into three panels: stock-level (Panel A), portfolio-level (Panel B), and differences in portfolio-specific variables across SOEs and NSOEs (Panel C). The variables are defined in Table IA.2; however, for convenience we redefine them in the text below when using them for specific hypotheses. Notably, Panel A reveals significant differences in almost all dimensions between SOEs and NSOEs. For instance, NSOEs demonstrate lower levels of openness to foreign investors, with SOEs typically issuing around 3% of their total capitalization in the external market, and NSOEs only issuing around 0.7% on average for foreign investors. NSOEs also exhibit better stock liquidity, with their stocks having only 80% of the fraction of zero daily returns compared to SOEs. NSOEs display superior growth potential, with average historical growth rates exceeding that of SOEs by 2 percentage points, while analysts' expected growth rates are even higher, surpassing SOEs' by 10 percentage points. These findings highlight inherent disparities between the two types of companies and emphasize the need to identify key determinants of valuation disparities.

When we aggregate individual stocks into industry or characteristic portfolios, as shown in Panel B, the differences between SOEs and NSOEs across various variables diverge: Some variables exhibit increased differences, while others show reduced differences.[28] Notably, the valuation difference at the stock-level is 0.961, but at the portfolio-level, this difference in MB decreases to 0.738, presenting a reduction of 23%. This result also aligns with the industry-based decomposition of valuation differences performed in Section 2.2.[29] Panel C provides additional statistics (standard deviation and median) on the differences between SOEs and NSOEs, offering relevant information to assess the dimensions along which SOEs differ from NSOEs.

We next present the results of our hypothesis tests, and then consider the relative explanatory power of the various hypotheses.

[28]We observe that the Amihud liquidity measure for SOE portfolios is smaller than that for NSOE portfolios, contrary to the larger Amihud measure observed for individual SOE stocks compared to NSOE stocks. We find that this pattern is due to the inclusion of portfolios with a small number of firms. When we exclude portfolio observations that use less than ten firms, the Amihud measure for SOE portfolios remains larger than that for NSOE portfolios. However, increasing the threshold for the minimum number of companies in the retained portfolios would result in a reduction in the empirical sample. We hence maintain the threshold at five, as described in Section 3.2.

[29]Note that among the 61 portfolios, there are not only industry-based portfolios but also other portfolios based on characteristics. This may introduces some slight differences from the industry decomposition results.

4.1 Results of Hypotheses Testing

First, we test hypothesis H1 to determine whether disparities in current profitability between SOEs and NSOEs are associated with differences in their valuations. We compute the return on equity (*ROE*) by taking the net profit from the trailing four quarters and dividing it by the book equity at the end of the most recent quarter, thereby providing a proxy for current profitability. Column (1) of Table 3 reports the estimation results of *ROE* as the explanatory variable in Eq. (6). We find that the regression coefficient of *ROE* is significantly positive. This finding indicates that differences in profitability between NSOEs and SOEs are positively related to valuation disparities, thereby supporting hypothesis H1.

Next, we test hypotheses H2a and H2b, which consider whether the systematic risk exposure and overall risk of stocks contribute to the valuation differences between NSOEs and SOEs. We use beta (*Beta*) and volatility (*Vol*) as proxies for systematic and overall risk, respectively. *Beta* is estimated by regressing the stock's daily excess returns over the past year against the market portfolio's excess returns, applying a five-lag correction (Dimson 1979) as per Liu, Stambaugh, and Yuan (2019). Volatility (*Vol*) is measured by the standard deviation of daily returns over the past quarter. The empirical results remain qualitatively robust regardless of the time window (3-month, 6-month, or one-year) used for estimating *Beta* and *Vol*.

Table 2 shows that, at both the individual stock and portfolio levels, NSOEs exhibit higher systematic risk and risk levels than SOEs. Theoretically, this should imply lower valuations for NSOEs compared to SOEs, which contradicts market observations. Nevertheless, we conduct regressions following the specification in Eq. (6), and present the results in columns (2) and (3) of Table 3. The regression coefficient for *Beta* is insignificant, indicating that systematic risk exposure does not help explain the valuation differences between SOEs and NSOEs.[30] The regression coefficient for *Vol* is significantly positive, which contradicts standard asset pricing theory. However, when we include both idiosyncratic volatility and volatility as explanatory variables,

[30] In this context, we do not use the three-factor model as the baseline model to estimate systematic risk exposure. The value factor in the three-factor model is defined as the return of low-valuation portfolios minus the return of high-valuation portfolios. Consequently, when individual stock returns are regressed on the returns of the three factors, stocks with lower valuations will exhibit higher exposure to the value factor compared to stocks with higher valuations. This introduces a "beta-valuation correlation" due to the calculation methodology. Figure IA.3 illustrates the relationship between stock valuation and exposure to the various factors. Our untabulated results indicate that, among the three risk exposures, only the risk exposure to the value factor is significantly negatively correlated with valuation differences. The regression coefficient of β_{VMB} (risk exposure to the value factor) in explaining the valuation differences is -0.190 (with a t-value of -3.63). The regression coefficients of the other two risk exposures are insignificant in explaining valuation differences: the market factor beta has an estimate of 0.056 (with a t-value of 0.53), and the size factor beta has an estimate of -0.062 (with a t-value of -0.96). Therefore, we do not consider these results as evidence that risk exposure can explain the valuation differences between NSOEs and SOEs.

as shown in column (4) of Table 3, the significance of volatility is absorbed by idiosyncratic volatility. This suggests that the relationship between volatility and valuation differences is driven by the idiosyncratic component of volatility. We revisit idiosyncratic volatility later in this section. Overall, the empirical evidence does not support hypotheses H2a and H2b.

State ownership has been found to be positively correlated with leverage (see Dewenter and Malatesta 2001; Li, Yue, and Zhao 2009). Over the past 20 years, the leverage of Chinese SOEs has steadily increased, whereas the leverage of NSOEs has either remained stable or declined (Zhong et al. 2016). Table 2 shows that, within our sample, the average leverage ratio (total liabilities to total assets) for SOEs is 51%, while that for NSOEs is 40%. Similar patterns are observed at the portfolio level. Given that leverage is positively associated with equity risk, we examine how the differences in leverage between SOEs and NSOEs relate to valuation disparities. Column (5) in Table 3 presents the results for hypothesis H2c. The regression coefficient for *Lev* is significantly negative, which supports Hypothesis H2c. We revisit leverage in a multivariate setting below.

To measure stock-level openness, we construct two international accessibility (IA) variables using information on the firm's stock issuance. The first variable, *IA Grade*, is a discrete variable, adding up two firm level dummy variables (the presence of B shares and H shares). The second variable, *IA degree*, is the ratio of the market capitalization sum of B and H shares to the firm's total market capitalization. To construct portfolio-level IA variables, we value-weight the firm-level IAs within the portfolio, using the firm's market equity as of last quarter's end as the weight. Column (6) in Table 3 reports the estimation results when the IAs are employed as proxies for hypothesis H2d. Both the IA coefficients are statistically insignificant, which indicates that hypothesis H2d is not supported: the level of stock openness does not explain the valuation difference between SOEs and NSOEs. It is worth noting that the number of companies issuing B shares or H shares and listed on the A-share market is less than 200, accounting for less than 10% of all listed companies. Additionally, stock issuances occur infrequently, with significant time gaps between consecutive issuances, often on an annual basis. This observation may partially influence why openness fails to explain disparities in valuation.

We consider two illiquidity indicators, *Zeros* (the proportion of zero daily returns per quarter, from Lesmond, Ogden, and Trzcinka 1999) and *Amihud* (the ratio of the absolute return to the trading volume, from Amihud 2002), to test the liquidity hypothesis (H2e).[31] The estimation

[31] Here, we do not use turnover as a liquidity measure since it may provide information other than liquidity (see Lee and Swaminathan 2000; Mei, Scheinkman, and Xiong 2009; Le and Gregoriou 2020). We discuss it in H4a-H4c.

results are presented in column (7) of Table 3. Both illiquidity measures exhibit significant negative coefficients, which implies that hypothesis H2e holds true: improved liquidity in stocks of NSOEs is associated with higher valuations compared to stocks of SOEs.

In terms of the hypotheses for growth (H3a-H3c), we employ six variables. Two of these indicators measure growth as reflected in financial reports, specifically the annual asset growth rate (*AGR Asset*) and the annual revenue growth rate (*AGR Rev*). Two additional indicators are based on analyst forecasts, namely, analyst-expected earnings growth rate (*AEEG*) and analyst-expected sales growth rate (*AESG*). The remaining two indicators are based on the number of innovation patent applications (*Inno*) and utility model patent applications (*UM*), which are scaled by the most recent year's revenue. These indicators correspond to hypotheses H3a, H3b, and H3c outlined in Section 3.1. Given the strong correlation between AGR Rev and AGR Asset, as well as between AEEG and AESG, columns (1) to (6) in Table 4 present the regression results from including each variable individually in Eq. (6). We find that the financial-report-based growth and analyst-expectation-based growth variables are both positively correlated with valuation differences, which suggests that hypotheses H3a and H3b are confirmed. On the other hand, the patent-based variables (*Inno* & *UM*) exhibit little relationship with valuation differences. Recalling the specification of Eq. (6), where the explanatory variables are lagged by only one period (one quarter), there may be concerns that the effect of patents on valuation takes a longer horizon to realize. We tackle this issue by lagging the explanatory variables of Eq. (6) by 1-12 periods (i.e. 0.25 years to 3 years). The unreported results still provide little evidence that the patent application variables show explanatory power for valuation differences. Thus, we deduce that hypothesis H3c is not supported. In summary, across all measures, our conclusion is that growth remains a pertinent mechanism for explaining the differences in valuation: NSOEs exhibit superior growth potential compared to SOEs, leading to higher valuations.

As demonstrated by Mei, Scheinkman, and Xiong (2009), investors trade more with each other when divergence in their beliefs increases. This increases valuation because the value of the resale option increases. Columns (1) to (4) in Table 5 present the impact of speculation on valuation differences between SOEs and NSOEs. We first regress the valuation difference on the difference in turnover and report the estimates in column (1). The coefficient of *Turnover* is 6.262 (with a t-stats of 1.80). Thus, the hypothesis H4a receives marginal support. Next, we replace the explanatory variable with the difference in idiosyncratic volatility, which is a proxy for difference in investors' belief divergence. As in column (2), the coefficient of *IdioVol* is significantly positive (with a coefficient of 1.711 whose t-stats is 7.42). Thus, hypothesis H4b is supported. Column (3) documents a positive correlation between the difference in stocks' turnover and the difference in investors' beliefs. This finding supports the claim that an increase in belief divergence leads to both more trading and higher stock valuation. Controlling for idiosyncratic volatility, as shown in column (4), weakens the explanatory power of differences in turnover on valuation differences: The coefficient of *Turnover* decreases from 6.262 to 3.506, representing a 40% decrease, and becomes statistically insignificant, which aligns with hypothesis H4c. These pieces of evidence suggest that the different levels of belief divergence in stocks of NSOEs and SOEs is related to their valuation disparities.

Column (5) in Table 5 presents the results of testing hypothesis H5a. Similar to the findings for current profitability, the regression coefficient for average past profitability is significantly positive in explaining valuation differences. We also include both profitability metrics as explanatory variables in the regression analysis and present the results in Column (6) of Table 5. The regression coefficients for both variables remain significantly positive. This suggests that both average past profitability and current profitability play a role in valuation, which aligns with the predictions of Pástor and Veronesi (2003). Column (7) examines the impact of listing age on valuations. The results indicate that the lower listing age of NSOEs is associated with higher valuations.

Column (2) in Table 6 reports the results of a multivariate regression incorporating leverage, liquidity, growth, speculation, profitability and its uncertainty, to explain the valuation differences. We select these variables based on their significant regression coefficients from the prior hypothesis tests, ensuring that their coefficients align with the expectations of the hypothesis. In the multivariate regression, most of the explanatory variables exhibit statistically significant coefficients, although some variables related to growth experience decreases in significance due to their correlation with each other. We note, however, the significance of leverage (*Lev*) and current profitability (*ROE*) disappears. Further analyses, as reported in Table IA.3, suggest that the explanatory power of leverage in accounting for valuation differences is subsumed by age since listing. In fact, although Chinese SOEs typically exhibit higher leverage than NSOEs, investors have a more positive outlook on the financial risks associated with SOEs due to the presence of implicit or explicit government guarantees; see, e.g., Jin, Wang, and Zhang (2023) and Geng and Pan (2024). We would expect guarantees to be even more pertinent to familiar SOEs which have been listed longer. Thus, the negative coefficient for *Lev* reported in column (5) of Table 3 may be attributed to the correlation between leverage and listing age, both of which affect valuation. To investigate the robustness of the impact of current profitability, we examine the roles of growth, average profitability, and listing age, as shown in Columns (4) to (6) of Table IA.3. Our findings indicate that none of these variables individually diminish the significance of current profitability; rather, their combined effect accounts for the influence of current profitability on valuation. In conclusion, our analysis indicates that differences in profitability remain a significant factor in explaining valuation disparities in the multivariate context (supporting H1). These valuation determinants provide independent information in explaining the valuation differences, as evidenced by the increase in adjusted R^2 in column (2) of Table 6 compared to Table 3 and Table 5. The results emphasize an important fact: when discussing the significant valuation differences between SOEs and NSOEs in the A-share market or suggesting that the value of SOEs is "underestimated," it is crucial to note that SOEs exhibit distinct differences from NSOEs along multiple valuation dimensions. The observed valuation differences between SOEs and NSOEs are not mere anomalies but are instead related to several intuitive determinants from classical valuation arguments.

4.2 The Explanatory Power of our Determinants

The set of determinants influencing valuation disparities between SOEs and NSOEs likely extends beyond the variables we have previously examined. It is impractical for our study to exhaustively address all aspects. However, it is meaningful to analyze the extent to which our discussed dimensions explain valuation differences. Such analysis enables us to assess our progress and ascertain whether there is still much to uncover in comprehending valuation disparities.

4.2.1 Results from Regressions by Industry

We conduct three sets of time series regressions based on the description in Section 3.3 for each industry. The estimated intercept values from each regression are reported in Panel A of Table 7. Here we consider only 34 industries.[32] Using the specification in Eq. (7a), we observe significant valuation differences between NSOEs and SOEs in 25 industries. With the regression setup changed to Eq. (7b), the number of industries with significant intercept estimates decreases to 21. Finally, when all the significant valuation determinants discussed in Section 4.1 are included as explanatory variables, as indicated by the setup in Eq. (7c), the number of industries with

[32]Some industries are excluded due to a lack of sufficient observations in the time series; specifically, those with less than 20 periods available for analysis.

significant intercept estimates decreases even further to 7, nearly one-fifth of the total number of industries.[33] Panel B of Table 7 provides a summary description of these intercept estimates. We observe that the average intercepts across industries for the three models are 0.315, 0.208, and 0.123, respectively, so that the estimate for Eq. (7c), is closest to zero. The average t-statistics of intercepts for Eqs. (7a), (7b), and (7c) are 10.4, 3.5, and 0.7, respectively. On average, the model in Equation (7c) accounts for 59% of the total variations in valuation differences across industries. Panel C reports the test results on the differences in intercept estimates, t-values, and adjusted R^2 across the regression settings. Overall, across the metrics, Eq. (7c) consistently exhibits superior performance compared to the other settings.

Table 8 reports the results of the time-series regressions conducted on the characteristic and board portfolios. As shown in column (7a), we observe greater valuation differences between NSOEs and SOEs in portfolios characterized by smaller size (Size L), higher liquidity (Zero L), higher turnover (Turn H), and lower ownership concentration (ShrPerHold L). The TMT portfolios exhibit larger valuation differences compared to Non-TMT portfolios; however, valuation differentials between NSOEs and SOEs are significantly greater than zero across all 13 portfolios. Models Eq. (7c) explains a substantial portion of the variation in the valuation differentials, with adjusted R^2 exceeding 70%, and only two portfolios exhibit significant intercept estimates.

4.2.2 Results from Principal Component Analysis

Figure 6 illustrates the results of the PCA regression. In Figure 6(a), it is evident that when explanatory variables are not taken into account, 25 out of the 34 industries exhibit significant intercept estimates at the 1% level. By incorporating the first two principal components, this number further decreases to 16, which is less than half of the total number of industries. As more principal components are added, the number of significant intercept estimates continues to diminish, eventually settling at approximately one-fifth of the total number of industries. Figure 6(b) demonstrates that when examining the average value of intercept estimates across industries, the inclusion of the first principal component reduces this measure by over 50%. Furthermore, considering the first two principal components further reduces the value to approximately one-

[33] As an alternative to the panel regression for variable selection via Eq. (7c), we also apply LASSO for this purposes. We find that LASSO drops only the *AGR Asset* variable. Qualitatively, there is virtually no difference between the test results based on the LASSO-selected variables and those reported here. The details are in Section IA.3 of the Internet Appendix.

fourth of its initial magnitude.

Figure 7 depicts the loadings of principal components on the original variables, which allows us to understand which variables are reflected in each principal component. We observe that the first principal component is predominantly driven by the variable "*List Age*", as indicated by its coefficient being close to 1, while the coefficients of other variables are close to 0. Therefore, the first principal component can be referred to as the "uncertainty component." The second principal component is primarily driven by the control variable "*Size*". The loadings of the third to fifth principal components are concentrated on growth-related variables (*AGR Rev*, *AEEG* and *AESG*). Therefore, these principal components can be considered collectively as the growth components. The other principal components can be categorized as: [PC6]-"speculation component", [PC7]-"profitability components", [PC8] and [PC9]-"Liquidity components". From Figure 6, it can be observed that when the "uncertainty component" and the "size component" are taken into account, the other principal components have limited marginal contributions to explaining valuation differences.[34]

4.3 Results from Dominance Analysis

Figure 8 presents the results of dominance analysis described in Section 3.4. We observe that variables which play a significant role in explaining valuation disparities in an industry typically hold similar importance in others. Specifically, the heatmap in Figure 8 exhibits vertical clustering of colors. Among all the explanatory variables, the column representing the *List Age* receives the highest number of dark-colored cells in the heatmap, indicating its strong association with valuation differences. The average explanatory power of the listing age for valuation differences across industries is about 17%.[35] Following age since listing, both size and average profitability play significant roles, each explaining approximately 9% of the valuation differences. The average explanatory power of the other variables for valuation differences ranges from 2% to 7%, with varying degrees of significance.

[34] We also conduct an investigation based on Instrumented Principal Component Analysis (IPCA), which is a dynamic factor analysis framework developed by Kelly, Pruitt, and Su (2021). The unreported results therein indicate that valuation differences are largely absorbed by the extracted principal components.

[35] In Figure 8, we present the incremental contribution of each variable to the goodness-of-fit in explaining valuation differences, as introduced in Eq. (11) from Section 3.4. Since the goodness-of-fit varies across different industries, we also display the relative importance of each variable in explaining valuation differences within each industry in Figure IA.4 in the Appendix. This relative importance is calculated as Eq. (13) in Section 3.4. This figure exhibits similar patterns, and on average, *List Age* remains the most important explanatory variable with an average relative importance of 26%.

As described in Section 3.4, the explanatory power of each variable is additive. Therefore, we group variables based on the mechanism that influences valuation. *Zero* and *Amihud* are categorized together as liquidity variables. *AGR Rev*, *AEEG* and *AESG* form the growth variables group. *IdioVol* forms the speculation variable. Long-term profitability (*Avg ROE*) and listing age (*List Age*) are categorized as profitability and its uncertainty. Figure 9 presents the explanatory power of each mechanism for valuation differences. The group representing the profitability and its uncertainty variables yield an average explanatory power of 26%. Overall, the dominance analysis results indicate that the listing age variable is an important contributor to valuation differences between SOEs and NSOEs, but the other determinants also play significant roles.

5 Extensions

In this section we consider additional determinants of the NSOE-SOE value differential, as well as a different metric for measuring valuation.

5.1 Shell Value

The shell effect is a notorious characteristic of the Chinese stock market. It refers to the circumstance where poorly performing listed companies are not promptly delisted due to ineffective delisting rules. These firms take advantage of their listed status by selling it, resulting in the emergence of a shell premium. The research sample in this study spans from 2003 to 2021, a period during which the listing management process in the A-share market was an approval-based system.[36] Two features of the approval-based system contribute to the shell effect. First, the IPO review committee's objective is to ensure that only "healthy" firms gain access to equity markets, requiring candidate firms to meet strict pre-specified profitability and revenue thresholds. Second, the regulatory authority, CSRC, frequently adjusts the speed of IPOs to mitigate the adverse impact of new listings on the market. Candidate firms are also required

[36]Prior to 1999, the A-share market operated under a quota-based listing system. Starting from 1999, the approval-based system was introduced and became the only listing management system until before 2019. In November 2018, President Xi Jinping announced the plan to establish the Science and Technology Innovation Board (STAR Market) at the Shanghai Stock Exchange, adopting a registration-based IPO system. On July 22, 2019, the first batch of companies on the STAR Market successfully completed their IPOs under the registration-based system. Subsequently, on April 27, 2020, CSRC issued a document titled "Administrative Measures for the Initial Public Offering of Stocks on the ChiNext Board," which followed the footsteps of the STAR Market in adopting the registration-based IPO process. On February 17, 2023, CSRC announced the comprehensive implementation of the rules and regulations related to the registration-based system for stock issuance. This marks the historical stage in which the approval-based system is phased out from the Chinese stock market.

to maintain the status quo in terms of their financial viability or else they may experience delayed review. These policies together substantially increase regulatory risk for firms seeking domestic market access. As a result, many companies looking to go public have resorted to Reverse Mergers (RM) to obtain substantial listing status. Underperforming companies that are already listed can capitalize on the demand for listings by selling their listed status to companies seeking to go public. This effectively allows them to act as a "shell" and acquire a valuation premium. The existence of a significant shell value in the Chinese stock market has been discussed by Liu, Stambaugh, and Yuan (2019) and Lee, Qu, and Shen (2023).

We examine whether shell value plays a role in the valuation difference between NSOEs and SOEs. We use the notion that shell values should increase dramatically during periods of IPO suspensions. Thus, if the lower valuation of SOEs relative to NSOEs is associated with higher shell values for NSOEs, then an IPO suspension event should amplify the valuation difference between the two. In line with this, we conduct the following regression to determine whether the IPO suspension event affects the valuation difference:

$$DV_{j,t+1} = \eta \, IPOSusp_{t+1} + \beta \, DX_{j,t} + \gamma \, DControl_{j,t} + \mu_j + \epsilon_{j,t}. \tag{14}$$

Eq. (14) and Eq. (6) have identical specifications except for the inclusion of an additional explanatory variable, $IPOSusp$, which is a dummy that takes the value of 1 when the corresponding period is during an IPO suspension event, and 0 otherwise.[37] If the shell value is capable of explaining the differences in valuation, the estimated coefficient (η) should be statistically significant.

