

Industrial Policy *via* the IPO Market

Zhiguo He^a Yiming Qian^b Xi Sun^c Wang Renxuan^c

^aStanford University ^bUniversity of Connecticut Business School ^cChina Europe International Business School

April 2026

Abstract

This paper studies a novel instrument of industrial policy: the regulation of access to public equity markets. Using data on Chinese A-share IPOs and measures of industrial policy derived from textual analysis of Five-Year Plans, we show that policy strongly predicts IPO activity in China, while industry Tobin's Q, a standard proxy for investment opportunities, does not. The effect operates mainly through firms' application decisions rather than regulatory approvals, suggesting that firms anticipate policy priorities. Favored firms also receive faster review and higher valuations. Cross-market placebo tests support a causal interpretation. Our findings show how states can direct private capital through equity market access.

JEL Classification: G14, G18, G24, G32, G38, L52, O25, P16

Keywords: Industrial policy, IPO regulation, capital allocation, China, Five-Year Plans, Tobin's Q, equity markets, state intervention

Zhiguo He is at Stanford Graduate School of Business (hezhg@stanford.edu). Yiming Qian is at the School of Business, University of Connecticut (yiming.qian@uconn.edu). Wang Renxuan is at China Europe International Business School (rxwang@ceibs.edu). Xi Sun is at China Europe International Business School (sxi@ceibs.edu).

1 Introduction

Industrial policy—targeted government interventions aimed at altering the sectoral composition of the economy—is experiencing a powerful resurgence around the world, shifting from a once-taboo topic in mainstream economics to a central pillar of development strategy in many countries (Baldwin, 1969; Krueger, 1990; Rodrik, 2004, 2008). Advanced economies have launched high-profile industrial initiatives (for example, the U.S. CHIPS Act and Europe’s green industrial programs), while emerging markets continue to expand their state-led development strategies, such as in China, where the state explicitly guides economic development through its Five-Year Plans (FYPs).

Despite this renewed interest, the existing literature has focused on traditional policy tools, such as fiscal subsidies, tax incentives, and directed credit through state-owned banks (Harrison and Rodríguez-Clare, 2010; Pack and Saggi, 2006; Lane, 2020; Juhász et al., 2023). There is a paucity of systematic evidence on how industrial policy might reshape public equity markets. This gap is critical because public equity is distinct from bank credit; it provides the risk-sharing capital essential for innovation-driven development. Unlike debt, which was the primary engine of the East Asian "miracle" economies of Japan and South Korea (Amsden, 1989; Wade, 1990), equity markets are becoming a vital venue for resource allocation as China attempts to transition from "high-speed" to "high-quality" growth.

This paper examines a novel form of state intervention: IPO-based industrial policy in China. We show that China’s IPO regulatory regime has been used to channel equity financing toward favored industries and firms aligned with national development priorities. Unlike traditional fiscal tools, IPO-based industrial policy allows the state to steer private capital toward priority sectors without eroding the country’s fiscal capacity. While the aggregate proceeds from IPOs are smaller than the total volume of corporate bond or bank credit, their strategic importance is disproportionately large; as a "capital multiplier," a successful listing unlocks a firm’s access to seasoned equity, lower-cost bank

credit, and bond markets. Furthermore, public listing provides the equity liquidity essential for attracting the high-level human capital required for innovations. Consequently, the IPO regulation can act as a primary valve controlling the flow of both subsequent capital and talent toward favored sectors.

In a frictionless capital market, the "invisible hand" allocates funds based on price signals: capital flows to sectors with the highest Tobin's Q, reflecting superior investment opportunities. However, China's financial system operates under a unique institutional logic where the state retains the ultimate prerogative to guide development. A simple comparison of IPO activity in the U.S. and China provides a striking illustration that motivates our study. Figure 1 plots industry-level IPO counts against industry Tobin's Q for both countries. In market-driven economies like the United States (Panel A), IPO activity strongly correlates with lagged industry valuations, the canonical measure of investment opportunities (Pástor and Veronesi, 2005). This foundational relationship, however, vanishes entirely in China (Panel B). This illustrative evidence suggests that a different logic governs capital allocation in China's equity market.