Columns (3) and (4) in Table 6 report the regression coefficient estimates for $IPOSusp$. We observe that when regressing valuation differences solely on $IPOsusp$, the coefficient is negative with weak significance (at the 10% level). This implies that the valuation gap between NSOEs and SOEs decreases during IPO suspension periods. In other words, SOEs tend to benefit more in terms of valuation during IPO suspension periods. However, when we include the variables discussed in Section 4, the significance of the coefficient for $IPOSusp$ in column (4) disappears. Overall, these results confirm that the shell premium cannot explain the higher valuation of NSOEs relative to SOEs.

To further examine the impact of shell value, we replicate the regression procedure used in

[37]There have been a total of 6 IPO suspension events in our sample period, occurring from Aug. 2004 to Jan. 2005, May. 2005 to Jun. 2006, Sep. 2008 to Jul. 2009, Nov. 2012 to Dec. 2013, and Jul. 2015 to Nov. 2015.

column (2) in Table 6 using a sample that excludes the bottom 30% of stocks based on market capitalization. The exclusion of these stocks is motivated by the empirical evidence of Liu, Stambaugh, and Yuan (2019), who find that firms with smaller market capitalization are more likely to be acquired, which indicates a higher shell premium in their valuation. Results for this subsample are reported in column (5) in Table 6. By comparing the coefficients of column (5) and column (2), we find that the direction and magnitude of the coefficients remain unchanged. Both regressions have R^2 of 72%. The only difference is that the significance of some variables in column (5) appears to weaken. However, we emphasize that this approach (excluding 30% of the smallest stocks) is conservative: Although smaller market-cap stocks are more likely to be targeted as reverse mergers (RM) and possess shell value, they also exhibit characteristics such as younger age, higher growth potential, and more speculative trading. As discussed earlier, these characteristics are associated with higher valuations. Therefore, it is not surprising to observe a decrease in significance when excluding small-cap companies. In conclusion, these findings suggest that the valuation differences between NSOEs and SOEs are largely unrelated to the shell value.

5.2 Social Responsibility

SOEs not only strive for profit maximization but also align their operations with government political objectives, with ensuring social stability being a crucial aspect (Lin, Cai, and Li 1998; Bai, Lu, and Tao 2006). Although the goal of maintaining social stability by the SOEs may sometimes deviate from profit maximization and potentially harm the interests of shareholders (especially minority shareholders), SOEs often enjoy some compensating benefits such as preferential bank loans and increased government subsidies (Gan, Guo, and Xu 2018). Therefore, it is difficult to determine whether the benefits or drawbacks of SOEs' social responsibilities outweigh. It is also challenging to anticipate the direction of the impact of social responsibilities on the valuation of SOEs in the first place. Nevertheless, we empirically examine whether corporate social responsibility plays a role in the valuation difference between SOEs and NSOEs.

Specifically, we aggregate firm-level social responsibility scores at the firm-level by averaging them at the portfolio-level. Then, we calculate the difference between the social responsibility scores for NSOEs and SOEs and incorporate this difference into the regression as

$$DV_{j,t+1} = \theta\, DS_{j,t} + \beta\, DX_{j,t} + \gamma\, DControl_{j,t} + \mu_j + \epsilon_{j,t}, \tag{15}$$

where DS denotes the difference in social responsibility. Furthermore, since S (social responsibility), E (environmental responsibility), and G (governance) are often considered key dimensions of corporate sustainability, we also examine the roles of E and G in the valuation differences between NSOEs and SOEs using the same specification (Eq. (15)).[38] We use the individual stock ESG ratings provided by Chindices (Huazheng Index), widely used in the market and related research, as well as the detailed scores for the E (Environmental), S (Social), and G (Governance) dimensions, to conduct the empirical analysis.[39] Since ESG data is only available starting from 2009, we use individual stock E/S/G scores from 2009 to fill in the missing values before 2009.

Columns (6) to (9) in Table 6 present the relationship between valuation differences and differences in the overall ESG score as well as the individual scores for Environment (E), Social Responsibility (S), and Corporate Governance (G). From column (6), we find that there is a significant relation between the difference in ESG scores and the difference in valuation between SOEs and NSOEs. The results reported in columns (7), (8), and (9) further show that this relationship is driven by the Social Responsibility (S) component of ESG, rather than the other two components. However, the small changes in R^2 indicate that social responsibility does not provide significantly higher incremental information compared to the variables already considered. Following the dominance analysis described in Section 3.4, we investigate the contribution of social responsibility in explaining valuation differences. The results, although not tabulated, reveal that social responsibility has an average contribution of approximately 5% in explaining valuation differences and it ranks eighth out of the ten variables examined, indicating that its impact is relatively limited compared to other variables.

5.3 Alternative Calculation for Valuation

In the previous analysis, we utilize the market-to-book ratio calculated based on quarterly average stock prices as a proxy for valuation. Here, we recalculate the market-to-book ratio using an

[38] ESG attributes of stocks can be jointly modeled with payoffs to understand investor behavior and its impact on asset prices (see Grant and Satchell 2020). Empirically, researchers have revealed found a positive correlation between the ESG performance of NSOEs and stock returns, whereas such a relationship is not evident in SOEs (see Wu et al. 2024).

[39] The Huazheng ESG evaluation system combines the information disclosure practices and characteristics of Chinese companies to construct the evaluation system. It includes three primary pillar indicators (E, S, and G), 16 secondary thematic indicators, 44 tertiary issue indicators, and over 300 underlying data indicators. It also integrates intelligent algorithms such as semantic analysis and natural language processing (NLP) to build an ESG big data platform, which covers all A-share listed companies. Through a comparison of various mainstream ESG rating systems for Chinese A-share listed companies, we find that Huazheng ESG Ratings system has the broadest coverage of stocks and the longest available time span.

alternative method. In this new calculation, we determine the numerator of MB by multiplying the closing price on the last trading day of each quarter by the total shares outstanding. The resulting market-to-book ratio is denoted as *MBR*. Then, we repeat the empirical analysis using *MBR* as the valuation variable.

Table 9 presents the regression results where *Ln MBR* is used as the valuation metric, and the NSOE-SOE valuation differential is regressed against the significant explanatory variables in Tables 3 to 6. Table 10 displays the time-series regression results conducted for the industry portfolios, again with *Ln MBR* as the dependent variable. Qualitatively, these results align with our previous findings.

6 Event Study: Mixed-Ownership Reform

SOE reforms have always been an important part of China's economic reforms. In the past two decades, mixed-ownership reform (MOR) has become a crucial avenue for the reform of SOEs.[40] For SOEs, mixed-ownership reform refers to the introduction of non-state capital to achieve a mixed ownership structure. Existing research has documented that the MOR of SOEs can enhance their performance via innovation (Lo, Gao, and Lin 2022; Wan and Yu 2022). However, the impact of MOR on the valuation of SOEs remains unknown.

We use the information disclosed in the periodic reports of Chinese listed companies to conduct the analysis for the effects of MOR. The database CSMAR classifies shareholders of companies into six categories: State-owned, private enterprise, individual and family, institutional investors, foreign, and other shareholders. We aggregate the shareholding percentages of the last five categories of shareholders for each company, which yields the proportion of non-state-owned shares in that company.[41] For SOEs where the actual controlling shareholder is a state-owned shareholder, we regard an MOR event to have occurred when the shareholding percentage of non-state-owned shareholders exceeds 10% in the post-MOR quarter, and is below this threshold

[40]The development of mixed-ownership economy was explicitly proposed for the first time at the 4th Plenary Session of the 15th Central Committee of the Communist Party of China (CCCPC) held in 1999. Since then, reform of the mixed-ownership economy has been repeatedly mentioned in subsequent important events such as the 3rd Plenary Session of the 16th CCCPC in 2003, the 3rd Plenary Session of the 18th CCCPC in 2013, and the report of the 19th National Congress of the CPC in 2017.

[41]Since we truncate shareholders beyond the top ten, this proportion of non-state-owned shares is an approximation. However, the A-share market demonstrates a considerable level of equity concentration (Wei and Geng 2008), where the top ten shareholders often hold significant influence over company decisions. Hence, this approximation is unlikely to cause serious problem.

in the pre-MOR quarter.[42] From 2003 to 2021, there were a total of 1601 companies in our sample that were (or had been) controlled by state-owned shareholders, referred to as SOEs. Among them, 844 companies underwent MOR.

Due to the occurrence of MOR events at different time periods, we employ a stacked difference-in-differences (DID) regression to estimate the impact of these MOR events. Following Gormley and Matsa (2011) and Cengiz et al. (2019), we create a cohort consisting of both MOR SOEs and "similar" non-MOR SOEs for each quarter in which any MOR event takes place. We gather firm-quarter observations for the eight quarters preceding and following the MOR event to form these cohorts. A cohort is retained if both the firms within the cohort have a minimum of nine observations before and after the event. Within each cohort, we employ Propensity Score Matching (PSM) to find the most similar non-MOR firm for each MOR firm. The matching process is performed at the initial period of each cohort, specifically during the first of eight quarters preceding the MOR event. We consider seven variables for matching: *Size*, *Lev*, *ROE*, *Amihud*, *AGR Rev*, *List Age*, and *SttShr* (state ownership ratio).[43] Subsequently, we pool the matched data across cohorts and use this dataset to estimate the average effects of MOR.

Table 11 reports the balance test results for the distribution of matching variables between the MOR and non-MOR groups. Results are presented before and after matching. As depicted in Panel A, companies undergoing MOR exhibit higher levels of state ownership compared to non-reform companies. On average, the MOR firms have a state ownership proportion of 49%, which is very close to the absolute controlling threshold of 50%. In contrast, the non-reform firms have an average state ownership proportion of 35%. This suggests that companies with a higher proportion of state ownership are more likely to engage in MOR. Panel B demonstrates that the matching method effectively identifies more comparable companies for the MOR group. The standardized bias for the state-ownership share proportion is reduced to within 5%, and the *t*-value is not statistically significant.

Next, we examine the pre-event and post-event trends in valuation for the MOR and non-MOR

[42]In China, the *company law* document explicitly states that "shareholders holding 10% or more of the company's shares have the right to request the convening of an extraordinary general meeting," which implies that the influence and decision-making power of these participating shareholders are significantly enhanced once they cross the 10% threshold. Therefore, we consider a 10% shareholding stake as the threshold for a mixed-ownership reform event to occur.

[43]We provide more details about the construction of the cohorts and the matching process in IA.2.

groups using the following specification:

$$LnMB_{Ei,Et} = \beta_{-8} + \sum_{j=-7}^{-1} \beta_j \, Treat_{Ei} \times Pre_{Et}^{j} + \sum_{k=1}^{8} \beta_k \, Treat_{Ei} \times Post_{Et}^{k} + \mu_E + \lambda_{Et} + \varepsilon_{Ei,Et}. \quad (16)$$

In this specification, the dependent variable is valuation (*Ln MB*), and the explanatory variables consist of a series of interaction terms between $Treat_{Ei}$ (MOR event indicators for event-specified individual *Ei*) along with Pre_{Et} or $Post_{Et}$ (event-specified period indicators for time *Et*). For example, let us consider firm A which undergoes an MOR. The interaction terms $Treat \times Pre^8$, $Treat \times Pre^7$, ..., $Treat \times Post^8$ are assigned a value of 1 for the respective time periods, ranging from eight periods preceding the reform event to eight periods succeeding the event. In contrast, for firm B in the same cohort that does not undergo MOR, the values of these interaction terms are all set to 0. Since the event-specific data sets are stacked together, we include event-specific unit- and time-fixed effects (μ_{Ei} and λ_{Et}) to ensure the accuracy of the estimation. The estimated βs excluding β_{-8} capture valuation differences between MOR and non-MOR companies for each period t ($t \neq -8$) relative to those observed in the base period ($t = -8$).

Figure 10, Panel (a), displays the estimated coefficients of βs in Eq. (16).[44] It can be observed that there is no significant fluctuation in the valuation difference between MOR and non-MOR firms during the interval $[t-8, t-5]$. However, in the year preceding the reform, the valuation difference between the two groups shows an increase relative to that in the base period. However, there is no significant difference in βs between the pre-event period ($[t-7, t-1]$) and the base period ($t-8$). Thus, the valuations of the treatment group (MOR firms) and the control group (non-MOR firms) adhere to the parallel trends assumption before the reform event. After the occurrence of the MOR event, there is a significant increase in β estimates: The valuation difference in the $t+1$ quarter is significantly different from that in the base period at a 95% confidence level. However, in the second quarter after the event ($t+2$), this difference narrows again and becomes insignificant. After one year ($t+5$), the valuation difference returns to the level of the base period. These evidence suggests that the introduction of private ownership into SOEs only triggers a temporary market response, rather than a permanent change.

Panel (b) in Figure 10 displays the results after including control variables in Eq. (16). The control variables are the matching variables used in the PSM.[45] After incorporating these variables,

[44] In the graph, we assign a value of 0 to the estimated value corresponding to $t = -8$ to reflect that $t = -8$ is our base period.

[45] The control variables include *Size*, *Lev*, *ROE*, *Amihud*, *AGR Rev*, and *ROE AbsDev*. Considering the potential

the estimated βs reflect the net changes in valuation over time between the MOR and the non-MOR group. We find that Panel (b) exhibits a similar pattern to Panel (a), but the estimates of βs are closer to zero.

To formally examine the valuation effects of MOR, we estimate the model as in Eq. (17):

$$LnMB_{Ei,Et} = \beta\, Treat \times After_{Ei,Et} + \sum_k \gamma_k X_{k,Ei,Et} + \mu_{Ei} + \lambda_{Et} + \varepsilon_{Ei,Et}. \tag{17}$$

The variable of interest in this regression is $Treat \times After_{Ei,Et}$ which takes a value of 1 when firm Ei undergoes or completes an MOR at time Et, and is zero otherwise. The coefficient β here represents the valuation effect of ownership type changes. We also include cohort-specific firm-fixed effects, μ_{Ei}, and cohort-specific quarter-fixed effects, λ_{Et}, to ensure that we reliably estimate the impact of MOR. We utilize two samples in our study to estimate Eq. (17). The first sample comprises eight pre-event quarters leading up to four immediately following post-event quarters. This sample is used to estimate the short-term effects of MOR on valuation. The second sample consists of eight pre-event quarters followed by four subsequent quarters that skip the immediately following post-event period. This sample is used to estimate the long-term effects of the event on valuation. All estimation results are reported in Table 12. Across almost all scenarios, the estimated βs are not statistically significant. In other words, the MOR per sé has only a limited impact on market valuation.

7 Conclusion

We study valuation differentials between state-owned-enterprises and non-state-owned-enterprises listed in the Chinese A-share market. We begin by analyzing temporal trends in these differences, and observe a persistence in the average difference over the years. Furthermore, in a cross-sectional comparison of valuation differences across industries, we find that the phenomenon of SOEs having lower valuations than NSOEs is prevalent in most industries. It is of interest to grasp the determinants that drive these valuation differentials in order to gain a comprehensive understanding of financial markets where the state has controlling ownership in a number of companies.

disruption caused by the MOR event and its impact on the uncertainty of a firm's profitability, the variable *List Age* may not have comparable meanings before and after the reform. Therefore, in this case, we utilize *ROE AbsDev* as a measure of the firm's earnings uncertainty, which is calculated as the absolute difference between the most recent period's ROE and the average ROE over the past three years.

Using the market-to-book ratio as the valuation measure, we examine economic explanations for valuation differences between SOEs and NSOEs. We consider five categories of potential explanations: market openness, liquidity, growth, speculation and uncertainty. For our sample (from 2003 to 2021), the most important variable is age since listing, which is inversely related to uncertainty (Pástor and Veronesi 2003); it accounts for more than 26% of the variation in the valuation differential. Additionally, differences in profitability, growth potential, divergence in beliefs, and liquidity are all related to valuation disparities. We do not find supportive evidence indicating that shell value contributes to the valuation difference between SOEs and NSOEs. We find that the effect of social responsibility on valuation is present but limited; it accounts for less than 5% of the explained variation. Our results also show that after accounting for the influence of all of the aforementioned variables, valuation differences between SOEs and NSOEs are no longer significant in 27 out of the 34 industries examined. We further conduct a multi-period Difference-in-Differences (DID) analysis on mixed-ownership reform events in SOEs. The purpose of this exercise is to examine the role of ownership structure per sé, relative to economic determinants of the valuation difference. The results reveal that the impact of such events on valuation is only significant for a short period of time (less than two quarters). Moreover, this impact is no longer statistically significant after considering the aforementioned determinats.

Overall, our work provides evidence in favor of the applicability of traditional valuation theories in the Chinese stock market. The valuation differences associated with ownership types are not necessarily "anomalies." Rather, these differences between NSOEs and SOEs stem from their disparities in classical valuation determinants extensively explored in earlier literature. Our analysis, however, raises an unexplored issue, namely, the impact of investor sentiment on the valuation differences between NSOEs and SOEs. Specifically, recent advancements in text analysis could be leveraged to compute a stock-level measure of investor sentiment and explore how it might influence the results of this paper. However, since our focus is on variables that affect the SOE-NSOE valuation differential from a classical perspective, we leave this intriguing avenue for future research.

References

Allen, F., J. Qian, C. Shan, and J. L. Zhu (2024). Dissecting the long-term performance of the Chinese stock market, *Journal of Finance* **79**(2): 993–1054.

Alok, S. and M. Ayyagari (2020). Politics, state ownership, and corporate investments, *Review of Financial Studies* **33**(7): 3031–3087.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* **5**(1): 31–56.

Bai, C.-E., D. D. Li, Z. Tao, and Y. Wang (2000). A multitask theory of state enterprise reform, *Journal of Comparative Economics* **28**(4): 716–738.

Bai, C.-E., J. Lu, and Z. Tao (2006). The multitask theory of state enterprise reform: Empirical evidence from China, *American Economic Review* **96**(2): 353–357.

Bailey, W. (1994). Risk and return on China's new stock markets: Some preliminary evidence, *Pacific-Basin Finance Journal* **2**(2-3): 243–260.

Bailey, W., Y. P. Chung, and J.-K. Kang (1999). Foreign ownership restrictions and equity price premiums: what drives the demand for cross-border investments? *Journal of Financial and Quantitative Analysis* **34**(4): 489–511.

Baker, M. and J. Wurgler (2002). Market timing and capital structure, *Journal of Finance* **57**(1): 1–32.

Bekaert, G., S. Ke, X. Wang, and X. Zhang (2022). The China-US equity valuation gap, Columbia Business School working paper.

Beuselinck, C., L. Cao, M. Deloof, and X. Xia (2017). The value of government ownership during the global financial crisis, *Journal of Corporate Finance* **42**: 481–493.

Boardman, A. E. and A. R. Vining (1989). Ownership and performance in competitive environments: A comparison of the performance of private, mixed, and state-owned enterprises, *Journal of Law and Economics* **32**(1): 1–33.

Boubakri, N., S. El Ghoul, O. Guedhami, and W. L. Megginson (2018). The market value of government ownership, *Journal of Corporate Finance* **50**: 44–65.

Bruton, G. D., M. W. Peng, D. Ahlstrom, C. Stan, and K. Xu (2015). State-owned enterprises around the world as hybrid organizations, *Academy of Management Perspectives* **29**(1): 92–114.

Budescu, D. V. (1993). Dominance analysis: a new approach to the problem of relative importance of predictors in multiple regression, *Psychological Bulletin* **114**(3): 542–551.

Carpenter, J. N. and R. F. Whitelaw (2017). The development of China's stock market and stakes for the global economy, *Annual Review of Financial Economics* **9**(1): 233–257.

Carpenter, J. N., F. Lu, and R. F. Whitelaw (2021). The real value of China's stock market, *Journal of Financial Economics* **139**(3): 679–696.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs, *Quarterly Journal of Economics* **134**(3): 1405–1454.

Chan, K., A. J. Menkveld, and Z. Yang (2008). Information asymmetry and asset prices: Evidence from the China foreign share discount, *Journal of Finance* **63**(1): 159–196.

Chen, G., M. Firth, and L. Xu (2009). Does the type of ownership control matter? evidence from China's listed companies, *Journal of Banking & Finance* **33**(1): 171–181.

Cong, L. W., H. Gao, J. Ponticelli, and X. Yang (2019). Credit allocation under economic stimulus: Evidence from China, *Review of Financial Studies* **32**(9): 3412–3460.

De Alessi, L. (1969). Implications of property rights for government investment choices, *American Economic Review* **59**(1): 13–24.

DeFusco, A. A., C. G. Nathanson, and E. Zwick (2022). Speculative dynamics of prices and volume, *Journal of Financial Economics* **146**(1): 205–229.

Dewenter, K. L. and P. H. Malatesta (2001). State-owned and privately owned firms: An empirical analysis of profitability, leverage, and labor intensity, *American Economic Review* **91**(1): 320–334.

Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns, *Journal of Finance* **57**(5): 2113–2141.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* **7**(2): 197–226.

Fernald, J. and J. H. Rogers (2002). Puzzles in the Chinese stock market, *Review of Economics and Statistics* **84**(3): 416–432.

Gan, J., Y. Guo, and C. Xu (2018). Decentralized privatization and change of control rights in China, *Review of Financial Studies* **31**(10): 3854–3894.

Geng, Z. and J. Pan (2024). The SOE premium and government support in China's credit market, *Journal of Finance* **79**(5): 3041–3103.

Gibbons, M. R., S. A. Ross, and J. Shanken (1989). A test of the efficiency of a given portfolio, *Econometrica* **57**(5): 1121–1152.

Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? Corporate responses to liability risk, *Review of Financial Studies* **24**(8): 2781–2821.

Grant, A. and S. Satchell (2020). Investment decisions when utility depends on wealth and other attributes, *Quantitative Finance* **20**(3): 499–513.

Grömping, U. (2007). Estimators of relative importance in linear regression based on variance decomposition, *American Statistician* **61**(2): 139–147.

Harrison, A., M. Meyer, P. Wang, L. Zhao, and M. Zhao (2019). Can a tiger change its stripes? Reform of Chinese state-owned enterprises in the penumbra of the state, NBER working paper.

Hirshleifer, D., P.-H. Hsu, and D. Li (2018). Innovative originality, profitability, and stock returns, *Review of Financial Studies* **31**(7): 2553–2605.

Jiang, G., D. Xu, and T. Yao (2009). The information content of idiosyncratic volatility, *Journal of Financial and Quantitative Analysis* **44**(1): 1–28.

Jin, S., W. Wang, and Z. Zhang (2023). The real effects of implicit government guarantee: evidence from Chinese state-owned enterprise defaults, *Management Science* **69**(6): 3650–3674.

Kelly, B. T., S. Pruitt, and Y. Su (2021). Instrumented principal component analysis, Yale SOM Working Paper.

Lang, L. H. and R. M. Stulz (1994). Tobin's q, corporate diversification, and firm performance, *Journal of Political Economy* **102**(6): 1248–1280.