Our paper's central thesis is that industrial policy is a dominant driver of equity market access. We construct a comprehensive dataset of A-share IPOs from 2002 to 2022 and combine it with novel measures of industrial policy intensity derived from textual analysis of Five-Year Plans documents. We find strong evidence that favored industries designated by these plans have dramatically higher IPO activity. Descriptively, favored industries account for 60–72% of all IPOs in recent years while contributing roughly 20% of GDP. Regression results imply that the effect of being a favored industry is economically large and operates through both extensive and intensive margins. Favored industries are 25 percentage points more likely to experience any IPO activity. Conditional on having at least one IPO, they have approximately 64% more IPOs. Overall, this translates into an increase of 94% in the expected number of IPOs, indicating that industrial policy affects both the likelihood and the intensity of IPO activity. The policy effect also strengthens

over time: the marginal effect is insignificant for the 10th five-year plan period and has steadily increased from 0.48 in the 11th FYP period to 1.736 in the 14th FYP period.

The mechanism through which policy shapes IPO outcomes is revealing. We find that policy operates primarily through firms application decisions rather than regulators approval choices. Firms in policy-favored industries are significantly more likely to apply for IPOs. Decomposing the marginal effects reveals that policy favor increases the probability of an industry having any IPO applications by 22.2 percentage points, and increases the volume of applications by approximately 111% conditional on activity. Meanwhile, approval rates remain statistically similar across favored and non-favored industries conditional on IPO application. This pattern suggests that market participants internalize policy priorities and adjust their strategies accordingly, a form of anticipatory governance where regulatory signals shape behavior before any formal selection occurs. This channel indicates that the government can guide capital allocation through credible signaling, causing firms to self-select and reducing the administrative burden of case-by-case evaluation.

Although policy favor does not affect the likelihood of approval conditional on IPO application, it does affect the speed of approval. Applications from favored industries are processed 75 days faster on average, a reduction of approximately 13.5% relative to the average processing time for IPO firms in non-favored industries. This accelerated review creates a tangible benefit for firms in strategic sectors, reducing financing uncertainty and allowing them to access capital markets more quickly when conditions are favorable.

Furthermore, we find that industrial policy affects asset pricing. Favored firms receive a 12% higher valuation upon listing on the first trading day than comparable non-favored IPO firms. This valuation premium is not reversed in the three years following the IPO. This persistent premium indicates that policy support creates lasting value recognized by investors, whether through reduced policy risk or coordination benefits from being in a government-prioritized sector. The fact that this premium does not reverse over three

years, and that it appears in both domestic and Hong Kong markets for dual-listed firms, suggests the market's assessment reflects expectations of tangible benefits rather than temporary sentiment. Importantly, the 12% market value premium underestimates the benefits of policy preference, in that it is compared with other IPO firms: the benefit of IPO access itself is not included in this estimate.

A potential endogeneity concern is that the relationship between industrial policy and IPO activity may be driven by omitted fundamentals that influence both policy and IPO activity, e.g., sectors like artificial intelligence attract both government support and private market enthusiasm. We address this in several different ways.

First, we document that the use of IPO regulation as an industrial policy tool is explicitly stated by Chinese authorities. For instance, a 2020 State Council directive on integrated circuits and software industry explicitly calls to “strongly support qualified companies to list and finance...[and] accelerate the domestic listing review process.” Similarly, the China Securities Regulatory Commission (CSRC) declared in 2014 that during IPO reviews, “issuers who do not comply with industrial policies will not be approved.” For systematic evidence, we examine State Council policy documents issued during 2002–2022. Of the 529 documents classified as industrial policy, 34% explicitly mention IPO support as a policy tool.

Second, we conduct placebo tests using overseas listings of Chinese firms. If policy simply reflected market fundamentals, we should observe similar patterns abroad. We do not. In the U.S. market, Chinese industrial policy does not predict IPO activity, while industry Tobin's Q reasserts its predictive power. This cross-market comparison addresses the most plausible alternative hypothesis: that our results reflect omitted fundamentals correlated with both policy and investment opportunities.

Third, we exploit an exogenous policy shock as a natural experiment. In July 2021, the Double Reduction policy banned for-profit K-12 tutoring and prohibited such firms from raising capital through IPOs. The policy was motivated by social objectives, including

promoting educational equity and reducing academic pressure on students, rather than by economic considerations. Prior to its implementation, the for-profit tutoring sector had been booming. Immediately after the policy, domestic IPO activity in the sector collapsed to zero. This natural experiment demonstrates that policy can override market forces decisively: when the state explicitly disfavors a sector, market access disappears regardless of economic fundamentals.

Fourth, to sharpen our tests, we construct a firm-level Government Policy Alignment (GPA) index from the textual analysis of IPO prospectuses. This measure allows us to conduct powerful within-industry analyses, showing that even within the same broad policy-favored sector, firms with higher GPA scores are more likely to achieve a successful IPO, strengthening the evidence of policy effects.

In the last portion of this study, we show that our findings extend beyond the IPO market, revealing a comprehensive capital-market industrial policy framework. We document that in China's corporate bond market, policy-favored industries issue significantly more bonds controlling for credit risk and financing needs. We also examine the National Equities Exchange and Quotations (NEEQ), a platform analogous to over-the-counter equity markets, and find that policy-favored industries have substantially more NEEQ listings. These extensions demonstrate that the mechanism we document is not specific to IPOs but represents a systematic approach to directing access to capital markets.

This paper contributes to several literatures. First, we add to the rapidly growing research on the new economics of industrial policy by identifying a distinct and potent policy tool: the regulation of public equity market access. The classic industrial policy literature focused on targeted credit, trade protection, and subsidies to nurture infant industries (Johnson, 1982; Amsden, 1989; Wade, 1990). Recent work has revisited industrial policy with more detailed data and refined empirical methods, documenting more subtle impacts of modern policies and emphasizing context and implementation (Juhász et al., 2023; Barwick et al., 2024a; Aghion et al., 2015). Juhász et al. (2023) apply textual analysis

to quantify global policy use, while [Cen et al. \(2022\)](#) study how U.S. firms react to China's industrial policy, underscoring the global spillovers of such interventions.

A good share of recent studies focus on China due to the prevalence and scale of its industrial policy. Estimates suggest that China industrial support programs amount to several percentage points of GDP ([Branstetter and Li, 2024](#); [Garcia-Macia et al., 2025](#)). [Fang et al. \(2025\)](#) use LLMs to analyze millions of government documents, uncovering the objectives, tools, and transmissions of policy across regions. Other studies examine various policy tools including subsidies ([Aghion et al., 2015](#); [Branstetter et al., 2023](#); [Barwick et al., 2024b](#)), technology for market access ([Bai et al., 2025](#)), and government venture capital ([Chen et al., 2026](#); [Beraja et al., 2025](#); [Pan et al., 2022](#)).

Distinct from the prior studies, our paper focuses on IPO regulation as a novel capital-market-based industrial policy. We show that controlling access to public equity financing enables the state to steer private capital toward priority sectors, complementing fiscal tools. This evidence underscores that industrial policy need not be limited to traditional tools: IPO regulation, often thought of as purely market-neutral infrastructure, can be repurposed to selectively promote industries.

Furthermore, our findings expand the taxonomy of industrial policy instruments ([Juhász et al., 2023](#)). While existing studies predominantly focus on fiscal tools—such as direct production subsidies, tax incentives, and government-guided equity funds—we highlight a powerful non-fiscal regulatory lever. Unlike traditional financial repression that channels household bank deposits to state-owned enterprises via artificially low interest rates, the IPO gatekeeping mechanism directs sophisticated private risk capital to innovative firms at zero direct cost to the government budget. This expands our understanding of how state capacity can shape capital allocation purely through regulatory authority over market access.