Lawson, C. (1994). The theory of state-owned enterprises in market economies, *Journal of Economic Surveys* **8**(3): 283–309.

Le, H. and A. Gregoriou (2020). How do you capture liquidity? A review of the literature on low-frequency stock liquidity, *Journal of Economic Surveys* **34**(5): 1170–1186.

Lee, C. M. and B. Swaminathan (2000). Price momentum and trading volume, *Journal of Finance* **55**(5): 2017–2069.

Lee, C. M., Y. Qu, and T. Shen (2023). Gate fees: The pervasive effect of IPO restrictions on Chinese equity markets, *Review of Finance* **27**(3): 809–849.

Leippold, M., Q. Wang, and W. Zhou (2022). Machine learning in the Chinese stock market, *Journal of Financial Economics* **145**(2): 64–82.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka (1999). A new estimate of transaction costs, *Review of Financial Studies* **12**(5): 1113–1141.

Li, K., H. Yue, and L. Zhao (2009). Ownership, institutions, and capital structure: Evidence from China, *Journal of Comparative Economics* **37**(3): 471–490.

Li, Q., C. Lin, and L. Xu (2020). Political investment cycles of state-owned enterprises, *Review of Financial Studies* **33**(7): 3088–3129.

Li, X., A. Subrahmanyam, and X. Yang (2021). Winners, losers, and regulators in a derivatives market bubble, *Review of Financial Studies* **34**(1): 313–350.

Li, Z., L. X. Liu, X. Liu, and K. John Wei (2023). Replicating and digesting anomalies in the Chinese A-share market, *Management Science* **70**(8): 5066–5090.

Liao, L., B. Liu, and H. Wang (2014). China's secondary privatization: Perspectives from the split-share structure reform, *Journal of Financial Economics* **113**(3): 500–518.

Lin, C. and D. Su (2008). Industrial diversification, partial privatization and firm valuation: Evidence from publicly listed firms in China, *Journal of Corporate Finance* **14**(4): 405–417.

Lin, J. Y. and G. Tan (1999). Policy burdens, accountability, and the soft budget constraint, *American Economic Review* **89**(2): 426–431.

Lin, J. Y., F. Cai, and Z. Li (1998). Competition, policy burdens, and state-owned enterprise reform, *American Economic Review* **88**(2): 422–427.

Liu, J., R. F. Stambaugh, and Y. Yuan (2019). Size and value in China, *Journal of Financial Economics* **134**(1): 48–69.

Lo, D., L. Gao, and Y. Lin (2022). State ownership and innovations: Lessons from the mixed-ownership reforms of China's listed companies, *Structural Change and Economic Dynamics* **60**: 302–314.

Megginson, W. L. and J. M. Netter (2001). From state to market: A survey of empirical studies on privatization, *Journal of Economic Literature* **39**(2): 321–389.

Megginson, W. L., R. C. Nash, and M. Van Randenborgh (1994). The financial and operating performance of newly privatized firms: An international empirical analysis, *Journal of Finance* **49**(2): 403–452.

Mei, J., J. A. Scheinkman, and W. Xiong (2009). Speculative trading and stock prices: Evidence from Chinese AB share premia, *Annals of Economics & Finance* **10**(2): 225–255.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information, *Journal of Finance* **42**(3): 483–510.

Pástor, L. and P. Veronesi (2003). Stock valuation and learning about profitability, *Journal of Finance* **58**(5): 1749–1789.

Pearson, N. D., Z. Yang, and Q. Zhang (2021). The Chinese warrants bubble: Evidence from brokerage account records, *Review of Financial Studies* **34**(1): 264–312.

Peng, M. W., G. D. Bruton, C. V. Stan, and Y. Huang (2016). Theories of the (state-owned) firm, *Asia Pacific Journal of Management* **33**: 293–317.

Ru, H. (2018). Government credit, a double-edged sword: Evidence from the China development bank, *Journal of Finance* **73**(1): 275–316.

Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles, *Journal of Political Economy* **111**(6): 1183–1220.

Shleifer, A. (1998). State versus private ownership, *Journal of Economic Perspectives* **12**(4): 133–150.

Shleifer, A. and R. W. Vishny (1994). Politicians and firms, *Quarterly Journal of Economics* **109**(4): 995–1025.

Sun, Q. and W. H. Tong (2003). China share issue privatization: the extent of its success, *Journal of Financial Economics* **70**(2): 183–222.

Tan, Y., X. Tian, X. Zhang, and H. Zhao (2020). The real effect of partial privatization on corporate innovation: Evidence from China's split share structure reform, *Journal of Corporate Finance* **64**: 101661.

Tirole, J. (1994). The internal organization of government, *Oxford Economic Papers* **46**(1): 1–29.

Wan, K. and X. Yu (2022). Impact of mixed ownership reforms on firm innovation–empirical evidence from China, *Journal of Applied Economics* **25**(1): 1339–1354.

Wang, S. S. and L. Jiang (2004). Location of trade, ownership restrictions, and market illiquidity: Examining Chinese A-and H-shares, *Journal of Banking & Finance* **28**(6): 1273–1297.

Wei, G. and M. Geng (2008). Ownership structure and corporate governance in China: some current issues, *Managerial Finance* **34**(12): 934–952.

Wei, Z., F. Xie, and S. Zhang (2005). Ownership structure and firm value in China's privatized firms: 1991–2001, *Journal of Financial and Quantitative Analysis* **40**(1): 87–108.

Wu, Z., R. Pownall, Y.-C. Shih, and C. Zhang (2024). ESG, state ownership, and stock returns: Evidence from china, *SSRN Working Paper (No. 4251519)*, pp. 1–48.

Xu, X. and Y. Wang (1999). Ownership structure and corporate governance in Chinese stock companies, *China Economic Review* **10**(1): 75–98.

Zhong, N., Z. Liu, J. He, and C. Su (2016). The structural problem of China's non-financial corporate debt [in Chinese], *Economic Research Journal* **51**(07): 102–17.

Table 1: **Comparison of holding period returns between portfolios of SOEs and NSOEs.** This table presents the returns of stock portfolios categorized as SOEs and NSOEs. Over the sample period from 2003 to 2021, we construct two portfolios on the first trading day of each quarter: portfolios of SOEs and NSOEs based on the ownership type of companies at the end of the previous quarter and the tradable stocks available on the portfolio formation day. We hold these portfolios for one year, 3 years, and 5 years. We next provide a detailed calculation process for statistics of NSOE portfolios. For each portfolio formation day and one specific holding period, we first compute the average (equal-weighted or value-weighted across individual stocks within the portfolio) monthly log returns. As such, for each portfolio formation day, we have three time series with length of 12 (one-year), 36 (3-year), and 60 (5-year) months. We then compute four statistics for each of the aforementioned time series: the averages (Ret), standard deviations (Std), Sharpe ratios (SR) and cumulative sum (Total Ret). We repeat the above process for each portfolio formation day and get twelve (three holding periods times four statistics) time series. Finally, we compute the sample averages (across portfolio formation day) for each of the twelve time series and report them in the column "NSOE". We use dividend-adjusted returns in this table. If stocks in the portfolios are delisted before the end of the holding period, their final trading prices are determined by subtracting a 30% delisting loss from the closing price on the last trading day right before delisting, and the corresponding holding period returns are adjusted accordingly. All returns are reported as percentages. The risk-free rate used to calculate the Sharpe ratio is the interest rate on fixed-term deposits of the corresponding maturity published by the People's Bank of China. The calculation process for SOE portfolios is similar, and the statistics are reported in the column "SOE". The column "Diff" reports the differences in sample averages between NSOEs and SOEs, together with t-statistics (reported in parentheses) for testing the null of no difference.

Term	Statistics	Equally weighted			Value weighted		
		NSOE	SOE	Diff (t-stat.)	NSOE	SOE	Diff (t-stat.)
1 Year	Ret	0.52	0.50	0.03 (0.28)	0.37	0.42	-0.05 (-0.43)
	Std	8.98	8.52	0.46 (4.03)	8.02	7.19	0.84 (5.46)
	SR	1.85	2.83	-0.99 (-0.85)	2.07	4.68	-2.61 (-1.09)
	Total ret	6.09	5.86	0.23 (0.21)	4.35	4.95	-0.60 (-0.41)
3 Year	Ret	0.73	0.65	0.08 (0.86)	0.55	0.55	0.01 (0.06)
	Std	9.72	9.33	0.39 (3.86)	8.96	7.99	0.97 (6.28)
	SR	2.81	2.52	0.29 (0.28)	1.67	2.46	-0.80 (-0.52)
	Total ret	25.63	22.99	2.64 (0.77)	19.44	19.31	0.13 (0.03)
5 Year	Ret	0.76	0.65	0.11 (1.79)	0.62	0.55	0.07 (0.94)
	Std	10.07	9.75	0.31 (4.13)	9.33	8.46	0.88 (6.58)
	SR	4.23	3.23	1.00 (1.49)	3.06	2.95	0.11 (0.11)
	Total ret	44.95	38.66	6.29 (2.38)	36.30	32.26	4.04 (1.05)

Table 2: **Summary statistics.** This table reports summary statistics of main variables in three ways. Panel A is at the stock level, Panel B is at the portfolio-level and Panel C is for differences in portfolio-specific variables. Panel A consists of two sub-panels, NSOE and SOE. The columns "NObs" and "Mean" report the number of observations and the mean value of each variable, respectively. The column "Diff" presents the difference in variable means between NSOE and SOE. Significance levels for the differences (from panel regressions of each variable on the NSOE dummy, with cluster-robust standard errors) are indicated as follows: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Panel B is organized in a similar way. Panel C displays summary statistics for differences in variables at the portfolio-level. Columns "Mean", "SD", and "Median" represent variables' mean, standard deviation and median, respectively. Definitions of all the variables appear in Table IA.2. Due to the small magnitudes of variables *ROE*, *IA Grade*, *IA Degree*, *Zero*, *Amihud* and *Turnover*, their values have been multiplied by 100 for displaying purposes.

	Panel A: Stock level					Panel B: Portfolio level					Panel C: Difference			
	NSOE		SOE			NSOE		SOE						
Variables	Nobs	Mean	Nobs	Mean	Diff	Nobs	Mean	Nobs	Mean	Diff	Nobs	Mean	SD	Median
MB	80,488	4.029	68,862	3.068	0.961***	3,074	3.136	3,074	2.398	0.738***	3,074	0.738	1.131	0.659
Ln(MB)	80,488	1.143	68,862	0.856	0.287***	3,074	0.914	3,074	0.628	0.286***	3,074	0.286	0.371	0.257
Size	83,489	21.190	70,290	21.672	-0.482***	3,121	21.701	3,121	22.368	-0.667***	3,121	-0.667	0.552	-0.635
Lev	83,489	0.405	70,290	0.514	-0.109***	3,121	0.475	3,121	0.538	-0.063***	3,121	-0.063	0.100	-0.065
ROE	83,489	7.498	70,290	7.046	0.452	3,121	11.144	3,121	10.505	0.639	3,121	0.639	6.121	0.514
β	83,185	1.213	70,196	1.204	0.010	3,121	1.163	3,121	1.091	0.072***	3,121	0.072	0.242	0.053
Vol	81,035	0.445	68,726	0.419	0.025***	3,121	0.425	3,121	0.386	0.039***	3,121	0.039	0.065	0.033
IA Grade	83,489	2.534	70,290	12.221	-9.686***	3,121	10.949	3,121	29.968	-19.019***	3,121	-19.019	25.151	-13.156
IA Degree	83,489	0.731	70,290	3.280	-2.549***	3,121	3.068	3,121	8.199	-5.130***	3,121	-5.130	7.231	-3.290
Zero	83,489	2.586	70,290	3.258	-0.671***	3,121	2.818	3,121	3.757	-0.939***	3,121	-0.939	2.134	-0.413
Amihud	83,489	0.884	70,290	1.335	-0.451***	3,121	1.056	3,121	0.807	0.249***	3,121	0.249	0.827	0.092
AGR Asset	83,489	0.132	70,290	0.108	0.023***	3,121	0.175	3,121	0.134	0.041***	3,121	0.041	0.123	0.037
AGR Rev	72,375	0.127	65,839	0.111	0.017**	3,059	0.171	3,054	0.136	0.035***	3,054	0.035	0.162	0.033
AEEG	27,260	0.440	27,112	0.326	0.114***	2,873	0.362	2,981	0.274	0.088***	2,807	0.091	0.315	0.100
AESG	28,720	0.261	28,558	0.169	0.093***	2,877	0.249	2,987	0.158	0.090***	2,813	0.093	0.162	0.086
Inno	83,464	6.081	70,140	9.985	-3.904**	3,121	0.139	3,121	0.123	0.016	3,121	0.016	0.275	0.024
UM	83,464	6.155	70,140	8.734	-2.579**	3,121	0.162	3,121	0.101	0.061**	3,121	0.061	0.335	0.030
Turnover	80,488	1.728	68,862	1.416	0.312***	3,074	1.337	3,074	1.047	0.290***	3,074	0.290	0.542	0.251
IdioVol	81,035	0.329	68,726	0.295	0.034***	3,121	0.301	3,121	0.266	0.035***	3,121	0.035	0.056	0.033
ListAge	83,489	8.535	70,290	12.851	-4.315***	3,121	9.521	3,121	12.443	-2.922***	3,121	-2.922	3.854	-1.924

Table 3: **Regression results (H1−H2e).** This table reports estimations of Eq. (6) for hypotheses H1 to H2e. The dependent variable is the portfolio level valuation differential between NSOEs and SOEs. All independent variables are differences between NSOE and SOE. *ROE* represents the current profitability (as of the most recent quarter), *Beta* captures the systematic risk exposure, *Vol* serves as a proxy for the risk level of stocks, and *Lev* measures the firms' financial distress. In all regressions, we include size differentials (*Size*) as a control. The market openness variables include *IA Grade* and *IA Degree*. The liquidity variables include *Zero* and *Amihud*, both of which are inverse indicators of liquidity. Definitions of all the variables are described in Table IA.2. The regressions include portfolio fixed effects and the standard errors are double clustered by portfolio and quarter. T-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels using two-tailed tests.

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)
Size	-0.282***	-0.265***	-0.214***	-0.215***	-0.204***	-0.259***	-0.221***
	(-4.94)	(-4.39)	(-4.26)	(-4.35)	(-3.51)	(-4.30)	(-4.64)
ROE	1.581***						
	(7.30)						
Beta		0.033					
		(0.56)					
Vol			1.499***	0.607			
			(6.29)	(1.13)			
IdioVol				1.129**			
				(2.19)			
Lev					-0.594***		
					(-2.77)		
IA Grade						-0.117	
						(-0.44)	
IA Degree						0.197	
						(0.22)	
Zero							-4.055***
							(-7.60)
Amihud							-7.909***
							(-4.48)
Observations	3,074	3,074	3,074	3,074	3,074	3,074	3,074
Adj. R^2	0.607	0.557	0.599	0.603	0.570	0.557	0.622
Portfolio FE	YES	YES	YES	YES	YES	YES	YES

Table 4: **Regression results (H3a−H3c).** This table reports the estimation results of Eq. (6) for testing hypotheses H3a to H3c, which propose various growth-related explanations for the valuation differences between NSOEs and SOEs. The dependent variable is the portfolio level valuation differential between NSOEs and SOEs. All independent variables are differences between NSOE and SOE. We control for size differentials (*Size*) in all regressions. The growth variables include two measures of business growth (*AGR Asset* and *AGR Rev*), two measures of analyst-predicted growth (*AEEG* and *AESG*), and two patent-based indicators (*Inno* and *UM*). Definitions of all the variables are described in Table IA.2. The regressions include portfolio fixed effects and the standard errors are double clustered by portfolio and quarter. T-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels using two-tailed tests.

Column	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)
Size	-0.288***	-0.261***	-0.225***	-0.234***	-0.266***	-0.264***
	(-5.14)	(-4.64)	(-3.85)	(-4.06)	(-4.33)	(-4.34)
AGR Asset	0.534***					
	(6.19)					
AGR Rev		0.360***				
		(7.08)				
AEEG			0.120***			
			(3.94)			
AESG				0.277***		
				(4.29)		
Inno					0.007	
					(0.12)	
UM						0.024
						(0.95)
Observations	3,074	3,007	2,759	2,765	3,074	3,074
Adj. R^2	0.585	0.588	0.576	0.581	0.557	0.557
Portfolio FE	YES	YES	YES	YES	YES	YES

Table 5: **Regression results (H4a−H4c, H5a, and H5b).** This table reports estimation results of Eq. (6) for hypotheses H4a to H5b. The dependent variable is the portfolio level valuation differential between NSOEs and SOEs, except for column (3), which takes the turnover differential between NSOEs and SOEs as the dependent variable. All independent variables are the differences in each variable between SOE and NSOE. We control for size differentials (*Size*) in all regressions. The speculative variables include two proxies for investor belief divergence, turnover (*Turnover*) and idiosyncratic volatility (*IdioVol*). The long-term profitability and uncertainty variables include average profitability (*AvgROE*) and listing age (*ListAge*). Definitions of all variables are described in Table IA.2. The regressions include portfolio fixed effects and the standard errors are double clustered by portfolio and time. T-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels using two-tailed tests.

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var	Ln(MB)	Ln(MB)	Turnover	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)
Size	-0.246***	-0.221***	-0.003***	-0.211***	-0.283***	-0.285***	-0.218***
	(-4.12)	(-4.43)	(-4.16)	(-4.22)	(-4.66)	(-4.84)	(-4.28)
Turnover	6.262*			3.506			
	(1.80)			(1.17)			
IdioVol		1.711***	0.014***	1.663***			
		(7.42)	(3.01)	(7.64)			
AvgROE					2.803***	1.748***	
					(5.38)	(2.68)	
ROE						0.885***	
						(3.64)	
ListAge							-0.034***
							(-4.27)
Observations	3,074	3,074	3,074	3,074	3,074	3,074	3,074
Adj. R^2	0.562	0.602	0.423	0.603	0.610	0.618	0.607
Portfolio FE	YES	YES	YES	YES	YES	YES	YES

Table 6: **Regression results (Multivariate).** This table reports estimations of Eq. (6) for the variables whose coefficients are significant in Table 3, 4 and 5, and align in the direction of hypothesized expectations. The dependent variable is the portfolio level valuation differential between NSOEs and SOEs. All independent variables are differences between SOE and NSOE. We control for size differentials (*Size*) in all regressions. *IPOSusp* is a dummy that takes the value of 1 when the period is during an IPO suspension period, and 0 otherwise. The variables *E*, *S*, *G*, and *ESG* represent the environmental responsibility score, social responsibility score, governance score, and overall ESG score, respectively. Definitions of other variables are described in Table IA.2. Column (5) has a slightly different portfolio construction compared to the other columns: In Column (5), portfolios are formed using stocks which exclude the bottom 30% of stocks based on market capitalization in each quarter, while the portfolios in the other columns are constructed using the complete stock universe. The regressions include portfolio fixed effects and the standard errors are double clustered by portfolio and quarter. T-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)
Size	-0.267***	-0.129***		-0.127***	-0.184***	-0.124***	-0.129***	-0.130***	-0.128***
	(-4.38)	(-3.48)		(-3.28)	(-3.43)	(-3.40)	(-3.49)	(-3.45)	(-3.53)
ROE		0.213		0.231	0.401**	0.257	0.214	0.230	0.250
		(1.10)		(1.10)	(2.04)	(1.35)	(1.09)	(1.17)	(1.30)
Lev		-0.294		-0.301	-0.338	-0.257	-0.295	-0.302	-0.272
		(-1.50)		(-1.53)	(-1.39)	(-1.31)	(-1.50)	(-1.56)	(-1.36)
Zero		-2.334***		-2.398***	-2.123***	-2.250***	-2.335***	-2.211***	-2.307***
		(-5.48)		(-3.98)	(-4.74)	(-5.28)	(-5.49)	(-5.44)	(-5.39)
Amihud		-5.361***		-4.854**	-4.572*	-5.267***	-5.352***	-5.538***	-5.091***
		(-3.21)		(-2.49)	(-1.95)	(-3.25)	(-3.20)	(-3.32)	(-3.16)
AGR Asset		0.020		0.018	-0.045	0.005	0.020	0.014	0.012
		(0.23)		(0.24)	(-0.47)	(0.05)	(0.23)	(0.15)	(0.14)
AGR Rev		0.102*		0.098	0.050	0.077	0.102*	0.100*	0.081
		(1.94)		(1.62)	(1.01)	(1.45)	(1.95)	(1.94)	(1.41)
AEEG		0.094***		0.092***	0.113***	0.086***	0.094***	0.087***	0.090***
		(3.56)		(2.99)	(3.46)	(3.17)	(3.59)	(3.33)	(3.35)
AESG		0.084*		0.081	0.057	0.084*	0.083*	0.082*	0.081*
		(1.90)		(1.66)	(1.00)	(1.83)	(1.91)	(1.82)	(1.76)
IdioVol		1.015***		1.011***	1.054***	1.011***	1.016***	1.009***	1.024***
		(6.30)		(6.96)	(6.30)	(6.67)	(6.21)	(6.89)	(6.32)
AvgROE		1.850***		1.795***	1.822***	1.972***	1.848***	1.999***	1.857***
		(3.71)		(3.45)	(3.44)	(3.98)	(3.65)	(4.09)	(3.73)
ListAge		-0.021**		-0.020**	-0.019**	-0.021**	-0.021**	-0.021**	-0.021**
		(-2.47)		(-2.46)	(-2.11)	(-2.48)	(-2.47)	(-2.48)	(-2.41)
IPOSusp			-0.108*	-0.028					
			(-1.94)	(-1.18)					
ESG						-0.015**			
						(-2.54)			
E							0.000		
							(0.10)		
S								-0.009***	
								(-3.33)	
G									-0.007
									(-1.25)
Observations	3,074	2,722	3,074	2,722	2,409	2,722	2,722	2,722	2,722
Adj. R^2	0.557	0.721	0.511	0.721	0.723	0.726	0.721	0.726	0.723
Sample	All	All	All	All	Exclude Small	All	All	All	All

Table 7: **Intercept estimates across industries.** Panel A reports the intercept estimates and corresponding t-values (within parentheses) for time series regressions conducted on various industries using three specifications: Eq. (7a), Eq. (7b), and Eq. (7c). The intercept estimates that are statistically significant at the 1% level are displayed in bold font. Panel B provides a summary of the average values for intercept estimates and t-values across industries, the total number of industries included in the regression analysis, the count of industries that exhibit statistical significance at the 1% level, and the average adjusted R^2 across the industries. Panel C reports the differences in intercept estimates, t-values, and adjusted R^2 between Eq. (7c) and Eq. (7a) and (7b). The t-values, which are based on heteroskedasticity-robust standard errors, for the significance of these intercepts are presented within parentheses.