Second, our paper contributes to the literature on China's financial markets, especially on the IPO market. China's financial system has historically been dominated by bank-

based financing. However, as the economy matures, the stock market is becoming an increasingly important channel for capital allocation, particularly for innovation-driven firms (Song and Xiong, 2018; Cong et al., 2020; He and Wei, 2023). We extend the recent survey by Qian et al. (2024), which highlights how regulatory constraints such as the approval system and price caps have led to persistent IPO underpricing and a costly listing process. Our findings show that IPO regulations are deployed with an industrial policy intent: the state actively skews the composition of listed firms toward strategic sectors. We also advance the literature on political connections and access to the IPO market (Fan et al., 2007; Piotroski and Zhang, 2014) by moving beyond case-by-case political favoritism (guanxi) to systematic policy mandates.

Many studies of China’s economy also document the effects of state ownership and the preferential treatments state-owned enterprises (SOEs) receive in fiscal support and bank loans. Qian et al. (2024) report that IPO firms are more likely to be SOEs in early periods (before 2008) but not in recent years. Our paper demonstrates that IPO regulations can promote priority industries regardless of state ownership.

The remainder of the paper is organized as follows. Section 2 describes the institutional background. Section 3 details data and methodology. Section 4 presents main findings on industrial policy and IPO volume with Section 4.3 providing identification tests and extensions. Section 5 examines IPO pricing. Section 6 extends the analysis to broader Chinese capital markets. Section 7 concludes.

2 Institutional Background

2.1 Industrial policy in China

Industrial policy usually refers to targeted public interventions that alter the sectoral allocation of resources to accelerate structural transformation, productivity, or strategic capacity. Views on its merits differ, but industrial policy is widely used across advanced

and developing economies and draws on broad toolkits (Rodrik, 2004; Harrison and Rodríguez-Clare, 2010; Stiglitz et al., 2013). China, among other emerging markets, has actively deployed industrial policy to promote structural upgrading and strategic industries (Fang et al., 2025).

Within China's hierarchical and top-down governance structure, industrial policies are organized and coordinated through Five-Year Plans (FYPs), which serve as the apex framework guiding sectoral priorities and policy implementation. By articulating strategic objectives and priority sectors over fixed five-year horizons, FYPs create time-bounded policy windows in which selected industries receive concentrated regulatory, fiscal, and administrative support (Naughton, 2021). China's system of Five-Year Plans constitutes a long-standing policy institution, beginning with the First Five-Year Plan (1953–1957) under the planned economy system. Over time, particularly since the early 2000s, their role has evolved from detailed production planning toward a more strategic and guideline-based framework, accompanied by increasingly formalized policymaking procedures. In each planning cycle, proposals for the national Five-Year Plan are typically formulated and adopted at the Fifth Plenum of the Central Committee in the year preceding implementation, several months before the new planning period begins. These proposals are subsequently translated by the State Council and the National Development and Reform Commission into a detailed planning outline, which is formally adopted by the National People's Congress and thereby endowed with substantial political authority.

The national Five-Year Plan sets macro-level objectives and priorities but does not operate in isolation. Once adopted, it is used to orient budgetary allocations, regulatory priorities, and administrative targets across levels of government, embedding industrial policy objectives within China's broader governance apparatus. Provincial, municipal, and county-level plans are subsequently formulated in alignment with the national blueprint. In addition, sectoral and cross-cutting plans, such as the "Internet Plus" Action Plan, are issued to operationalize Five-Year Plan priorities through specific programs, standards,

and regulatory arrangements. Together, these planning documents constitute a vertically integrated framework that links central directives to local implementation. During the subsequent five-year policy period, implementation is delegated to line ministries, regulators, and local governments, which translate plan priorities into concrete policies, regulatory guidance, and enforcement actions. Through this nested structure, subordinate policy instruments are aligned with the overarching objectives of the Five-Year Plan, ensuring coherence in China's industrial policy across administrative levels and sectors.

2.2 IPO Listing Review and Government Oversight in China

IPO listing procedures in China differ fundamentally from those in market-oriented economies such as the United States. In the U.S., IPO access is a registration system in which regulators ensure the adequacy of information disclosure, while market participants determine whether an offering proceeds and, if so, its pricing. By contrast, China's IPO process involves substantive regulatory review and administrative approval, making listing a regulated admission rather than an automatic outcome conditional on disclosure (see [Qian et al. \(2024\)](#) for a survey paper on China's IPO market).