Panel A

Industry	(7a)	(7b)	(7c)	Industry	(7a)	(7b)	(7c)
Agriculture	**0.215**	**0.207**	0.196	Special Equipment	**0.551**	**-0.340**	-0.379
	(9.193)	**(9.893)**	(2.450)		**(12.265)**	**(-3.792)**	(-2.505)
Mining	**0.817**	**1.011**	0.736	Automobile	**0.421**	-0.074	0.215
	(26.866)	**(6.203)**	(1.345)		**(12.124)**	(-0.768)	(1.389)
Agro-Food Processing	0.064	0.069	0.098	Railway, Shipbuilding, Aerospace	**0.208**	**0.293**	0.444
	(2.109)	(1.806)	(1.506)		**(9.175)**	**(5.203)**	(1.823)
Food Manufacturing	0.065	**0.256**	-0.070	Electrical Machinery	-0.003	**-0.194**	-0.109
	(1.747)	**(3.553)**	(-0.476)		(-0.120)	**(-4.247)**	(-2.554)
Alcohol, Drink, Tea	**-0.167**	0.065	**0.308**	Computer, Communication	**0.483**	**0.352**	0.114
	(-3.357)	(0.817)	**(3.446)**		**(30.467)**	**(7.861)**	(1.112)
Textile	0.048	0.050	0.079	Other Manufacturing	-0.057	-0.008	0.138
	(2.515)	(2.515)	(0.903)		(-1.035)	(-0.193)	(0.870)
Papermaking	**0.372**	**0.374**	0.158	Electricity, Heat, Gas and Water	**0.608**	**0.695**	**0.650**
	(21.885)	**(21.528)**	(1.739)		**(24.987)**	**(4.387)**	**(3.369)**
Petroleum Processing	**0.260**	**0.429**	0.476	Construction	**0.795**	**-0.319**	-0.006
	(5.722)	**(12.038)**	(1.899)		**(19.189)**	**(-2.685)**	(-0.039)
Chemical Raw Materials	**0.236**	0.090	0.011	Wholesale and Retail	**0.321**	**0.180**	0.150
	(11.638)	(1.248)	(0.143)		**(20.728)**	**(9.293)**	(2.374)
Pharmaceutical Manufacturing	**0.079**	-0.066	-0.133	Transportation, Warehousing, and Postal Services	**0.583**	**0.537**	**0.507**
	(6.631)	(-2.270)	(-2.493)		**(14.052)**	**(4.109)**	**(9.338)**
Chemical Fiber Manufacturing	0.006	0.004	**0.585**	IT	**1.183**	**0.632**	-0.368
	(0.159)	(0.102)	**(2.600)**		**(23.552)**	**(2.982)**	(-1.031)
Rubber and Plastic Products	**0.271**	0.105	-0.043	Finance	**0.231**	**0.133**	-0.003
	(8.463)	(2.180)	(-0.699)		**(13.541)**	**(7.113)**	(-0.017)
Non-Metal Mineral Products	**0.358**	-0.027	0.039	Real Estate	**0.184**	**0.257**	**0.439**
	(8.379)	(-0.826)	(0.796)		**(7.030)**	**(3.546)**	**(6.231)**
Ferrous Metals	**0.409**	**0.356**	0.324	Leasing Services	-0.094	**-0.154**	**-0.325**
	(9.449)	**(2.716)**	(0.841)		(-1.658)	**(-2.950)**	**(-6.480)**
Nonferrous Metals	0.045	0.130	-0.230	Environmental and Public Facilities Management	**0.640**	**0.643**	0.258
	(0.927)	(0.584)	(-1.667)		**(13.908)**	**(10.018)**	(2.393)
Metal Products	**0.681**	**1.041**	0.712	Culture, Sports, and Entertainment	**0.510**	**0.364**	0.021
	(17.695)	**(7.806)**	(2.030)		**(15.306)**	**(7.808)**	(0.121)
General Equipment	**0.329**	-0.056	**-0.742**	Comprehensive Service	0.050	0.025	-0.058
	(8.057)	(-0.624)	**(-4.847)**		(1.694)	(0.695)	(-1.427)

Panel B				Panel C		
	(7a)	(7b)	(7c)		(7c) - (7a)	(7c) - (7b)
Avg intercepts	0.315	0.208	0.123	Diff in intercepts	-0.191	-0.084
Avg t-values	10.391	3.460	0.720		(-2.671)	(-1.692)
Number of industries	34	34	34	Diff in t	-9.671	-2.740
Number of sig. intercepts	25	21	7		(-6.495)	(-3.284)
Avg adj. R^2	0.000	0.186	0.585	Diff in adj. R^2	0.585	0.399
					(15.715)	(10.936)

Table 8: **Intercept estimates across other portfolios.** Panel A reports the intercept estimates and corresponding t-values (within parentheses) for time series regressions conducted on various portfolios using three different specifications: Eq. (7a), Eq. (7b), and Eq. (7c). Section 3.2 outlines the construction of these portfolios. The symbols "L" and "H" in the "Characteristic" column represent portfolios formed by the stocks with the lowest and highest 30% of characteristic values, respectively. The intercept estimates that are statistically significant at the 1% level are displayed in bold font. Panel B provides a summary of the average values for intercept estimates and t-values across portfolios, the total number of portfolios included in the regression analysis, the count of portfolios that exhibit statistical significance at the 1% level, and the average adjusted R^2 across the portfolios. Panel C reports the differences in intercept estimates, t-values, and adjusted R^2 between Eq. (7c) and Eq. (7a) and (7b). The t-values, which are based on heteroskedasticity-robust standard errors, for the significanceof these intercepts are presented within parentheses.

Panel A

Characteristic	(7a)	(7b)	(7c)	Sector & Board	(7a)	(7b)	(7c)
Size H	**0.195**	0.184	**-0.249**	TMT	**0.788**	0.047	0.202
	(6.598)	(1.251)	**(-3.784)**		**(28.322)**	(0.285)	(1.266)
Size L	**0.336**	**-0.238**	**0.197**	Non TMT	**0.395**	**-0.394**	0.039
	(12.265)	**(-6.092)**	**(2.587)**		**(11.500)**	**(-11.276)**	(0.357)
Zero H	**0.261**	**-0.275**	-0.199	Main	**0.334**	**-0.272**	0.097
	(6.243)	**(-4.439)**	(-1.624)		**(13.027)**	**(-6.957)**	(1.000)
Zero L	**0.358**	**-0.182**	0.023	SME	**0.111**	-0.033	-0.055
	(12.900)	**(-3.891)**	(0.237)		**(5.972)**	(-0.417)	(-1.506)
Turnover H	**0.433**	**-0.313**	0.158	GEM	**0.108**	0.022	-0.076
	(14.507)	**(-4.007)**	(0.992)		**(3.216)**	(0.906)	(-1.261)
Turnover L	**0.205**	**-0.150**	-0.069				
	(9.926)	**(-3.820)**	(-1.745)				
ShrPerHold H	**0.203**	-0.011	-0.158				
	(9.516)	(-0.232)	(-1.892)				
ShrPerHold L	**0.452**	-0.126	0.002				
	(17.600)	(-2.556)	(0.013)				

Panel B

	(7a)	(7b)	(7c)
Avg intercepts	0.322	-0.134	-0.007
Avg t-values	11.661	-3.173	-0.412
Number of portfolios	13	13	13
Number of sig. intercepts	13	7	2
Avg adj. R^2	0.000	0.456	0.745

Panel C

	(7c) - (7a)	(7c) - (7b)
Diff in intercepts	-0.328	0.127
	(-8.929)	(1.735)
Diff in t	-12.073	2.760
	(-7.905)	(2.095)
Diff in adj. R^2	0.745	0.289
	(22.110)	(4.365)

Table 9: **Robustness test for Tables 3-6.** This table reports results of a robustness check for Eq. (6). All settings are identical to Tables 3-6 except that the dependent variable has been changed from Ln(MB) to Ln(MBR), where the latter is based on market values that use end-of-quarter closing prices.

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var	Ln(MBR)	Ln(MBR)	Ln(MBR)	Ln(MBR)	Ln(MBR)	Ln(MBR)	Ln(MBR)
Size	-0.268***	-0.283***	-0.194***	-0.237***	-0.222***	-0.241***	-0.130***
	(-4.30)	(-4.84)	(-3.90)	(-4.26)	(-4.35)	(-4.45)	(-3.32)
ROE		1.599***					0.202
		(7.42)					(1.02)
Lev			-0.305				-0.273
			(-1.66)				(-1.33)
Zero			-3.762***				-2.204***
			(-6.84)				(-4.88)
Amihud			-7.016***				-4.938***
			(-4.10)				(-2.90)
AGR Asset				0.283***			0.007
				(2.70)			(0.07)
AGR Rev				0.188***			0.105**
				(3.61)			(2.04)
AEEG				0.088***			0.099***
				(2.83)			(3.47)
AESG				0.063			0.077
				(1.34)			(1.67)
IdioVol					1.713***		1.030***
					(7.19)		(5.72)
AvgROE						2.460***	1.952***
						(5.32)	(3.91)
ListAge						-0.029***	-0.020**
						(-3.70)	(-2.38)
Observations	3,074	3,074	3,074	2,722	3,074	3,074	2,722
Adj. R^2	0.539	0.589	0.601	0.587	0.583	0.626	0.695
Portfolio FE	YES	YES	YES	YES	YES	YES	YES

Table 10: **Robustness test for Table 7.** This table reports results of a robustness check for Table 7. All settings are identical to Table 7 except that the dependent variable has been changed from Ln(MB) to Ln(MBR), where the latter is based on market values that use end-of-quarter closing prices.

Panel A

Industry	(7a)	(7b)	(7c)	Industry	(7a)	(7b)	(7c)
Agriculture	**0.197**	**0.192**	0.128	Special Equipment	**0.551**	**-0.331**	-0.410
	(7.891)	**(8.197)**	(1.127)		**(12.118)**	**(-3.341)**	(-2.527)
Mining	**0.799**	**1.003**	0.618	Automobile	**0.415**	-0.086	0.201
	(26.718)	**(5.922)**	(1.391)		**(11.483)**	(-0.915)	(1.137)
Agro-Food Processing	0.067	0.071	0.123	Railway, Shipbuilding, Aerospace	**0.206**	**0.320**	0.375
	(2.160)	(1.740)	(1.776)		**(8.062)**	**(4.865)**	(1.474)
Food Manufacturing	0.052	**0.228**	-0.057	Electrical Machinery	-0.004	**-0.199**	-0.115
	(1.357)	**(3.243)**	(-0.348)		(-0.155)	**(-4.021)**	(-2.320)
Alcohol, Drink, Tea	**-0.184**	0.043	0.243	Computer, Communication	**0.483**	**0.377**	0.087
	(-3.606)	(0.502)	(2.542)		**(28.614)**	**(6.992)**	(0.849)
Textile	0.045	0.047	0.014	Other Manufacturing	-0.074	-0.029	0.174
	(1.915)	(2.169)	(0.088)		(-1.400)	(-0.715)	(1.216)
Papermaking	**0.367**	**0.369**	0.149	Electricity, Heat, Gas and Water	**0.581**	**0.860**	**0.890**
	(19.331)	**(19.169)**	(1.415)		**(22.110)**	**(5.099)**	**(3.844)**
Petroleum Processing	**0.228**	**0.434**	0.646	Construction	**0.780**	**-0.335**	-0.070
	(4.566)	**(13.723)**	(2.180)		**(18.501)**	**(-2.892)**	(-0.353)
Chemical Raw Materials	**0.229**	0.067	-0.021	Wholesale and Retail	**0.308**	**0.177**	0.160
	(10.698)	(0.891)	(-0.259)		**(18.962)**	**(8.028)**	(1.742)
Pharmaceutical Manufacturing	**0.072**	-0.063	-0.138	Transportation, Warehousing, and Postal Services	**0.572**	**0.497**	**0.457**
	(5.768)	(-2.071)	(-2.258)		**(13.345)**	**(3.834)**	**(7.062)**
Chemical Fiber Manufacturing	-0.007	-0.009	**0.750**	IT	**1.172**	**0.623**	-0.457
	(-0.156)	(-0.240)	**(2.656)**		**(22.306)**	**(2.838)**	(-1.263)
Rubber and Plastic Products	**0.263**	0.096	-0.035	Finance	**0.221**	**0.133**	0.029
	(8.060)	(2.004)	(-0.519)		**(12.656)**	**(5.883)**	(0.108)
Non-Metal Mineral Products	**0.348**	-0.048	0.029	Real Estate	**0.177**	**0.208**	**0.377**
	(7.778)	(-1.305)	(0.516)		**(6.824)**	**(2.927)**	**(5.859)**
Ferrous Metals	**0.416**	**0.344**	0.239	Leasing Services	-0.115	**-0.172**	**-0.344**
	(9.507)	**(2.597)**	(0.570)		(-2.004)	**(-3.118)**	**(-6.859)**
Nonferrous Metals	0.040	0.100	-0.289	Environmental and Public Facilities Management	**0.606**	**0.615**	0.317
	(0.780)	(0.432)	(-2.120)		**(12.018)**	**(9.281)**	(1.802)
Metal Products	**0.684**	**1.072**	0.947	Culture, Sports, and Entertainment	**0.487**	**0.358**	0.018
	(17.245)	**(8.077)**	(2.295)		**(13.209)**	**(6.231)**	(0.102)
General Equipment	**0.320**	-0.060	**-0.778**	Comprehensive Service	0.035	0.006	-0.045
	(7.856)	(-0.644)	**(-4.367)**		(1.220)	(0.186)	(-1.287)

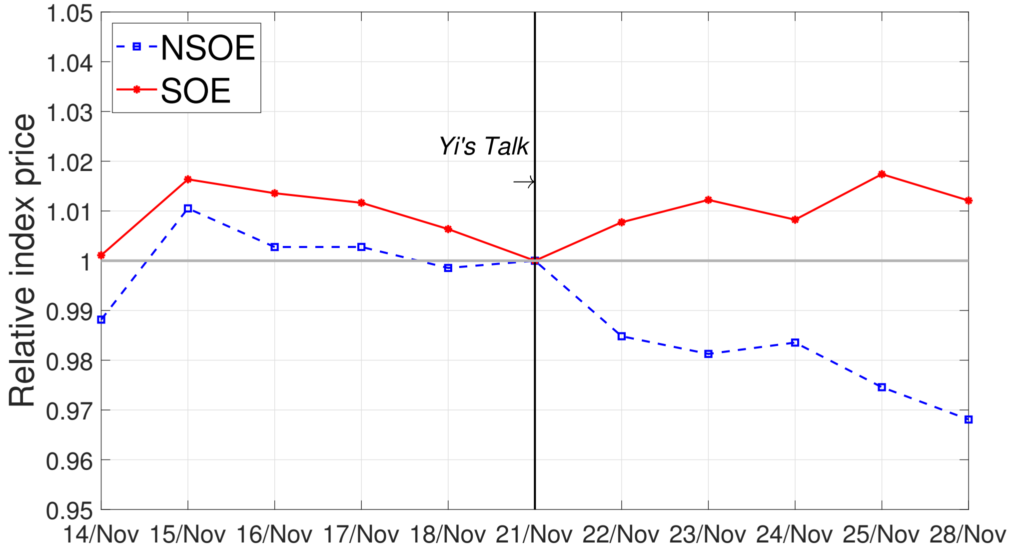
Panel B				Panel C		
	(7a)	(7b)	(7c)		(7c) - (7a)	(7c) - (7b)
Avg intercepts	0.304	0.203	0.124	Diff in intercepts	-0.180	-0.079
Avg t-values	9.581	3.105	0.508		(-2.313)	(-1.483)
Number of industries	34	34	34	Diff in t	-9.073	-2.597
Number of sig. intercepts	25	21	6		(-6.433)	(-3.347)
Avg adj. R^2	0.000	0.172	0.533	Diff in adj. R^2	0.533	0.361
					(13.804)	(9.887)

Table 11: **Balance test.** This table reports the results of balance tests on the distribution of matching variables between the treatment group (Treat) and the control group (Control) before and after matching. The "Mean Treat" and "Mean Control" columns report the average values of variables for the treatment and control groups, respectively. The "Stand. Bias" column represents the standardized bias between the Treat and Control groups. For a given variable X and two sample groups (denoted as A and B), the standardized bias is calculated as $(mean(X_A) - mean(X_B))/\sqrt{1/2(var(X_A) + var(X_B))}$. The "$t$-stat." and "$p$-val." columns indicate the t-statistic and significance level for testing the differences in means. Panel A displays the results before matching, and Panel B presents the results after matching.

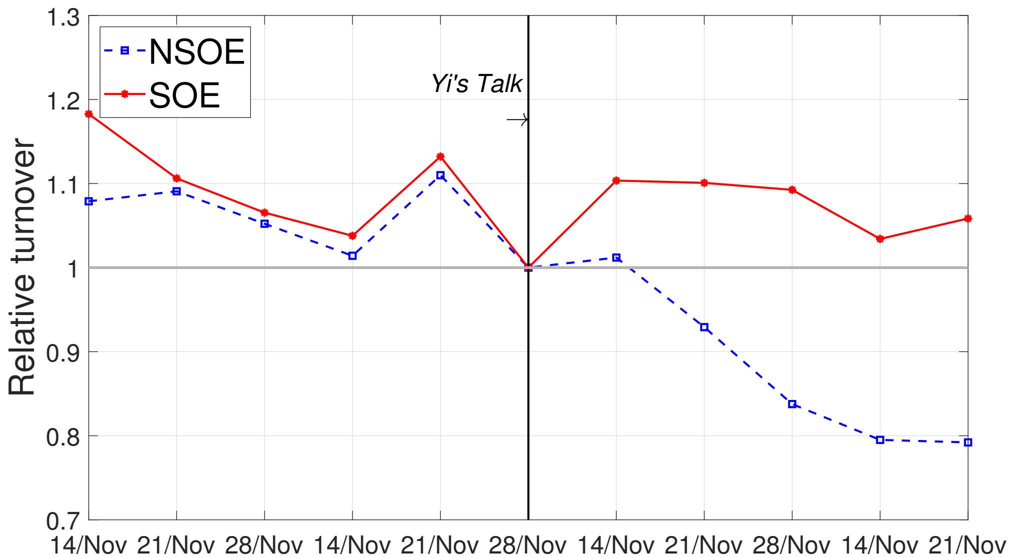
Variable	Mean Treat	Mean Control	Stand. Bias (%)	t-stat.	p-val.
Panel A: Pre-matching					
Variable	Mean Treat	Mean Control	Stand. Bias (%)	t-stat.	p-val.
Size	19.555	19.757	16.7	-3.949	0.000
Lev	0.516	0.505	-5.9	1.402	0.161
ROE	0.085	0.083	-1.5	0.334	0.739
Amihud	0.017	0.014	-8.1	1.946	0.052
AGR Rev	0.195	0.212	3.7	-0.773	0.439
IdioVol	0.303	0.305	1.4	-0.340	0.734
ListAge	11.043	11.604	10.3	-2.402	0.016
SttShr	0.486	0.351	-65.1	13.291	0.000
Panel B: Post-matching					
Variable	Mean Treat	Mean Control	Stand. Bias (%)	t-stat.	p-val.
Size	19.569	19.618	-4.2	-0.697	0.486
Lev	0.516	0.534	-9.6	-1.595	0.111
ROE	0.088	0.091	-2.4	-0.397	0.691
Amihud	0.017	0.021	-8.8	-1.461	0.144
AGR Rev	0.197	0.199	-0.5	-0.082	0.935
IdioVol	0.305	0.292	11.9	1.965	0.050
ListAge	11.259	11.462	-3.9	-0.652	0.515
SttShr	0.479	0.486	-4.0	-0.657	0.511

Table 12: **MOR's effect on valuations.** This table reports coefficients from firm-panel regressions of valuations on an indicator for mixed-ownership reform (Treat $\times$ After), firm-by-cohort fixed effects, and quarter-by-cohort fixed effects. Columns (1) and (2) cover a sample period of eight quarters before and after each MOR event. Columns (3) and (4) cover a sample period of eight quarters before the MOR event and four quarters after. Columns (5) and (6) cover a sample period of eight quarters before the MOR event and the fifth to eighth quarters after the MOR. The *Expl. Var* denotes the independent variables, include *Size*, *Lev*, *ROE*, *Amihud*, *AGR Rev*, *IdioVol*, and *ROE AbsDev*. The selection of independent variables aligns with the matching variables used in the Propensity Score Matching (PSM) as described in Section 6. *ROE AbsDev* is calculated based on the absolute deviation between the most recent quarter's ROE and the average ROE over the past 12 quarters (three years), and the calculations for other independent variables are described in Table IA.2. The regressions include firm-by-cohort (FbC) fixed effects, and quarter-by-cohort (QbC) fixed effects and the standard errors are double clustered by firm and quarter. *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels using two-tailed tests.

Column	(1)	(2)	(3)	(4)	(5)	(6)
Sample period	$[t-8, t+8]$		$[t-8, t+4]$		$[t-8, t+8] \backslash [t+1, t+4]$	
Dep. Var.	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)
Treat$\times$After	0.008	0.015	0.033	0.030*	-0.014	0.005
	(0.40)	(0.79)	(1.60)	(1.67)	(-0.56)	(0.23)
Expl. Var	NO	YES	NO	YES	NO	YES
Observations	15,762	15,706	11,844	11,809	11,770	11,732
Adj. R^2	0.850	0.874	0.875	0.895	0.843	0.866
FbC FE	YES	YES	YES	YES	YES	YES
QbC FE	YES	YES	YES	YES	YES	YES



(a) Response of stock prices



(b) Response of trading activity

Figure 1: **Market response to a speech by Yi Huiman (chairman of CSRC).** This figure depicts the comparison of stock prices and trading volumes between Chinese state-owned enterprises (denoted as SOE and presented in the red solid line) and non-state-owned enterprises (denoted as NSOE and presented in the blue dashed line) in the A-share market before and after a speech delivered by Yi Huiman, who was then the chairman of the China Securities Regulatory Commission (CSRC), at the Beijing Financial Street Forum on November 21, 2022. In subplot (a), we set the values of the stock price indices for SOEs and NSOEs to 1 on the event day. Then, we calculate the prices of the two indices for the five trading days before and after the event day based on the size-weighted average returns of the two types of enterprises. In subplot (b), we first calculate the average turnover for the two types of enterprises for the five trading days before and after the event. Then, we normalize the turnover series of the two types by dividing each value by the turnover on the event day.

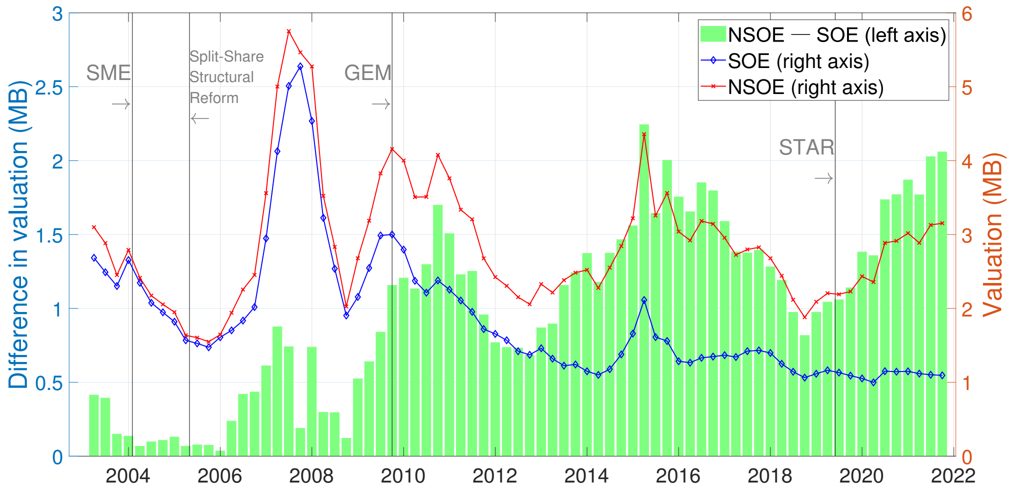


Figure 2: **The time series of average valuations for SOEs and NSOEs.** This figure displays the time series of average valuations for SOEs and NSOEs in the Chinese A-share market during 2003 to 2021. The valuation metric used is the market-to-book ratio (MB). SOEs are represented by a solid line with diamond markers, while NSOEs are represented by a solid line with cross markers. The shaded bars depict the difference between the average valuations of NSOEs and SOEs for each period. The right vertical axis indicates valuation levels, while the left vertical axis represents valuation differentials. The vertical lines denote significant institutional events in the A-share market, including the establishment of the Small and Median Enterprises board (SME), the Growth Enterprise Market (GEM), the Science and Technology Innovation Board (STAR), and the Split-Share Structural Reform.

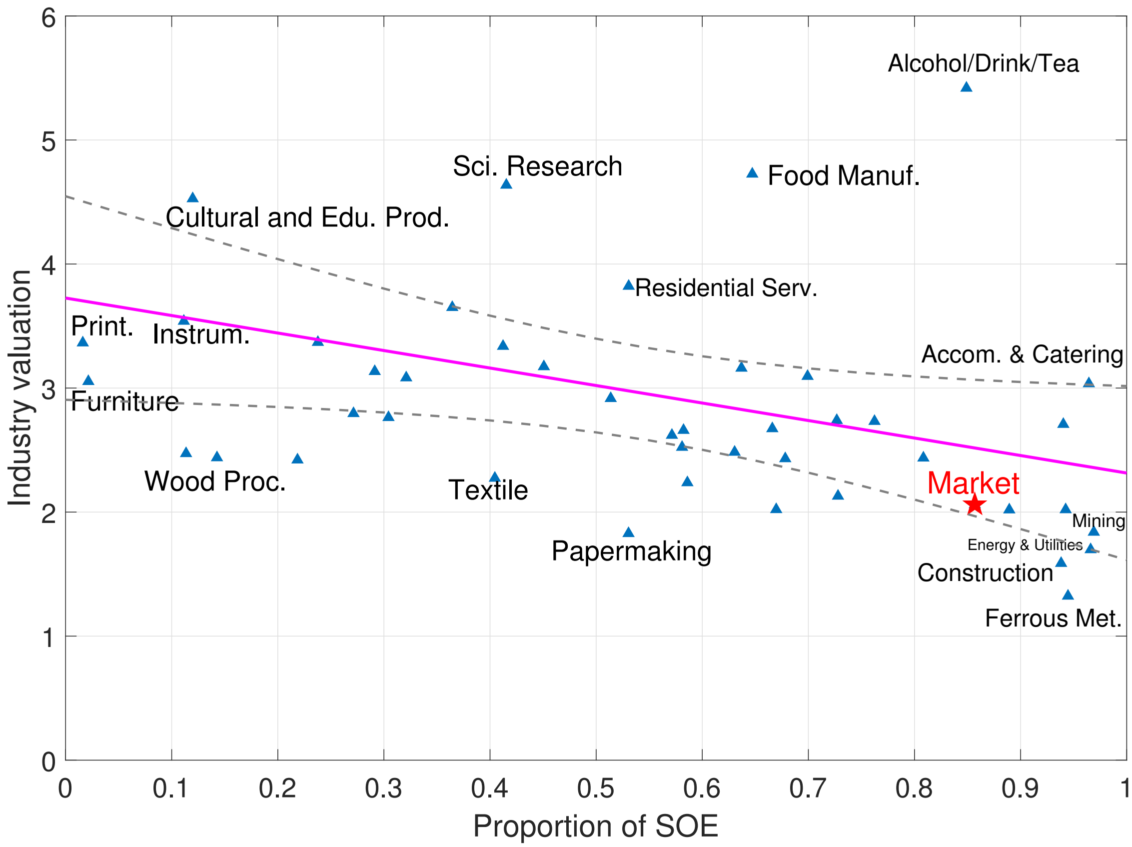


Figure 3: **SOE proportions and valuations across industries.** The figure displays a scatter plot depicting the proportion of SOEs and their corresponding valuations in each industry. The proportion of SOEs in each industry is calculated as the ratio of the sum of total assets of all listed SOEs in that industry to the sum of total assets of all listed companies in that industry. The industry valuation is calculated as the mean market-to-book ratio (MB) weighted by the book value of equity of all firms within each industry. These calculations are carried out quarterly from 2003 to 2021 and averaged over the time series. Industries with fewer than 5 observed companies in a particular quarter are excluded from the calculation of the time series average for valuations and SOE proportions. The solid line represents the fitted line obtained through least squares regression of valuation against the proportion of SOEs. The dashed line represents the 95% confidence interval for the fitted line.

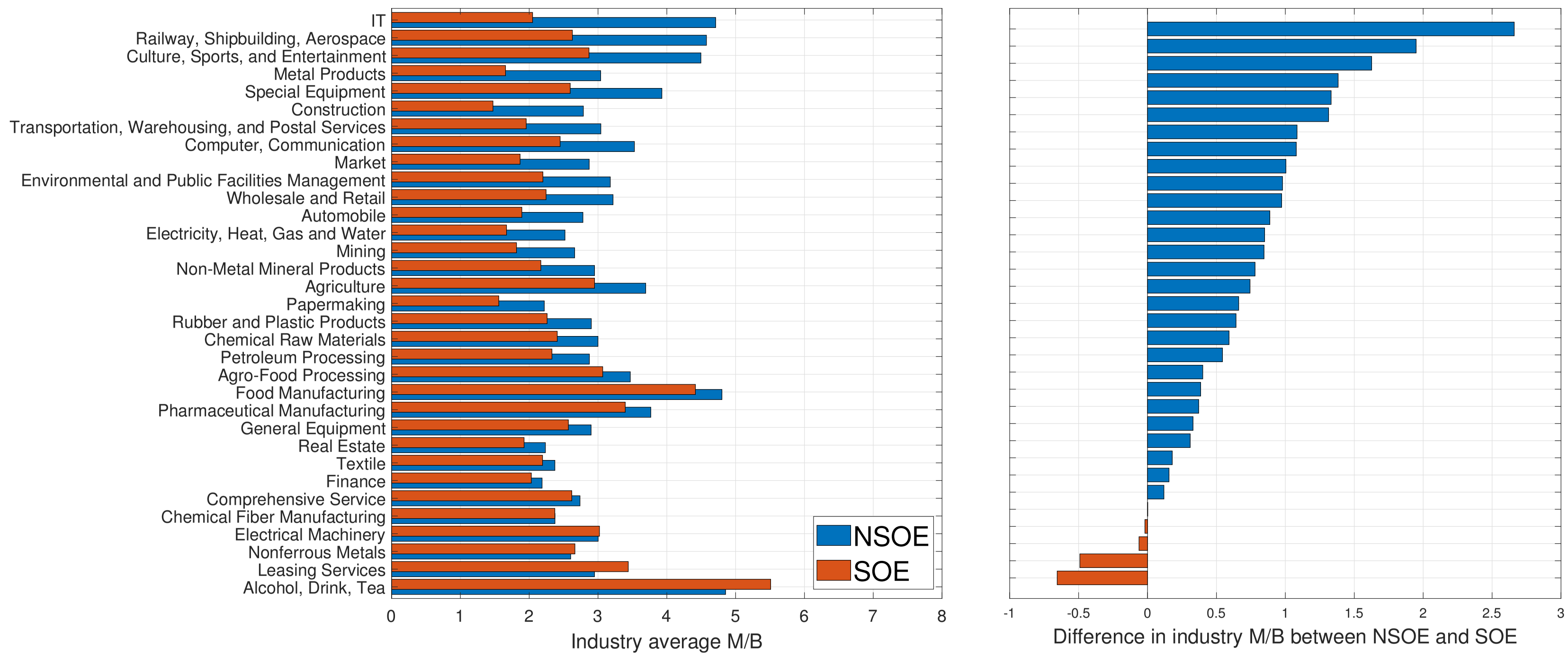


Figure 4: **The average valuations of SOEs and NSOEs and the valuation differential within each industry.** This figure presents separate visuals for the average valuations of NSOEs and SOEs within each industry (left graph) and their valuation differentials (right graph). The average valuations are calculated using equity book value as the weight. Averages are separately calculated for NSOEs (red bars in left graph) and SOEs (blue bars in left graph) in each quarter throughout the sample period (2003-2021), and the average valuations are then averaged over time. The difference between the average valuations of NSOEs and SOEs within each industry is obtained by subtracting the average SOE valuation from the average NSOE valuation. In the right graph, the red bars represent industries where the average valuation of NSOEs is lower than that of SOEs, while the blue bars represent industries where the average valuation of NSOEs is higher.

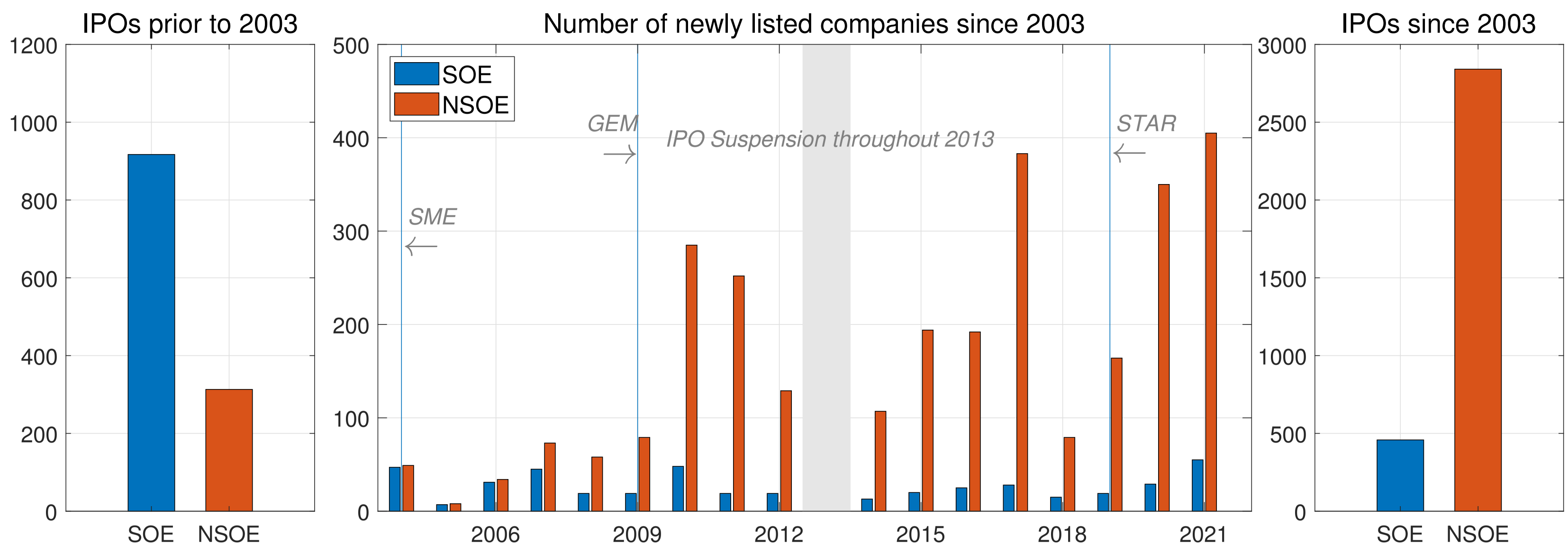
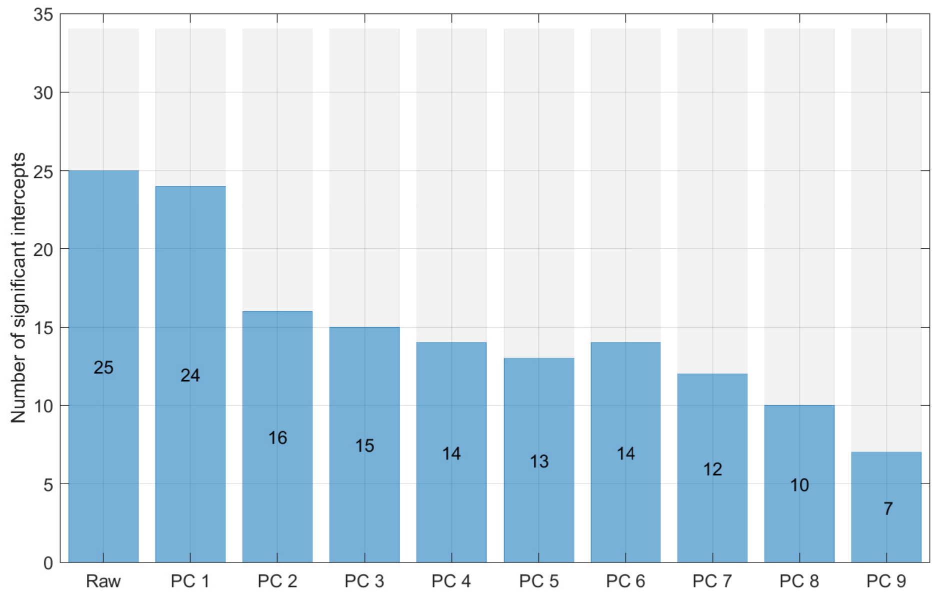
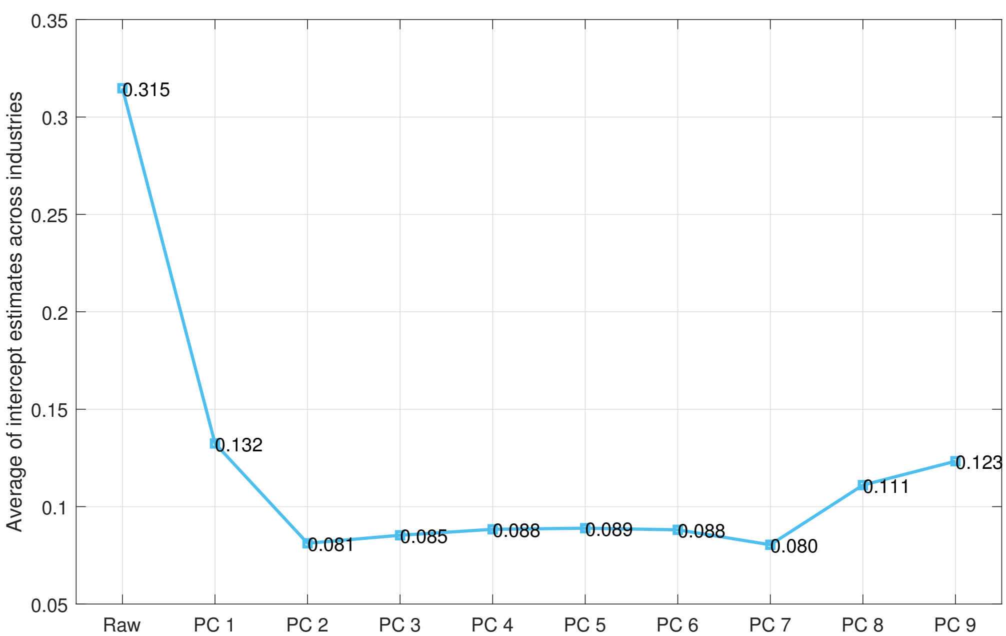


Figure 5: **Comparison of time since listing for SOEs and NSOEs.** The figure displays the distribution of time since listing for SOEs and NSOEs. The left subplot summarizes the total number of listed SOEs and NSOEs before 2003. The middle subplots present the annual number of newly listed SOEs and NSOEs during the sample period from 2003 to 2021. The right subplot summarizes the cumulative number of listed SOEs and NSOEs over the sample period (2003-2021). SOEs are represented by blue bars, while NSOEs are represented by red bars.



(a) Number of significant intercept estimates



(b) Average of intercept estimates across industries

Figure 6: **PCA regression results.** This figure presents the results of regressions where principal components of explanatory variables in Eq. (7c) are used on the right-hand side of Eq. (8). The horizontal axis in the both graphs represents principal components, with "PC 1" indicating the first principal component in the regression, "PC 2" indicating the first and second principal components, and so on. The "Raw" category represents the result of a regression without any explanatory variables, only a constant term. The top graph displays the number of industries with significant intercept estimates at the 1% level, while the bottom graph shows the average values of intercept estimates across industries.

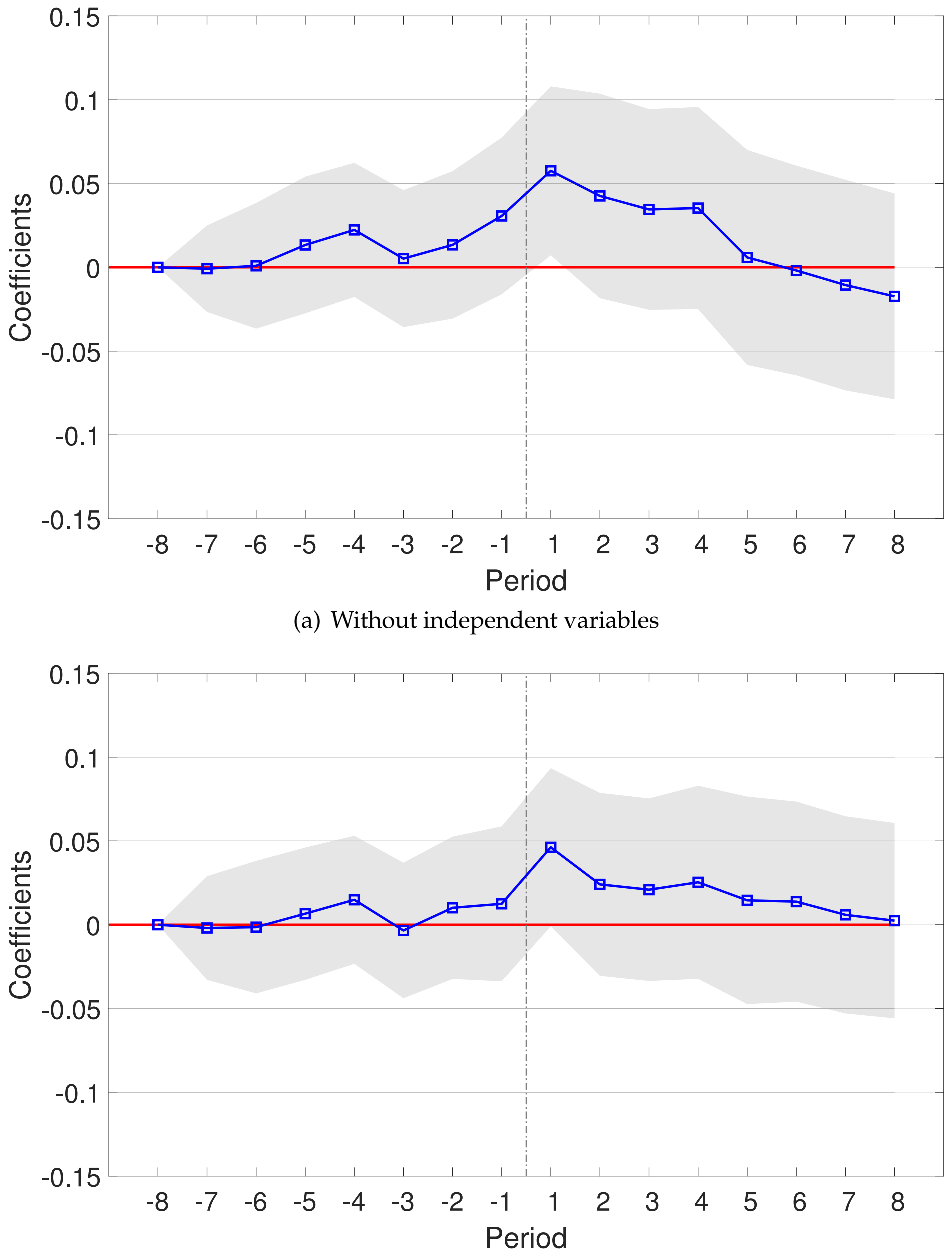
Figure 7: **PCA factor loadings.** This heatmap reports the loadings obtained from the principal component analysis of the explanatory variables in Eq (7c). Each row represents the coefficients of the all variables corresponding to that principal component, and the rows are in descending order of component variance. For example, the first row, labeled as "PC 1", represents the coefficients of the considered variables corresponding to the first principal component. The color blocks in this heatmap are scaled based on the magnitude of the values, where the darkest (lightest) color blocks represent the maximum (minimum) values.