Under the traditional approval system, the China Securities Regulatory Commission (CSRC) serves as the central authority overseeing IPO issuance. Firms must satisfy baseline listing requirements, such as minimum size and profitability, but the regulator ultimately determines which firms are permitted to go public and when. In making these decisions, the CSRC evaluates not only firm-level characteristics (e.g., firm quality) but also broader considerations, including the market condition and the states strategic priorities ([Qian et al., 2024](#)). One manifestation of this discretion is the use of IPO suspensions. Between the 1990s and mid-2010s, the CSRC periodically suspended IPO approvals for extended periods, during which no new firms were allowed to list ([Cong and Howell, 2021](#)).

The IPO process involves substantial time and cost. The review period is often lengthy

and uncertain. The typical time between application and approval exceeds 400 days, substantially longer than in the U.S. In addition, offer prices have often been subject to regulatory caps on price-to-earnings ratios, which contributes to high levels of IPO underpricing (Qian et al., 2024). These issues impose severe direct and indirect costs on issuing firms.

Beginning in 2019, China initiated a transition toward a registration-based IPO system, first implemented on the STAR Market and subsequently extended to other boards, including the Shenzhen Growth Enterprise Market and the main boards by 2023. Under this framework, stock exchanges such as the Shanghai and Shenzhen Stock Exchanges are responsible for conducting the primary review of IPO applications, with greater emphasis on information disclosure relative to the prior approval system. However, the reform represents a reallocation rather than a removal of regulatory authority. IPOs must still be formally registered with CSRC following exchange review before issuance can proceed. The current regime is therefore commonly characterized as a two-tier system in which exchanges perform front-end screening, while CSRC conducts rulemaking, ensures compliance, and retains the ultimate authority over market access.

Importantly, the current system continues to incorporate substantive regulatory criteria beyond disclosure. The CSRC's *Administrative Measures for Initial Public Offerings* explicitly require that issuers' business operations comply with national industrial policies, thereby introducing a policy-based criterion into the listing review framework.¹ As a result, although the reform reduces certain administrative constraints and delegates re-

¹Under the approval-based system, Article 11 of the *Administrative Measures for Initial Public Offerings and Listing* (CSRC Order No. 32, 2006; amended 2020) states: "The issuer's production and business operations shall comply with laws, administrative regulations, and the company's articles of association, and shall comply with national industrial policies." See <https://www.csrc.gov.cn/csrc/c106256/c1653753/content.shtml>. Under the registration-based system, this requirement is not only retained but strengthened. Article 13 of the *Measures for the Administration of Initial Public Offering Stocks Registration* (CSRC Order No. 205, 2023) preserves the identical industrial policy compliance condition. In addition, Article 23 stipulates that the CSRC shall, from the date the exchange receives the registration application, "simultaneously monitor whether the issuer complies with national industrial policies and the board's positioning," thereby formalizing the CSRC's active oversight of industrial policy alignment throughout the review process. See <http://www.sse.com.cn/lawandrules/regulations/csrcorder/c/10116583/files/fbb4578ae47a4f0686713232e2692e67.pdf>.

view responsibilities to exchanges, IPO listing in China remains a regulated admission process in which the CSRC exercises final registration authority.

These institutional features motivate a cross-market comparison of how industry fundamentals map into IPO activity. In a market-driven capital market, such as the U.S., industries with stronger fundamentals, such as larger economic scale or higher valuations, should exhibit greater IPO activity (Pástor and Veronesi, 2005). With the influence of industrial policy guidance and other government oversight, these relationships become ambiguous.