	Size	Zero	Amihud	AGR Rev	AEEG	AESG	IdioVol	AvgROE	ListAge
Agriculture	0.019	0.024	0.123	0.012	0.047	0.008	0.028	0.014	0.048
Mining	0.020	0.058	0.124	0.010	0.023	0.087	0.002	0.035	0.107
Agro-Food Processing	0.008	0.020	0.215	0.003	0.003	0.015	0.047	0.042	0.094
Food Manufacturing	0.073	0.071	0.264	0.028	0.085	0.058	0.033	0.072	0.066
Alcohol, Drink, Tea	0.021	0.016	0.018	0.002	0.012	0.020	0.031	0.109	0.664
Textile	0.045	0.020	0.044	0.067	0.176	0.024	0.029	0.034	0.082
Papermaking	0.018	0.012	0.131	0.015	0.006	0.003	0.039	0.027	0.068
Petroleum Processing	0.227	0.013	0.284	0.072	0.008	0.057	0.097	0.010	0.021
Chemical Raw Materials	0.056	0.013	0.013	0.020	0.078	0.081	0.033	0.119	0.172
Pharmaceutical Manufacturing	0.129	0.001	0.006	0.007	0.003	0.040	0.046	0.061	0.248
Chemical Fiber Manufacturing	0.139	0.032	0.019	0.123	0.024	0.064	0.008	0.026	0.170
Rubber and Plastic Products	0.111	0.142	0.064	0.006	0.007	0.051	0.115	0.081	0.255
Non-Metal Mineral Products	0.222	0.078	0.017	0.004	0.039	0.047	0.180	0.068	0.187
Ferrous Metals	0.044	0.007	0.047	0.047	0.013	0.057	0.105	0.122	0.241
Nonferrous Metals	0.010	0.021	0.049	0.004	0.041	0.011	0.029	0.037	0.663
Metal Products	0.041	0.024	0.070	0.032	0.020	0.016	0.036	0.245	0.146
General Equipment	0.128	0.017	0.035	0.004	0.132	0.025	0.094	0.063	0.358
Special Equipment	0.249	0.095	0.024	0.100	0.010	0.028	0.035	0.114	0.196
Automobile	0.072	0.059	0.063	0.020	0.133	0.043	0.111	0.018	0.166
Railway, Shipbuilding, Aerospace	0.048	0.058	0.017	0.003	0.018	0.037	0.031	0.025	0.023
Electrical Machinery	0.073	0.045	0.046	0.024	0.054	0.078	0.168	0.142	0.170
Computer, Communication	0.095	0.017	0.016	0.001	0.004	0.006	0.093	0.053	0.028
Other Manufacturing	0.141	0.058	0.039	0.015	0.082	0.048	0.119	0.191	0.194
Electricity, Heat, Gas and Water	0.010	0.003	0.070	0.013	0.088	0.051	0.142	0.056	0.119
Construction	0.279	0.144	0.039	0.069	0.045	0.081	0.114	0.060	0.016
Wholesale and Retail	0.375	0.022	0.033	0.036	0.026	0.039	0.017	0.151	0.040
Transportation, Warehousing, and Postal Services	0.006	0.099	0.053	0.017	0.013	0.030	0.045	0.256	0.350
IT	0.128	0.016	0.053	0.019	0.045	0.033	0.161	0.058	0.092
Finance	0.137	0.008	0.099	0.014	0.013	0.033	0.028	0.157	0.160
Real Estate	0.017	0.055	0.233	0.013	0.030	0.015	0.040	0.218	0.010
Leasing Services	0.058	0.005	0.018	0.094	0.022	0.050	0.118	0.137	0.266
Environmental and Public Facilities Management	0.016	0.071	0.062	0.046	0.089	0.096	0.003	0.228	0.133
Culture, Sports, and Entertainment	0.117	0.066	0.022	0.011	0.007	0.064	0.181	0.012	0.226
Comprehensive Service	0.071	0.134	0.052	0.016	0.049	0.113	0.008	0.048	0.139
Average	0.094	0.045	0.072	0.028	0.043	0.044	0.070	0.091	0.174

Figure 8: **Dominance analysis for individual variables.** The figure depicts a heatmap showcasing the explanatory power of each variable in explaining the valuation differences across industries, with the last row (labelled as "Average") displaying the average values across industries. The method for evaluating the explanatory power of each variable is outlined in Section 3.4, specifically in Eq. (11). The horizontal axis displays variable names, while the vertical axis displays industry labels. The heatmap's color scale is applied row-wise, with the darkest (lightest) color representing the maximum (minimum) value within each row.

	Control	Liquidity	Growth	Speculation	Uncertainty
Agriculture	0.019	0.147	0.067	0.028	0.061
Mining	0.020	0.182	0.120	0.002	0.143
Agro-Food Processing	0.008	0.235	0.021	0.047	0.137
Food Manufacturing	0.073	0.336	0.170	0.033	0.138
Alcohol, Drink, Tea	0.021	0.034	0.035	0.031	0.773
Textile	0.045	0.064	0.267	0.029	0.115
Papermaking	0.018	0.143	0.024	0.039	0.095
Petroleum Processing	0.227	0.297	0.137	0.097	0.031
Chemical Raw Materials	0.056	0.026	0.179	0.033	0.291
Pharmaceutical Manufacturing	0.129	0.007	0.050	0.046	0.309
Chemical Fiber Manufacturing	0.139	0.051	0.210	0.008	0.195
Rubber and Plastic Products	0.111	0.206	0.064	0.115	0.335
Non-Metal Mineral Products	0.222	0.095	0.090	0.180	0.255
Ferrous Metals	0.044	0.054	0.118	0.105	0.363
Nonferrous Metals	0.010	0.069	0.056	0.029	0.700
Metal Products	0.041	0.094	0.069	0.036	0.391
General Equipment	0.128	0.052	0.161	0.094	0.421
Special Equipment	0.249	0.119	0.138	0.035	0.311
Automobile	0.072	0.121	0.196	0.111	0.184
Railway, Shipbuilding, Aerospace	0.048	0.075	0.058	0.031	0.049
Electrical Machinery	0.073	0.090	0.156	0.168	0.313
Computer, Communication	0.095	0.034	0.010	0.093	0.081
Other Manufacturing	0.141	0.097	0.145	0.119	0.385
Electricity, Heat, Gas and Water	0.010	0.073	0.152	0.142	0.175
Construction	0.279	0.184	0.194	0.114	0.075
Wholesale and Retail	0.375	0.054	0.101	0.017	0.191
Transportation, Warehousing, and Postal Services	0.006	0.152	0.060	0.045	0.606
IT	0.128	0.069	0.097	0.161	0.150
Finance	0.137	0.107	0.060	0.028	0.317
Real Estate	0.017	0.288	0.059	0.040	0.228
Leasing Services	0.058	0.022	0.167	0.118	0.403
Environmental and Public Facilities Management	0.016	0.133	0.230	0.003	0.361
Culture, Sports, and Entertainment	0.117	0.088	0.083	0.181	0.237
Comprehensive Service	0.071	0.186	0.178	0.008	0.188
Average	0.094	0.117	0.115	0.070	0.265

Figure 9: **Dominance analysis at the mechanism level.** This figure presents a heatmap representing the explanatory power of each variable group in explaining the valuation differences across industries, with the last row (labelled as "Average") displaying the average values across industries. The method for evaluating the explanatory power of each variable is outlined in Section 3.4, specifically in Eq. (11). As described in Section 3.4, the decomposition of R^2 into individual variables is additive. In this figure, we aggregate the explanatory power of variable groups based on the mechanism through which the variables influence the estimated values. The **Control** variable group includes *Size*. The **Liquidity** variable group comprises *Zero* and *Amihud* variables. The **Growth** variable group consists of *AGR Rev*, *AEEG*, and *AESG*. The **Speculation** variable group includes the *IdioVol* variable. The **Uncertainty** variable group includes *ListAge* and *AvgROE*. The color scale in this heatmap follows the same row-wise scaling as depicted in Figure 8, where each row's color intensity is determined by the maximum (or minimum) value within that row.



(a) Without independent variables

(b) With independent variables

Figure 10: **The effect of the mixed-ownership reform (MOR) on valuation.** This figure displays the coefficient estimates (βs) of Eq. (16). The horizontal axis represents the quarter relative to the MOR event. The vertical axis represents the estimated values of the coefficients. The point corresponding to the baseline period (eighth pre-event period) is set to zero in this figure as a reference point. The shaded area represents the 95% confidence interval for the regression coefficients. The upper graph (a) displays the estimation results without explanatory variables, while the lower graph (b) incorporates the variables. The explanatory variables are Size, Lev, ROE, Amihud, AGR Rev, and ROE AbsDev. ROE AbsDev is calculated based on the absolute deviation between the most recent quarter's ROE and the average ROE over the past 12 quarters (three years), and the calculations for other independent variables are described in Table IA.2.

Internet Appendix to

"Understanding the Valuation Gap between State-Owned and Non-State-Owned Enterprises"

Yuanlan Cao, Avanidhar Subrahmanyam, Xuewei Yang, and Peng Zhu

March 7, 2025

In this appendix, we provide some supplementary illustrations and ancillary empirical results.

IA.1 More details about dataset and share transactions of SOEs

IA.1.1 Classification of SOE/NSOE

The CSMAR (China Stock Market & Accounting Research) database has been widely used in studies on the Chinese stock market; see Allen et al. (2024), Li et al. (2023), and Liu, Wang, and Zhu (2021) amongst others. Following the literature,[1] we extract ownership information for all listed firms from the Equity of Nature Database in CSMAR, which, in turn, obtains ownership properties from annual reports of Chinese listed companies.[2] When identifying the controlling shareholder, the database first attempts to pinpoint the "actual controller" by analyzing shareholding chains disclosed in annual reports. The CSMAR database calculates shareholder ownership percentages from the chains, and then uses these to determine the controlling shareholder for each firm. The database then classifies firms into ownership categories based on the identity of the controlling shareholder. When direct disclosure of the controlling shareholder is unavailable from public sources, classifications of controlling shareholder type are determined by the CSMAR team via queries to enterprise registration data.[3]

The CSMAR database classifies controlling shareholders into 13 groups: 1100 - state-owned enterprises; 1210 - collective-owned enterprises; 1200 - private enterprises; 1220 - Hong Kong, Macau, and Taiwan-funded enterprises; 1230 - foreign-funded enterprises; 2000 - government agencies and institutions; 2100 - central government and departments; 2120 - local government and departments; 2500 - social organizations; 3110 - domestic natural persons; 3120 - Hong Kong, Macau, and Taiwan natural persons; 3200 - foreign natural persons; and 9999 - Others. If the controller is labeled as 1100 (state-owned enterprises), 2000 (government agencies and institutions), 2100 (central government and departments), and 2120 (local government and departments), the listed company is categorized as an SOE; otherwise, it is a NSOE. CSMAR maintains unchanged classification rules over time, thus avoiding variations in the definition of SOE/NSOE.

[1]See, e.g., p. 5084 in Li et al. (2023) and p. 8 in Liu, Wang, and Zhu (2021). Allen et al. (2024) utilized ownership structure information from the WIND database; see p. 1001 and Table I therein. We opted to use ownership information from CSMAR because it has slightly fewer missing data points than WIND, and when both sets of observations are available, they are consistent in 99.3% of the cases.

[2]For companies listed on the Shanghai Stock Exchange, the designated information disclosure website is: http://www.sse.com.cn; for companies listed on the Shenzhen Stock Exchange, the designated information disclosure website is: http://www.cninfo.com.cn.

[3]For more questions about this aspect, one can consult with the official customer service of CSMAR at service@csmar.com.

IA.1.2 Share transactions in SOEs and NSOEs

In the Chinese stock market, investors can trade the float of both SOEs and NSOEs. Before 2005, the float only included those shares that were issued by companies during their initial public offerings (IPOs). In contrast, pre-IPO existing shares were not allowed to be traded on the public market and were commonly referred to as non-tradable shares. Following the split-structure reform initiated in 2005, which aimed to address the issue of dual-class shares (where shares of the same firm have different trading rights), all shares of listed companies (with few exceptions) became tradable (see Liao, Liu, and Wang (2014) for details). All shares have exactly the same dividend rights and voting rights, regardless of whether they are held by individuals or state-owned shareholders.

For both SOEs and NSOEs, if a state-owned shareholder intends to sell a net proportion of shares that reaches 5% of the total shares of the listed company, it must obtain approval from the State-owned Assets Supervision and Administration Commission (SASAC) of the State Council before proceeding. For SOEs, if the state-owned *controlling* shareholder intends to sell shares that meet either of the following three conditions, they need to obtain approval from the SASAC of the State Council before proceeding: (1) For companies with a billion or fewer shares outstanding, the transaction amount in shares is at least 5% of the total; (2) For companies with outstanding shares exceeding a billion, the transaction transaction is at least 50 million shares or accounts for no less than 3% of shares outstanding; (3) the transaction involves a transfer of control rights. For other cases, the trading of state-owned shareholders only requires an internal decision-making process.[4]

The aforementioned conditions regulate significant share transactions by state-owned shareholders. However, investors are not necessarily required to acquire shares from state-owned shareholders to gain control of state-owned enterprises. An example is the Vanke equity incident spanning 2015 to 2017. Prior to 2015, Vanke (trading code: 000002.SZ), a Chinese real estate listed company, recorded China Resources Group, one of the central-government-owned SOEs, as its largest shareholder. In 2015, a private entity named Baoneng Group and its affiliates initiated the acquisition of Vanke shares (excluding the shares held by China Resources Group) in the open market. By 2016, Baoneng had amassed a 25% stake in Vanke, thereby becoming the leading shareholder. In this scenario, China Resources Group did not sell its holdings but effectively lost its controlling stake. Nonetheless, changes in the controller of equity in listed companies via this

[4]Please refer to the administrative regulations jointly issued by the SASAC and CSRC, titled "Administrative Measures for the Supervision and Management of State-owned Equity in Listed Companies."

pathway are exceedingly uncommon.

IA.2 More details on the MOR event study

In Section 6, we examine the impact of mixed-ownership reform (MOR) events on firm valuations. Since these events occurred at different time periods, we employ a stacked Difference-in-Differences (DID) method to estimate the event effects. This method involves matching a "comparable" non-reformed company for each reformed company to form a cohort, and then estimating the average treatment effect of the MOR events across the cohorts. In this appendix, we provide a detailed description of how the matching process is conducted.

First, we track the Top 10 Shareholders document for all companies to determine which enterprises are state-owned enterprises (SOEs) at each time point (refer to Section 2). Then, based on the Top 10 Shareholders document for each company in two consecutive quarters, we determine which identified SOEs have a non-state-owned ownership percentage below a certain threshold (10%) in the previous quarter and exceed that threshold in the following quarter. We set the threshold at 10% to determine the occurrence of MOR events, aligning with Chinese *Corporate Law* and relevant practices. During the sample period from 2003 to 2021, we identify a total of 1,601 SOEs. Among these, 844 companies underwent MOR.

Next, we examine the firms that undergo MOR at time t and ensure that they simultaneously meet the following conditions. First, there should be no missing values in the matching variables[5] at time $t-8$ (when we match them with similar non-MOR firms). Second, these firms should have a minimum of nine observations in the interval $[t-8, t+8]$. The firms that meet these criteria are used to form the treatment group for period t (referred to as the TG_t). We also search for potential control groups based on the following three conditions: First, there are no missing values in the matching variables at time $t-8$. Second, there are at least nine observations in the interval $[t-8, t+8]$. Third, no MOR events occurred in the interval $[t-8, t+8]$. The companies that simultaneously meet the three conditions form the potential control group (referred to as the PCG_t). Based on the matching variables at time $t-8$, we estimate the propensity scores using a Logit model for the companies in the TG_t (with the outcome variable set to 1) and the PCG_t (with the outcome variable set to 0). Then, employing a 1:1 matching ratio and a caliper of 0.05, we apply the nearest neighbor matching method with replacement to find the corresponding matched

[5] We consider seven variables as matching criteria, including: Size, Lev, ROE, Amihud, AGR Rev, List Age, and State-owned Ratio.

companies from the PCG_T for each company in the TG_t. Subsequent to the matching process, we conduct a balance test using the Rubin R statistic (Rubin, 2001) as the criterion. If the balance test is not passed, we re-estimate the Logit model by including quadratic and interaction terms of the matching variables and determine the matched companies using the same rules. Subsequently, we perform another balance test. If this second balance test also fail to meet the desired criteria, we conclude that it was not feasible to find similar non-MOR companies for the firms of TG_t and exclude the samples from the TG_t group in the subsequent analysis. If the balance test is passed, we combine the treated companies from the TG_t and the matched companies from the PCG_t, considering their observations in the interval $[t-8, t+8]$, to form a cohort. The processes is repeated for each quarter t within the sample period, resulting in a series of cohorts. These cohorts are then combined to form a dataset that are used for examining the effects of MOR.

IA.3 Variable selection by LASSO and Related Results

In this appendix, we examine the use of an variable selection method. Specifically, we replace variable selection based on coefficient significance from the panel regression (as shown in Table 6 of the paper) with variable selection using the Least Absolute Shrinkage and Selection Operator (LASSO), a widely-used technique for variable selection.

To ensure self-containment, we first provide a brief overview of LASSO. Suppose we have a set of n observations with p variables, and the linear regression model is given by $y = X\beta + \epsilon$, where y is the dependent variable vector of length n, X is the design matrix of dimension $n \times p$, β is the coefficient vector of length p, and ϵ is the error term. LASSO aims to solve the optimization problem of minimizing the objective function:

$$\min_{\beta} \left\{ \frac{1}{2n} \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 + \lambda ||\beta||_1 \right\}. \tag{IA.1}$$

The first term in Eq. IA.1 represents the mean squared error (MSE) between the observed responses and the fitted values, which is the objective function in standard ordinary least square regression. The second term is the L_1-norm penalty, with the regularization parameter λ. As λ increases, the coefficients are forced to be smaller. When λ is large enough, some of the coefficients will be shrunk to exactly zero. The variables corresponding to these zero coefficients are effectively removed from the model, which achieves the purpose of variable selection. In practice, to find the optimal set of variables, one usually considers a sequence of λ values and solves the LASSO problem for each λ. By choosing an appropriate value for λ, we can obtain a model with a parsimonious set of variables, effectively performing variable selection. Cross-validation (CV) or the Bayesian Information Criterion (BIC) is commonly used to determine the optimal value of λ. The variables with non-zero coefficients under the optimal penalty parameter (which minimizes mean CV loss or BIC value) are considered the selected variables by LASSO.

In our study, one key issue when performing LASSO variable selection is the inclusion of portfolio fixed effects. To address this, we introduce portfolio fixed effects by demeaning the variables within each portfolio. After this demeaning operation, we can apply LASSO to the data in the usual manner. We define the sequence of λ as a grid of 100 equally spaced points ranging from 0.0000001 to 0.1. Figure IA.5 illustrates the variable coefficient estimates from LASSO. We find that LASSO excludes fewer candidate variables than the panel regression. For example, when using CV as the selection rule, the optimal penalty parameter excludes none of the candidate variables. When BIC is used as the selection rule, the optimal penalty parameter excludes only the *AGR Asset* variable. In contrast, the original approach of selecting variables based on the significance from the panel regression filters out three variables: *Lev*, *ROE*, *AGR Asset*.

Nevertheless, we use the variables selected by LASSO under the BIC rule to redo the relevant analyses and report the results in this appendix. Note that replacing the variable selection method with LASSO affects only the time-series regression results. Specifically, it changes only the explanatory variables included in Eq. (7c) of the paper. Accordingly, we regenerate the time-series regression results. Tables IA.4, IA.5, and IA.6 in this appendix correspond to Tables 7, 8, and 10 in the paper, respectively. Figures IA.6(b), IA.7, and IA.8 in this appendix correspond to Figures 6(b), 7, and 8 in the paper, respectively.

It can be observed that the new results are qualitatively consistent with the original ones. For instance, in both cases (LASSO and panel regressions), significant intercepts remain for seven industry portfolios and two characteristic portfolios in the time-series regression. By incorporating the first two principal components of the explanatory variables, the number of industries exhibiting significant intercept estimates decreases to 16, which is less than half of the total number of industries. The first principal component is predominantly driven by the variable "List Age," while the second principal component is primarily driven by "Size." Among all the explanatory variables, "List Age" plays the largest role in explaining the valuation differences, according to the results of the dominance analysis. Overall, these results show little deviation from those reported in the paper using variable selection via a panel regression.

References

Allen, F., J. Qian, C. Shan, and J. L. Zhu (2024). Dissecting the long-term performance of the Chinese stock market, *Journal of Finance* **79**(2): 993–1054.

Bekaert, G., S. Ke, X. Wang, and X. Zhang (2022). The China-US equity valuation gap, Columbia Business School working paper.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* **7**(2): 197–226.

Li, Z., L. X. Liu, X. Liu, and K. John Wei (2023). Replicating and digesting anomalies in the Chinese A-share market, *Management Science* **70**(8): 5066–5090.

Liao, L., B. Liu, and H. Wang (2014). China's secondary privatization: Perspectives from the split-share structure reform, *Journal of Financial Economics* **113**(3): 500–518.

Liu, J., R. F. Stambaugh, and Y. Yuan (2019). Size and value in China, *Journal of Financial Economics* **134**(1): 48–69.

Liu, J., Z. Wang, and W. Zhu (2021). Does privatization reform alleviate ownership discrimination? evidence from the split-share structure reform in china, *Journal of Corporate Finance* **66**: 101848.

Table IA.1: **Comparison of holding period returns between portfolios of SOEs and NSOEs.** This table is the counterpart of Table 1. The only difference from Table 1 is that we now use real returns, which are obtained by adjusting for inflation on nominal returns. Here inflation is measured by the Consumer Price Index (CPI).

Term	Statistics	Equally weighted			Value weighted		
		NSOE	SOE	Diff (*t*-stat.)	NSOE	SOE	Diff (*t*-stat.)
1 Year	Ret	0.31	0.28	0.03 (0.28)	0.15	0.21	-0.05 (-0.43)
	Std	8.96	8.50	0.45 (4.03)	7.98	7.16	0.83 (5.28)
	SR	-0.94	-0.17	-0.77 (-0.66)	-1.18	0.91	-2.09 (-0.88)
	Total ret	3.49	3.26	0.23 (0.21)	1.75	2.35	-0.60 (-0.41)
3 Year	Ret	0.51	0.43	0.08 (0.86)	0.34	0.33	0.01 (0.06)
	Std	9.69	9.30	0.39 (3.91)	8.93	7.96	0.97 (6.21)
	SR	0.44	0.06	0.38 (0.36)	-0.91	-0.53	-0.38 (-0.25)
	Total ret	17.60	14.96	2.64 (0.77)	11.41	11.28	0.13 (0.03)
5 Year	Ret	0.54	0.43	0.11 (1.79)	0.40	0.33	0.07 (0.94)
	Std	10.05	9.74	0.32 (4.18)	9.31	8.44	0.88 (6.53)
	SR	2.05	0.99	1.06 (1.59)	0.69	0.27	0.42 (0.40)
	Total ret	31.03	24.74	6.29 (2.38)	22.38	18.34	4.04 (1.05)

Table IA.2: **Variable Descriptions.** The table provides definitions of the variables mentioned in the main text. The three columns from left to right represent the variable's category, name (identifier), and calculation method, respectively.

Dimension	**Variable (Identifier)**	**Calculation Method**
Valuation	MB (MB)	The average daily closing price of the stock in the next quarter divided by the company's book value per share in the current quarter.
Valuation	Log MB (Ln(MB))	Logarithm of the average daily closing price of the stock in the next quarter divided by the company's book value per share in the current quarter.
Profitability	Return on equity (ROE)	The trailing twelve months (TTM) net profit for the current quarter divided by the net equity for the current quarter.
Risk Exposure	Beta (β)	Beta is estimated by regressing the stock's daily excess returns over the past 242 trading days against the market portfolio's excess returns in the same period, accounting for a five-lag Dimson (1979) correction as per Liu, Stambaugh, and Yuan (2019).
Risk	Volatility (Vol)	Standard deviation of the stock's daily returns
Leverage	Leverage ratio (Lev)	Total liabilities for the current quarter divided by total assets for the current quarter.
Openness	Degree of openness (IA Grade)	Discrete Indicator. Takes a value of unity if the stock corresponds to a firm that has a) issued B-shares or b) H-shares.
Openness	Level of openness (IA Degree)	Proportion of overseas issued shares to total shares. It is the sum of of B- and H-share capitalization to total capitalization.
Illiquidity	Proportion of zero returns (Zero)	Number of trading days with zero daily returns in the quarter, divided by the total number of trading days for that stock in the quarter.
Illiquidity	Amihud liquidity (Amihud)	Average daily Amihud measure for the quarter. Daily Amihud measure is the ratio of absolute daily returns to daily trading amount. For the sake of convenience in representation, we multiply this measure by a factor of 10 million.
Growth	12-month growth rate (AGR Rev & AGR Asset)	(Current quarter value / Value from the same quarter one year ago) - 1. We calculate this variable for total assets and revenue separately and denote them as AGR Asset and AGR Rev, respectively.
Growth	Analyst expected earnings growth rate (AEEG & AESG)	In each quarter, we take the median of analyst forecasts for the firm's future three-year earnings (sales). Then, we calculate the expected growth rates of earnings (sales) for each future fiscal year, adjusting for CPI values. Finally, we calculate AEEG (AESG) as the weighted average of the analysts' expected earnings (sales) growth rates for the company's next three years based on the forecast horizon (or see Bekaert et al. 2022).
Growth	Patent density (invention) (Inno)	Number of new INNOvation patents applied for by the company in the past year divided by the TTM (Trailing Twelve Months) revenue for the current quarter (in billion yuan).
Growth	Patent density (utility model) (UM)	Number of new Utility Model patents applied by the company in the past year divided by the TTM (Trailing Twelve Months) revenue for the current quarter (in billion yuan).
Differences in beliefs	Turnover (Turnover)	Average daily turnover of the stock's circulating shares in the current quarter. Daily turnover is calculated as the daily trading volume divided by the number of circulating shares on that day.
Investor disagreement	Idiosyncratic volatility (Idio Vol)	Standard deviation of the residuals from regressing the stock's daily returns in the most recent quarter on the factor returns from the model proposed by Liu, Stambaugh, and Yuan (2019). This standard deviation multiplied by $\sqrt{242}$ yields the annualized idiosyncratic volatility.
Profitability	Average return on equity (Avg ROE)	We calculate the average return on equity for the past 3 years in each quarter.
Uncertainty	List age (List Age)	We calculate the age since listing of the company in each quarter (rounded down).
Control	Size	Logarithm of total assets for the current quarter.

Table IA.3: **Further analysis of hypotheses on leverage and current profitability (Hypotheses H1 and H2c).** This table reports some additional analyses for hypotheses H1 and H2c. The dependent variable is the portfolio-level valuation differential between NSOEs and SOEs. All independent variables are the differences in each variable between SOE and NSOE. Detailed definitions and calculations of all variables are provided in Table IA.2. The regressions include portfolio fixed effects, and the standard errors are double clustered by portfolio and time. We report *t*-statistics in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, using two-tailed tests.

Column	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)	Ln(MB)
Size	-0.178***	-0.223***	-0.190***	-0.246***	-0.241***	-0.209***
	(-3.33)	(-3.96)	(-3.87)	(-4.62)	(-4.75)	(-4.49)
Lev	-0.602***	-0.566***	-0.299			
	(-2.89)	(-2.94)	(-1.42)			
ROE				1.174***	0.921***	0.384*
				(4.90)	(4.07)	(1.83)
AGR Asset	0.285***			0.123		0.104
	(2.84)			(1.13)		(1.06)
AGR Rev	0.201***			0.089		0.116**
	(3.58)			(1.50)		(2.29)
AEEG	0.087***			0.078**		0.111***
	(3.00)			(2.61)		(3.64)
AESG	0.062			0.096**		0.076
	(1.47)			(2.14)		(1.58)
AvgROE		2.770***			1.294**	1.943***
		(5.63)			(2.49)	(4.04)
ListAge			-0.032***		-0.029***	-0.027***
			(-3.69)		(-3.85)	(-3.33)
Observations	2,722	3,074	3,074	2,722	3,074	2,722
Adj. R^2	0.620	0.622	0.610	0.626	0.654	0.675
Portfolio FE	YES	YES	YES	YES	YES	YES

Table IA.4: **Intercept estimates across industries.** This table reports the counterparts of Table 7 in the paper. All setings are exactly the same as those in Table 7, except that we select the explanatory variables in Eq. (7c) by LASSO (using the BIC) in this figure.

Panel A

Industry	(7a)	(7b)	(7c)	Industry	(7a)	(7b)	(7c)
Agriculture	**0.215**	**0.207**	0.176	Special Equipment	**0.551**	**-0.340**	-0.352
	(9.193)	**(9.893)**	(2.303)		**(12.265)**	**(-3.792)**	(-2.315)
Mining	**0.817**	**1.011**	0.280	Automobile	**0.421**	-0.074	0.141
	(26.866)	**(6.203)**	(0.325)		**(12.124)**	(-0.768)	(0.949)
Agro-Food Processing	0.064	0.069	-0.126	Railway, Shipbuilding, Aerospace	**0.208**	**0.293**	0.439
	(2.109)	(1.806)	(-2.347)		**(9.175)**	**(5.203)**	(1.346)
Food Manufacturing	0.065	**0.256**	-0.054	Electrical Machinery	-0.003	**-0.194**	**-0.121**
	(1.747)	**(3.553)**	(-0.432)		(-0.120)	**(-4.247)**	**(-2.944)**
Alcohol, Drink, Tea	**-0.167**	0.065	**0.287**	Computer, Communication	**0.483**	**0.352**	0.193
	(-3.357)	(0.817)	**(3.523)**		**(30.467)**	**(7.861)**	(2.259)
Textile	0.048	0.050	0.084	Other Manufacturing	-0.057	-0.008	0.067
	(2.515)	(2.515)	(0.900)		(-1.035)	(-0.193)	(0.083)
Papermaking	**0.372**	**0.374**	0.206	Electricity, Heat, Gas and Water	**0.608**	**0.695**	**0.595**
	(21.885)	**(21.528)**	(2.189)		**(24.987)**	**(4.387)**	**(2.765)**
Petroleum Processing	**0.260**	**0.429**	0.275	Construction	**0.795**	**-0.319**	0.026
	(5.722)	**(12.038)**	(0.819)		**(19.189)**	**(-2.685)**	(0.158)
Chemical Raw Materials	**0.236**	0.090	-0.003	Wholesale and Retail	**0.321**	**0.180**	**0.164**
	(11.638)	(1.248)	(-0.033)		**(20.728)**	**(9.293)**	**(2.914)**
Pharmaceutical Manufacturing	**0.079**	-0.066	-0.128	Transportation, Warehousing, and Postal Services	**0.583**	**0.537**	**0.628**
	(6.631)	(-2.270)	(-2.312)		**(14.052)**	**(4.109)**	**(8.119)**
Chemical Fiber Manufacturing	0.006	0.004	0.615	IT	**1.183**	**0.632**	0.133
	(0.159)	(0.102)	(2.317)		**(23.552)**	**(2.982)**	(0.379)
Rubber and Plastic Products	**0.271**	0.105	0.045	Finance	**0.231**	**0.133**	-0.020
	(8.463)	(2.180)	(0.774)		**(13.541)**	**(7.113)**	(-0.107)
Non-Metal Mineral Products	**0.358**	-0.027	0.036	Real Estate	**0.184**	**0.257**	**0.373**
	(8.379)	(-0.826)	(0.746)		**(7.030)**	**(3.546)**	**(4.558)**
Ferrous Metals	**0.409**	**0.356**	0.530	Leasing Services	-0.094	**-0.154**	-0.263
	(9.449)	**(2.716)**	(1.168)		(-1.658)	**(-2.950)**	(-2.205)
Nonferrous Metals	0.045	0.130	-0.074	Environmental and Public Facilities Management	**0.640**	**0.643**	0.256
	(0.927)	(0.584)	(-0.385)		**(13.908)**	**(10.018)**	(2.427)
Metal Products	**0.681**	**1.041**	0.601	Culture, Sports, and Entertainment	**0.510**	**0.364**	0.032
	(17.695)	**(7.806)**	(1.399)		**(15.306)**	**(7.808)**	(0.202)
General Equipment	**0.329**	-0.056	**-0.660**	Comprehensive Service	0.050	0.025	-0.052
	(8.057)	(-0.624)	**(-3.728)**		(1.694)	(0.695)	(-1.380)

Panel B

	(7a)	(7b)	(7c)
Avg intercepts	0.315	0.208	0.127
Avg t-values	10.391	3.460	0.719
Number of industries	34	34	34
Number of sig. intercepts	25	21	7
Avg adj. R^2	0.000	0.186	0.623

Panel C

	(7c) - (7a)	(7c) - (7b)
Diff in intercepts	-0.187	-0.080
	(-3.023)	(-1.743)
Diff in t	-9.672	-2.742
	(-6.638)	(-3.363)
Diff in adj. R^2	0.623	0.437
	(18.710)	(12.090)

Table IA.5: **Intercept estimates across other portfolios.** This table reports the counterparts of Table 8 in the paper. All setings are exactly the same as those in Table 8, except that we select the explanatory variables in Eq. (7c) by LASSO (using the BIC) in this figure.

Panel A

Characteristic	(7a)	(7b)	(7c)	Sector & Board	(7a)	(7b)	(7c)
Size H	**0.195**	0.184	**-0.250**	TMT	**0.788**	0.047	0.434
	(6.598)	(1.251)	**(-3.655)**		**(28.322)**	(0.285)	(2.322)
Size L	**0.336**	**-0.238**	**0.245**	Non TMT	**0.395**	**-0.394**	-0.056
	(12.265)	**(-6.092)**	**(2.687)**		**(11.500)**	**(-11.276)**	(-0.409)
Zero H	**0.261**	**-0.275**	-0.032	Main	**0.334**	**-0.272**	0.064
	(6.243)	**(-4.439)**	(-0.218)		**(13.027)**	**(-6.957)**	(0.586)
Zero L	**0.358**	**-0.182**	0.041	SME	**0.111**	-0.033	-0.060
	(12.900)	**(-3.891)**	(0.431)		**(5.972)**	(-0.417)	(-1.413)
Turnover H	**0.433**	**-0.313**	0.217	GEM	**0.108**	0.022	-0.127
	(14.507)	**(-4.007)**	(1.396)		**(3.216)**	(0.906)	(-1.697)
Turnover L	**0.205**	**-0.150**	-0.070				
	(9.926)	**(-3.820)**	(-1.684)				
ShrPerHold H	**0.203**	-0.011	-0.077				
	(9.516)	(-0.232)	(-0.750)				
ShrPerHold L	**0.452**	-0.126	0.167				
	(17.600)	(-2.556)	(1.257)				

Panel B	(7a)	(7b)	(7c)	Panel C	(7c) - (7a)	(7c) - (7b)
Avg intercepts	0.322	-0.134	0.038	Diff in intercepts	-0.283	0.172
Avg t-values	11.661	-3.173	-0.088		(-10.326)	(2.237)
Number of portfolios	13	13	13	Diff in t	-11.749	3.084
Number of sig. intercepts	13	7	2		(-8.078)	(2.439)
Avg adj. R^2	0.000	0.456	0.770	Diff in adj. R^2	0.770	0.314
					(28.319)	(4.738)

Table IA.6: **Robustness test for Table 10.** This table reports the counterparts of Table 10 in the paper. All setings are exactly the same as those in Table 10, except that we select the explanatory variables in Eq. (7c) by LASSO (using the BIC) in this figure.

Panel A

Industry	(7a)	(7b)	(7c)	Industry	(7a)	(7b)	(7c)
Agriculture	**0.197**	**0.192**	0.061	Special Equipment	**0.551**	**-0.331**	**-0.432**
	(7.891)	**(8.197)**	(0.566)		**(12.118)**	**(-3.341)**	**(-2.741)**
Mining	**0.799**	**1.003**	0.170	Automobile	**0.415**	-0.086	0.111
	(26.718)	**(5.922)**	(0.195)		**(11.483)**	(-0.915)	(0.668)
Agro-Food Processing	0.067	0.071	-0.119	Railway, Shipbuilding, Aerospace	**0.206**	**0.320**	0.414
	(2.160)	(1.740)	(-1.735)		**(8.062)**	**(4.865)**	(1.080)
Food Manufacturing	0.052	**0.228**	-0.046	Electrical Machinery	-0.004	**-0.199**	**-0.146**
	(1.357)	**(3.243)**	(-0.276)		(-0.155)	**(-4.021)**	**(-3.001)**
Alcohol, Drink, Tea	**-0.184**	0.043	0.226	Computer, Communication	**0.483**	**0.377**	0.154
	(-3.606)	(0.502)	(2.557)		**(28.614)**	**(6.992)**	(1.633)
Textile	0.045	0.047	0.022	Other Manufacturing	-0.074	-0.029	0.166
	(1.915)	(2.169)	(0.149)		(-1.400)	(-0.715)	(0.201)
Papermaking	**0.367**	**0.369**	0.198	Electricity, Heat, Gas and Water	**0.581**	**0.860**	**0.838**
	(19.331)	**(19.169)**	(1.776)		**(22.110)**	**(5.099)**	**(3.156)**
Petroleum Processing	**0.228**	**0.434**	0.410	Construction	**0.780**	**-0.335**	-0.065
	(4.566)	**(13.723)**	(1.369)		**(18.501)**	**(-2.892)**	(-0.301)
Chemical Raw Materials	**0.229**	0.067	-0.037	Wholesale and Retail	**0.308**	**0.177**	0.175
	(10.698)	(0.891)	(-0.362)		**(18.962)**	**(8.028)**	(1.817)
Pharmaceutical Manufacturing	**0.072**	-0.063	-0.143	Transportation, Warehousing, and Postal Services	**0.572**	**0.497**	**0.525**
	(5.768)	(-2.071)	(-2.221)		**(13.345)**	**(3.834)**	**(7.006)**
Chemical Fiber Manufacturing	-0.007	-0.009	0.791	IT	**1.172**	**0.623**	0.046
	(-0.156)	(-0.240)	(2.554)		**(22.306)**	**(2.838)**	(0.125)
Rubber and Plastic Products	**0.263**	0.096	0.047	Finance	**0.221**	**0.133**	-0.002
	(8.060)	(2.004)	(0.679)		**(12.656)**	**(5.883)**	(-0.006)
Non-Metal Mineral Products	**0.348**	-0.048	0.026	Real Estate	**0.177**	**0.208**	**0.306**
	(7.778)	(-1.305)	(0.461)		**(6.824)**	**(2.927)**	**(3.945)**
Ferrous Metals	**0.416**	**0.344**	0.501	Leasing Services	-0.115	**-0.172**	**-0.344**
	(9.507)	**(2.597)**	(1.109)		(-2.004)	**(-3.118)**	**(-2.723)**
Nonferrous Metals	0.040	0.100	-0.136	Environmental and Public Facilities Management	**0.606**	**0.615**	0.323
	(0.780)	(0.432)	(-0.662)		**(12.018)**	**(9.281)**	(1.822)
Metal Products	**0.684**	**1.072**	0.805	Culture, Sports, and Entertainment	**0.487**	**0.358**	0.017
	(17.245)	**(8.077)**	(1.545)		**(13.209)**	**(6.231)**	(0.083)
General Equipment	**0.320**	-0.060	**-0.694**	Comprehensive Service	0.035	0.006	-0.041
	(7.856)	(-0.644)	**(-3.651)**		(1.220)	(0.186)	(-1.254)

Panel B	(7a)	(7b)	(7c)	Panel C	(7c) - (7a)	(7c) - (7b)
Avg intercepts	0.304	0.203	0.121	Diff in intercepts	-0.183	-0.082
Avg t-values	9.581	3.105	0.458		(-2.652)	(-1.666)
Number of industries	34	34	34	Diff in t	-9.123	-2.647
Number of sig. intercepts	25	21	7		(-6.555)	(-3.463)
Avg adj. R^2	0.000	0.172	0.565	Diff in adj. R^2	0.565	0.393
					(15.863)	(10.649)

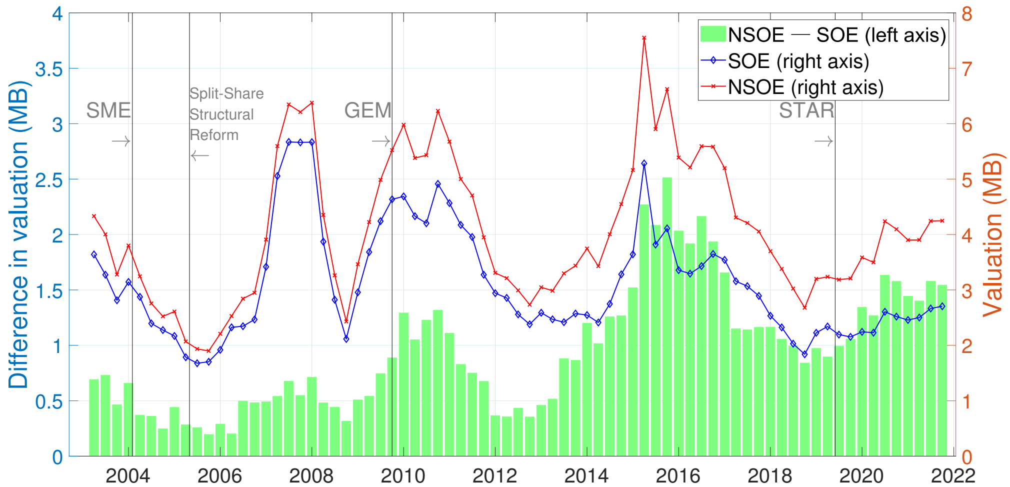


Figure IA.1: **The time series of average valuations for SOEs and NSOEs.** This figure displays the time series of equal weighted average valuations for SOEs and NSOEs in the Chinese A-share market during 2003 to 2021. The valuation metric used is the market-to-book ratio (MB). SOEs are represented by a blue line with diamond markers, while NSOEs are represented by a red line with cross markers. The green bars depict the difference between the average valuations of NSOEs and SOEs for each period. The right vertical axis indicates valuation levels, while the left vertical axis denotes valuation differentials. The gray vertical lines denote significant institutional events in the A-share market, including the establishment of the Small and Median Enterprises board (SME), the Growth Enterprise Market (GEM), the Science and Technology Innovation Board (STAR), and the Split-Share Structural Reform.

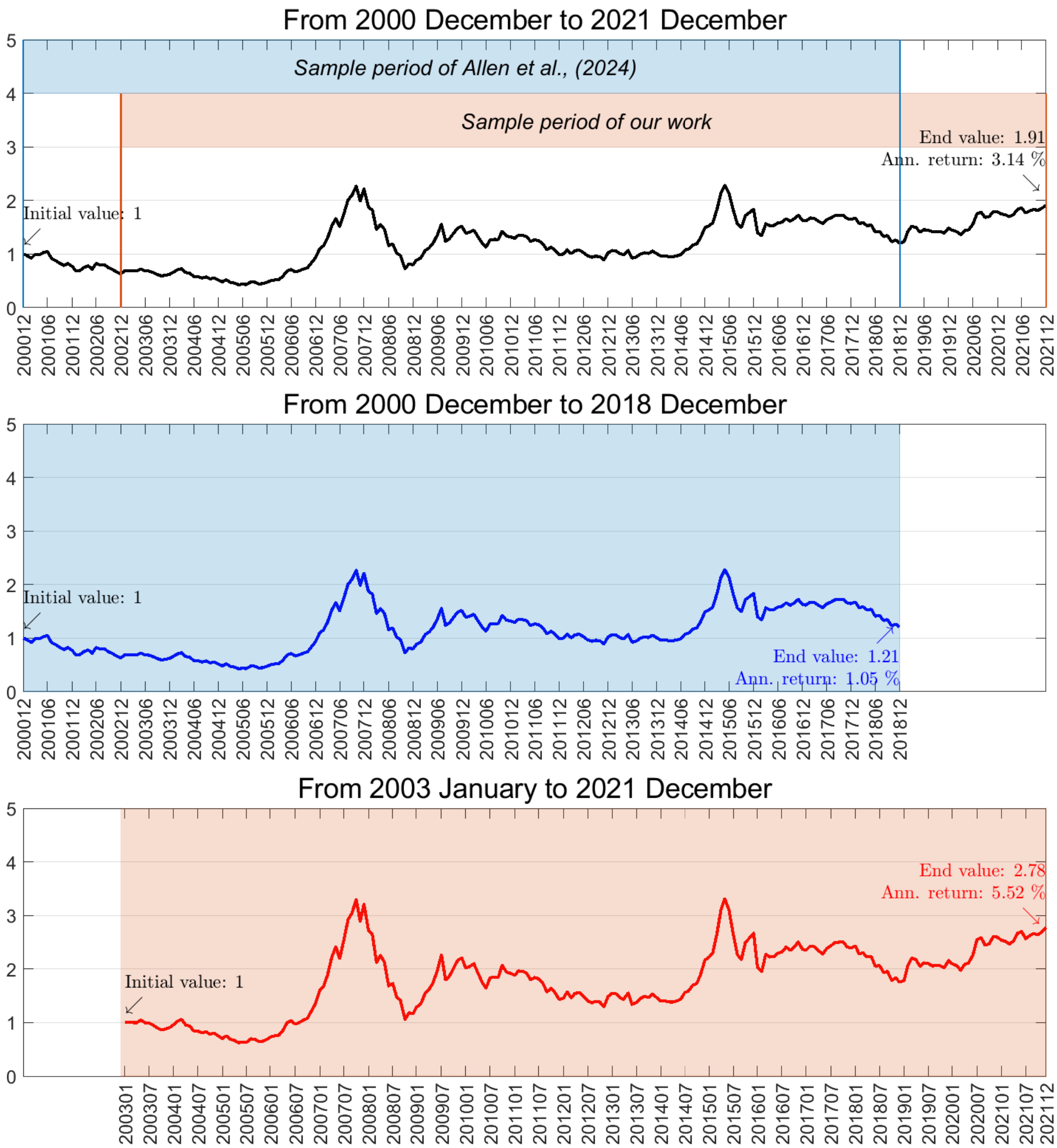


Figure IA.2: **Buy-and-hold returns in different sample periods.** This figure plots the value-weighted buy-and-hold returns (BHRs) of stocks listed in the Chinese A-share market for different periods. BHRs are calculated by cumulating value-weighted monthly returns of all stocks listed in the A-share market. The weight is the lagged one-year total market capitalization. The returns are calculated at month-end, adjusted for stock splits, and include cash dividends. Nominal returns are adjusted for inflation to convert to real returns as per Allen et al. (2024). Inflation is measured by the monthly CPI rate. In this figure, "End Value" represents the terminal value of the portfolio, and "Ann. Return" represents the annualized return of the portfolio during the sample period.