As a demonstration, we examine how industry size and valuation relate to IPO volume and proceeds in China and the United States. We estimate Tobit models on industry-year panels, regressing $\log(\#IPOs)$ and $\log(IPO\ proceeds)$ on industry GDP and lagged industry Q in parallel for each country. The results (in the Internet Appendix) shows a clear contrast between the two countries. Industry size is positively associated with IPO activity in both countries, but the elasticity is substantially larger in the U.S. than in China. In addition, industry valuation is strongly positively related to IPO activity only in the U.S., consistent with equity issuance into high-valuation windows, whereas in China the estimated coefficients on Q are small and statistically indistinguishable from zero.

3 Data and Empirical Measurement

3.1 Industry Policy Measures

To capture the government's industrial policy orientation at the industry level, we construct measures of policy support based on language in China's Five-Year Plans. These plans articulate the government's medium-term strategic priorities across economic, technological, and social domains and contain extensive narrative descriptions of targeted sectors and strategic objectives, including the development of strategic emerging indus-

tries and the modernization of core manufacturing and service sectors.

To render these qualitative statements into tractable measures, we draw on the structured policy-text database from the China Research Data Services Platform (CNRDS), echoing the approach of previous studies (e.g. [Chen et al., 2017](#); [Cen et al., 2022](#)). For each Five-Year Plan, CNRDS identifies industry mentions in the plan text, maps them to the CSRC 2001 industry classification, and assigns a policy attitude label based on the language used in the surrounding context. Encouraging mentions are those in which the plan calls for the active development or promotion of an industry; neutral mentions involve adjustment-oriented language; and restrictive mentions indicate discouragement or phase-out.

Not all encouraging mentions, however, reflect the kind of substantive policy support we aim to measure. Some convey only directional guidance on how an industry should develop, while others explicitly designate an industry as a key strategic priority. CNRDS captures this distinction through a separate indicator for key priority industries, flagging mentions accompanied by language such as “key support,” “pillar industry,” or “priority development.” We construct our main indicator *Favored* based on this key priority designation, and manually verify the pre-assigned labels by examining the context surrounding each mention.² We also revise industry mappings where the initial assignment does not align with the best-matching CSRC 2001 code.

We also construct a continuous measure, *FavorIndex*, which quantifies the intensity of policy support directed toward an industry in the Five-Year Plans. Each supportive reference contributes one unit to an industry’s *FavorIndex* score, so multiple favorable references within the same plan reflect cumulative policy emphasis. A higher *FavorIndex* score therefore reflects more frequent affirmative policy support for the industry. The complete list of favored industries and additional details are provided in the Internet Appendix.

²In the baseline implementation, a slightly stricter cutoff is applied to a small number of borderline mapped observations, without materially affecting the classification.

Table 1 lists the favored industries identified under each Five-Year Plan window. The table shows that policy favor is neither universal nor fixed over time. Some broad strategic sectors persist across planning cycles, but the set of favored industries also rotates meaningfully from one Five-Year Plan to the next. This pattern is consistent with the changing content of Chinese industrial policy. For example, biological-products manufacturing does not appear in 2001–2005 but enters the favored list in later plans, consistent with the rising official emphasis on biotechnology and other strategic emerging industries. This time variation is central to our empirical design because it helps distinguish policy designation from permanent industry characteristics.

[INSERT TABLE 1 HERE]

3.2 Measuring Firm-Level Policy Alignment

To further exploit within-industry heterogeneity and help separate policy-related effects from persistent industry characteristics, we construct a firm-level measure of government policy alignment based on firms' pre-IPO disclosures, denoted as *GPA*.

Specifically, we use the business scope descriptions disclosed in IPO prospectuses from Cninfo to proxy firms' strategic positioning prior to listing. These disclosures summarize firms' core business activities and development focus and are subject to regulatory scrutiny, making them a credible and standardized source of information on firms' stated business orientation at the time of IPO. Because business scope descriptions are determined before listing and remain relatively stable in the short run, they provide a suitable basis for measuring firms' alignment with prevailing policy priorities. We measure *GPA* based on the semantic proximity between the policy guidance articulated in the Five-Year Plans and a firm's business scope.