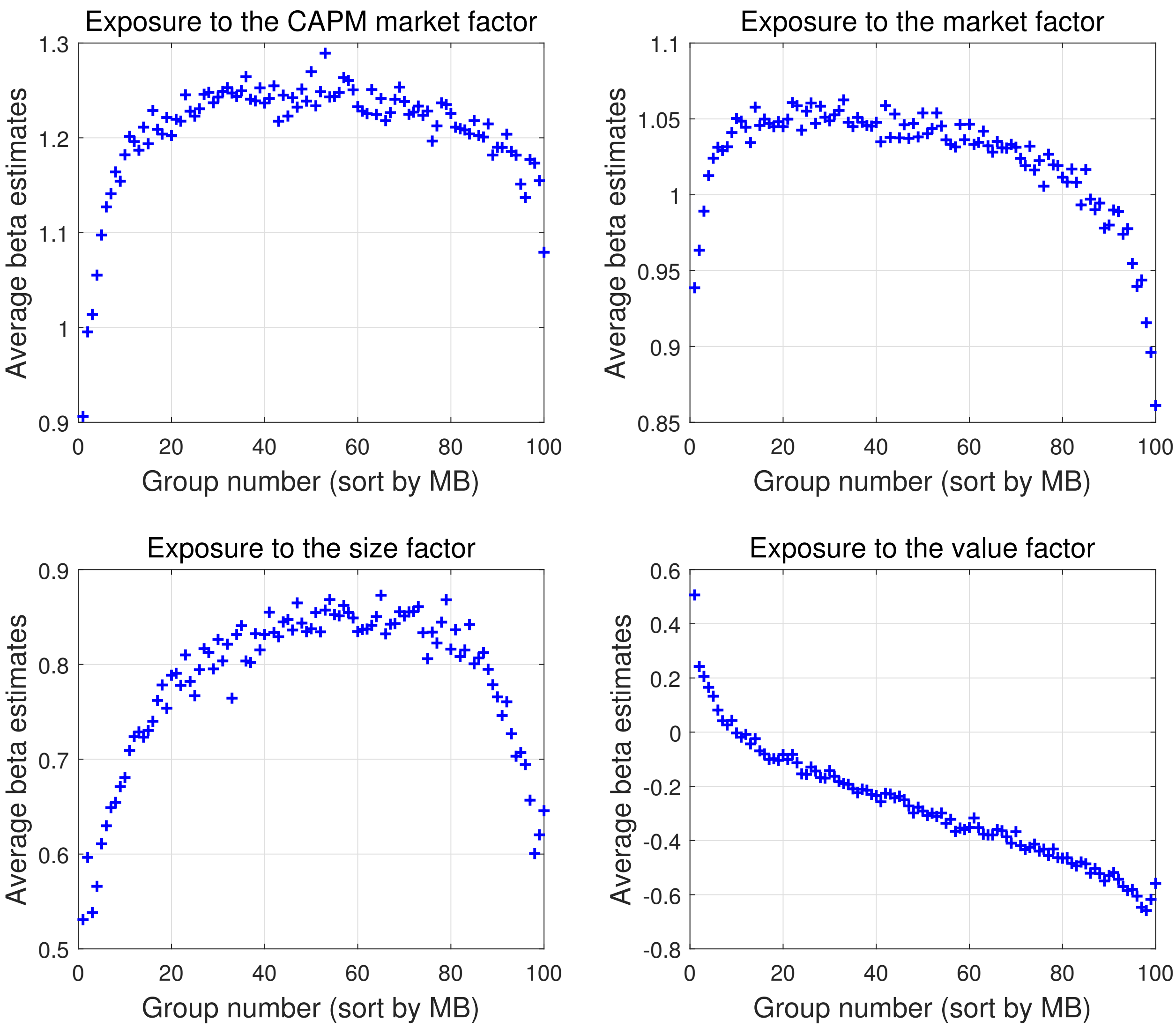


Figure IA.3: **Average beta by valuation group.** This figure plots the average beta estimates for stocks grouped by their valuations. The stocks are sorted by their valuation (MB) and then divided into 100 groups. The x-axis represents group numbers from 1 to 100, while the y-axis shows the average beta within each group. The top left subplot shows the betas estimated from the CAPM, while the top right, bottom left, and bottom right subplots correspond to the risk loadings (betas) for the market factor (MKT), size factor (SMB), and value factor (VMG) from the three-factor model (Liu, Stambaugh, and Yuan 2019), respectively.

	Size	Zero	Amihud	AGR Rev	AEEG	AESG	IdioVol	AvgROE	ListAge
Agriculture	0.060	0.074	0.382	0.038	0.146	0.024	0.087	0.042	0.147
Mining	0.043	0.125	0.266	0.021	0.049	0.187	0.004	0.075	0.230
Agro-Food Processing	0.018	0.045	0.481	0.006	0.007	0.033	0.104	0.095	0.211
Food Manufacturing	0.097	0.095	0.352	0.037	0.113	0.077	0.044	0.096	0.088
Alcohol, Drink, Tea	0.024	0.018	0.020	0.003	0.014	0.023	0.035	0.122	0.743
Textile	0.086	0.039	0.084	0.128	0.339	0.046	0.056	0.065	0.157
Papermaking	0.055	0.037	0.412	0.046	0.019	0.010	0.123	0.085	0.213
Petroleum Processing	0.288	0.016	0.360	0.091	0.010	0.072	0.123	0.013	0.026
Chemical Raw Materials	0.096	0.023	0.022	0.035	0.133	0.138	0.056	0.204	0.293
Pharmaceutical Manufacturing	0.238	0.002	0.011	0.012	0.006	0.074	0.085	0.112	0.459
Chemical Fiber Manufacturing	0.230	0.052	0.032	0.203	0.040	0.105	0.014	0.042	0.281
Rubber and Plastic Products	0.134	0.170	0.077	0.007	0.009	0.061	0.138	0.097	0.306
Non-Metal Mineral Products	0.264	0.093	0.020	0.005	0.046	0.056	0.213	0.081	0.222
Ferrous Metals	0.064	0.010	0.068	0.069	0.020	0.084	0.154	0.178	0.353
Nonferrous Metals	0.012	0.024	0.056	0.005	0.047	0.012	0.033	0.043	0.767
Metal Products	0.065	0.038	0.112	0.052	0.032	0.025	0.056	0.389	0.231
General Equipment	0.150	0.020	0.041	0.005	0.154	0.029	0.109	0.074	0.418
Special Equipment	0.293	0.112	0.028	0.118	0.012	0.033	0.041	0.134	0.231
Automobile	0.106	0.085	0.091	0.029	0.195	0.062	0.162	0.027	0.242
Railway, Shipbuilding, Aerospace	0.183	0.222	0.066	0.011	0.070	0.141	0.120	0.096	0.090
Electrical Machinery	0.092	0.056	0.057	0.030	0.067	0.098	0.210	0.178	0.213
Computer, Communication	0.303	0.055	0.052	0.004	0.012	0.018	0.297	0.170	0.089
Other Manufacturing	0.159	0.065	0.044	0.017	0.092	0.054	0.134	0.215	0.219
Electricity, Heat, Gas and Water	0.018	0.005	0.127	0.024	0.159	0.093	0.257	0.101	0.215
Construction	0.330	0.171	0.047	0.081	0.053	0.096	0.134	0.071	0.018
Wholesale and Retail	0.507	0.029	0.044	0.048	0.036	0.053	0.023	0.204	0.055
Transportation, Warehousing, and Postal Services	0.006	0.114	0.061	0.020	0.015	0.035	0.052	0.295	0.403
IT	0.211	0.027	0.088	0.032	0.074	0.055	0.266	0.095	0.153
Finance	0.211	0.012	0.153	0.022	0.020	0.051	0.043	0.243	0.246
Real Estate	0.026	0.087	0.369	0.021	0.048	0.024	0.064	0.345	0.016
Leasing Services	0.076	0.006	0.023	0.123	0.029	0.065	0.154	0.178	0.346
Environmental and Public Facilities Management	0.021	0.095	0.083	0.061	0.119	0.129	0.003	0.308	0.179
Culture, Sports, and Entertainment	0.166	0.093	0.031	0.016	0.011	0.091	0.257	0.017	0.319
Comprehensive Service	0.112	0.213	0.082	0.026	0.078	0.179	0.013	0.077	0.221
Average	0.142	0.068	0.109	0.043	0.064	0.067	0.105	0.137	0.263

Figure IA.4: **Dominance analysis of individual variables.** The figure depicts a heatmap showcasing the relative importance of each variable in explaining the valuation differences across industries, with the last row (labelled as "Average") displaying average values across industries. The method for evaluating the relative importance of each variable is outlined in Section 3.4, specifically in Eq. (13). The horizontal axis displays variable names, while the vertical axis displays industry labels. The heatmap's color scale is applied row-wise, with the darkest (lightest) color representing the maximum (minimum) value within each row.

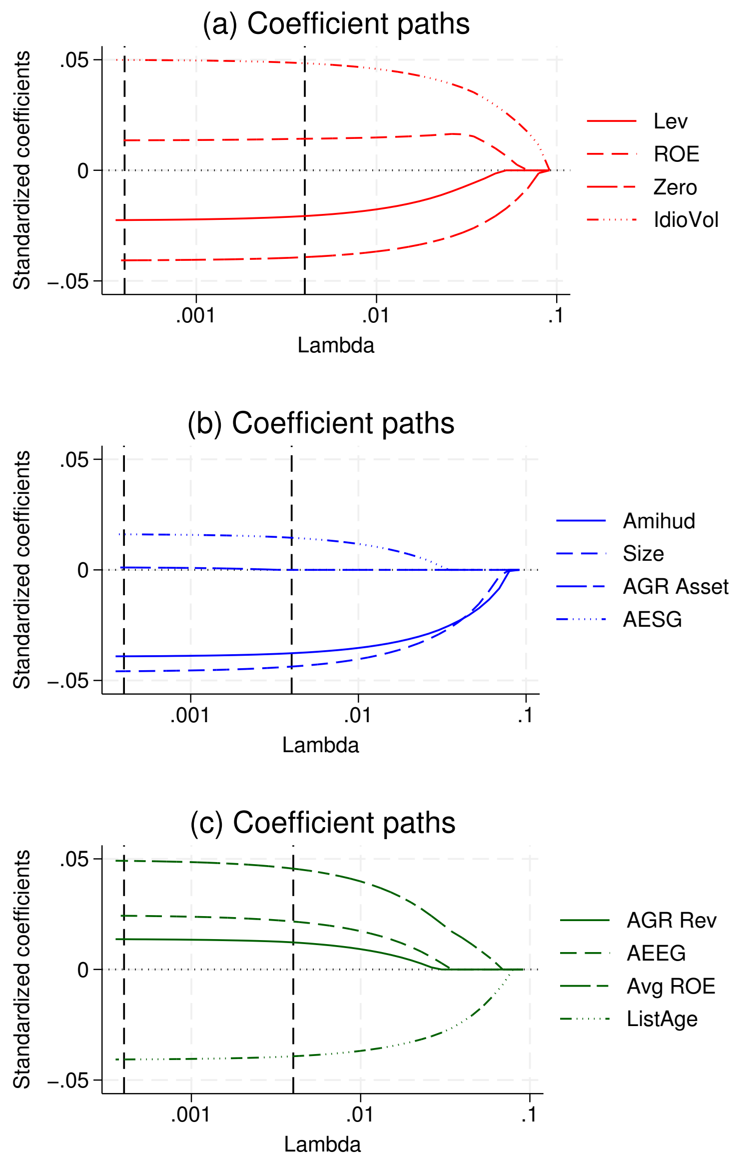
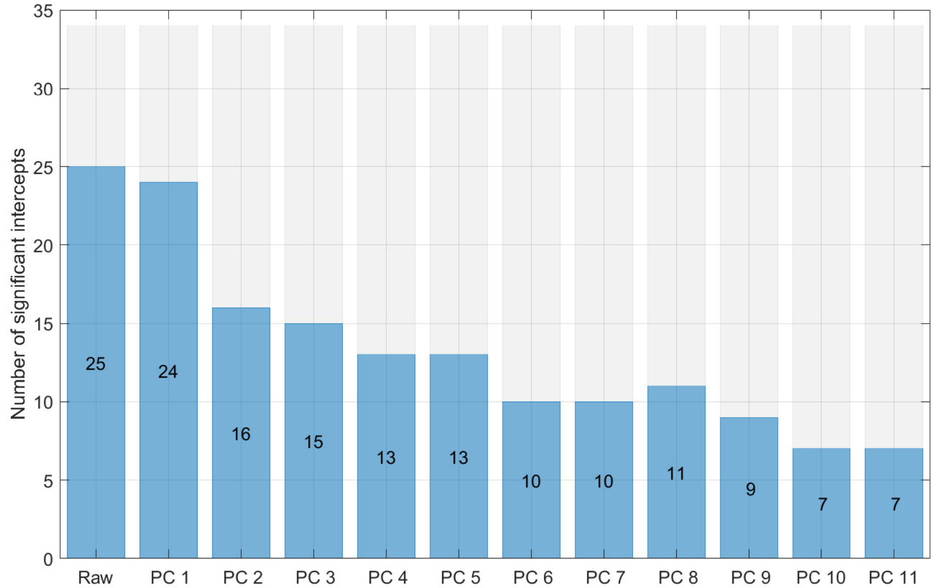
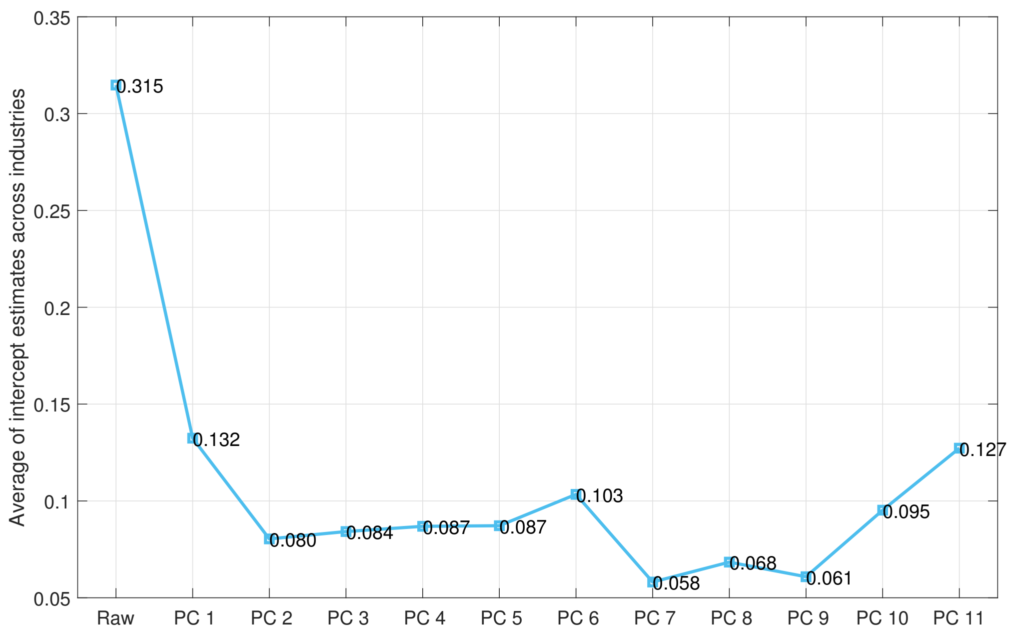


Figure IA.5: **LASSO Coefficients Paths.** This figure plots the variable coefficient estimation results of LASSO. Under a series of candidate Lambdas (penalty parameters), LASSO generates estimated coefficients that minimize the value of the objective function. We define the sequence of Lambdas as a grid of 100 equally spaced points ranging from 0.0000001 to 0.1. In this figure, the horizontal axis represents the values of the candidate lambdas, while the vertical axis represents the estimated regression coefficients. The right vertical dashed line indicates the optimal Lambdas value (penalty parameter) that minimizes the BIC metric, and the left vertical dashed line corresponds to the optimal Lambdas that minimizes the cross-validation error.



(a) Number of significant intercept estimates



(b) Average of intercept estimates across industries

Figure IA.6: **PCA regression results.** This figure depicts the counterpart of Figure 6 in the paper. All setings are exactly the same as those in Figure 6, except that we select the explanatory variables in Eq. (7c) by LASSO (using the BIC) in this figure.

	Size	ROE	Lev	Zero	Amihud	AGR Rev	AEEG	AESG	Idio Vol	Avg ROE	List Age
PC 1	0.081	-0.002	0.013	0.001	-0.000	-0.007	-0.009	-0.012	-0.005	-0.002	0.996
PC 2	0.977	0.010	0.057	0.011	-0.002	-0.013	-0.165	-0.082	-0.043	0.010	-0.083
PC 3	0.182	0.016	0.035	-0.003	0.000	0.132	0.931	0.284	0.023	-0.012	-0.002
PC 4	0.005	0.139	0.047	-0.019	-0.002	0.791	-0.276	0.521	0.041	0.055	0.009
PC 5	0.040	-0.078	-0.135	0.000	0.002	-0.560	-0.165	0.796	-0.005	-0.004	0.002
PC 6	-0.052	-0.168	0.970	0.009	0.007	-0.093	-0.037	0.078	0.090	-0.058	-0.008
PC 7	-0.023	0.824	0.158	-0.058	-0.010	-0.177	0.019	-0.010	-0.012	0.510	0.001
PC 8	0.044	0.011	-0.087	-0.132	-0.002	-0.033	-0.015	-0.035	0.985	0.006	0.002
PC 9	0.002	-0.508	-0.027	-0.279	-0.010	0.046	0.018	-0.014	-0.038	0.812	0.001
PC 10	-0.005	-0.093	-0.019	0.949	-0.033	0.015	0.004	0.002	0.126	0.271	0.001
PC 11	0.002	0.001	-0.005	0.028	0.999	0.002	0.000	-0.002	0.005	0.023	0.000

Figure IA.7: **PCA factor loadings.** This figure depicts the counterpart of Figure 7 in the paper. All setings are exactly the same as those in Figure 7, except that we select the explanatory variables in Eq. (7c) by LASSO (using the BIC) in this figure.

	Size	ROE	Lev	Zero	Amihud	AGR Rev	AEEG	AESG	IdioVol	AvgROE	ListAge
Agriculture	0.035	0.009	0.112	0.030	0.098	0.011	0.042	0.009	0.028	0.011	0.042
Mining	0.017	0.007	0.040	0.062	0.077	0.012	0.025	0.095	0.002	0.045	0.119
Agro-Food Processing	0.032	0.033	0.266	0.010	0.154	0.006	0.003	0.013	0.042	0.032	0.226
Food Manufacturing	0.056	0.129	0.079	0.085	0.173	0.019	0.063	0.034	0.030	0.065	0.047
Alcohol, Drink, Tea	0.017	0.044	0.013	0.016	0.016	0.003	0.011	0.017	0.031	0.095	0.637
Textile	0.056	0.056	0.063	0.019	0.039	0.036	0.147	0.033	0.022	0.021	0.057
Papermaking	0.011	0.008	0.026	0.011	0.146	0.013	0.006	0.003	0.038	0.037	0.036
Petroleum Processing	0.154	0.019	0.216	0.011	0.212	0.059	0.007	0.044	0.072	0.016	0.017
Chemical Raw Materials	0.046	0.084	0.051	0.011	0.010	0.019	0.056	0.068	0.024	0.076	0.172
Pharmaceutical Manufacturing	0.132	0.011	0.009	0.001	0.006	0.007	0.003	0.038	0.047	0.048	0.246
Chemical Fiber Manufacturing	0.114	0.093	0.088	0.022	0.023	0.073	0.021	0.043	0.007	0.015	0.137
Rubber and Plastic Products	0.106	0.050	0.031	0.126	0.068	0.006	0.009	0.052	0.108	0.064	0.237
Non-Metal Mineral Products	0.226	0.028	0.011	0.071	0.018	0.005	0.036	0.046	0.176	0.048	0.188
Ferrous Metals	0.058	0.018	0.099	0.008	0.029	0.045	0.011	0.062	0.119	0.115	0.181
Nonferrous Metals	0.009	0.019	0.100	0.021	0.084	0.007	0.041	0.015	0.029	0.031	0.519
Metal Products	0.047	0.117	0.021	0.022	0.057	0.029	0.016	0.025	0.024	0.176	0.111
General Equipment	0.109	0.012	0.063	0.017	0.031	0.004	0.116	0.023	0.089	0.066	0.335
Special Equipment	0.172	0.082	0.177	0.076	0.025	0.066	0.008	0.019	0.029	0.090	0.149
Automobile	0.063	0.015	0.067	0.051	0.051	0.021	0.129	0.041	0.104	0.013	0.148
Railway, Shipbuilding, Aerospace	0.076	0.093	0.020	0.063	0.035	0.004	0.017	0.035	0.023	0.071	0.026
Electrical Machinery	0.085	0.063	0.023	0.042	0.046	0.019	0.050	0.072	0.160	0.089	0.180
Computer, Communication	0.068	0.044	0.126	0.011	0.015	0.003	0.005	0.007	0.089	0.052	0.025
Other Manufacturing	0.108	0.109	0.087	0.049	0.029	0.015	0.062	0.039	0.113	0.145	0.133
Electricity, Heat, Gas and Water	0.011	0.007	0.114	0.002	0.061	0.018	0.086	0.039	0.098	0.046	0.090
Construction	0.192	0.014	0.192	0.120	0.030	0.054	0.043	0.068	0.096	0.038	0.012
Wholesale and Retail	0.261	0.072	0.129	0.014	0.042	0.049	0.022	0.036	0.018	0.105	0.035
Transportation, Warehousing, and Postal Services	0.008	0.011	0.017	0.099	0.048	0.015	0.013	0.028	0.045	0.252	0.356
IT	0.067	0.035	0.226	0.010	0.038	0.017	0.057	0.027	0.128	0.038	0.053
Finance	0.125	0.055	0.008	0.007	0.089	0.013	0.013	0.032	0.024	0.144	0.148
Real Estate	0.017	0.030	0.022	0.051	0.240	0.016	0.027	0.015	0.039	0.204	0.007
Leasing Services	0.050	0.114	0.032	0.004	0.013	0.079	0.021	0.044	0.106	0.102	0.211
Environmental and Public Facilities Management	0.011	0.074	0.113	0.049	0.040	0.041	0.083	0.084	0.004	0.159	0.112
Culture, Sports, and Entertainment	0.096	0.036	0.033	0.078	0.021	0.015	0.008	0.061	0.164	0.024	0.227
Comprehensive Service	0.066	0.009	0.055	0.139	0.066	0.012	0.046	0.116	0.008	0.047	0.090
Average	0.079	0.047	0.080	0.041	0.063	0.024	0.038	0.041	0.063	0.076	0.156

Figure IA.8: **Dominance analysis for individual variables.** This figure depicts the counterpart of Figure 8 in the paper. All setings are exactly the same as those in Figure 8, except that we select the explanatory variables in Eq. (7c) by LASSO (using the BIC) in this figure.