The construction of *GPA* proceeds in two steps. First, we quantify the semantic proximity between firms' business scope keywords and policy-related terms extracted from

the corresponding Five-Year Plan using a word-embedding-based cosine similarity measure. Second, we aggregate these pairwise semantic proximities into a firm-level alignment index by weighting business-related terms based on their relative importance to the firm. Policy-related terms are weighted to reflect their informativeness in distinguishing industries classified as policy-favored from non-favored ones based on industry-level policy designation.

This aggregation yields a continuous firm-level measure of policy alignment, where higher values of *GPA* indicate closer alignment between a firm's stated business focus and prevailing government policy priorities. Detailed descriptions of keyword construction, similarity computation, and weight calibration procedures are provided in the Internet Appendix. The Internet Appendix also reports the timeline matching between Five-Year Plans, firm disclosures, and IPO dates.

3.3 Data and Summary Statistics

Our empirical analysis is mainly based on a sample of China's A-share IPO market over the period from 2002 to 2022, which falls across five Five-Year Plan periods (from the 10th to the 14th). IPO-related information is obtained from the Wind database. Industry-level information is obtained from official industry accounts published by the National Bureau of Statistics and provincial statistical yearbooks. In particular, our industry GDP measure is an economy-wide industry output measure rather than an aggregate constructed from listed firms. Firm-level financial and accounting variables are obtained from THS iFinD.

Panel A of Table 2 reports summary statistics for the industry-year panel. From the indicator variable *Favored*, we can see that approximately 26% of industry-year observations are classified as policy-favored. Turning to the continuous measure *FavorIndex*, we observe substantial dispersion across industry-year observations, indicating meaningful variation in the intensity of policy emphasis beyond the binary designation and captur-

ing differences along the intensive margin. Our IPO pricing analysis is conducted in the IPO sample, which covers 3,483 IPO events over the sample period. As shown in Panel B of Table 2, approximately 61% of IPOs are from policy-favored industries. This share is substantially higher than the corresponding fraction at the industry-year level, suggesting that IPOs are not evenly distributed across policy-favored and non-favored industries.

[INSERT TABLE 2 HERE]

Table 3 provides a descriptive comparison of IPO activity and GDP contributions between policy-favored and non-favored industries over time. Across most years in the sample, a substantial fraction of IPOs and IPO proceeds originates from policy-favored industries. This fraction exceeds the corresponding GDP contribution of these industries, indicating that IPO activity is more concentrated in policy-favored industries relative to their size in the real economy. Moreover, this pattern appears to strengthen gradually over time.

[INSERT TABLE 3 HERE]

For the U.S. analysis, IPO data are obtained from SDC Platinum, and industry GDP is measured using U.S. Bureau of Economic Analysis industry accounts, which likewise cover overall industry activity rather than only public firms. Additional details are provided in the Internet Appendix.

4 Empirical Results: Industrial Policy and IPOs

This section presents the main test results of our hypothesis: industrial policy directs capital allocations through IPO markets. We first examine the empirical relationship between industrial policy and IPO activity. We then investigate the mechanisms through which policy influences the IPO process, such as the IPO approval process. Finally, we provide identification tests to address endogeneity concerns.

4.1 Industrial Policy and IPO Activity

We begin by testing whether IPO access is correlated with industrial policy. A key implication of our hypothesis is that industries designated as strategic priorities should exhibit a greater propensity for IPOs and raise more capital.

As a visual preview of the baseline specification, Figure 2 plots the residual distribution of $\log(\#IPOs)$ after controlling for industry GDP and industry Q using the corresponding Tobit specification reported in the Internet Appendix. The residual distribution for favored industries is shifted to the right relative to non-favored industries, consistent with favored industries exhibiting systematically higher IPO activity even after conditioning on standard market-based fundamentals.

[INSERT FIGURE 2 HERE]

We test this hypothesis by estimating Tobit models at the industry-year level. The Tobit specification accounts for the fact that many industry-year observations have zero IPOs, treating the observed outcome as censored at zero. Specifically, the model we esti-

mate is:

$$y_{i,t}^* = \alpha + \gamma_t + \beta_1 \cdot \text{PolicyFavor}_{i,t} + \beta_2 \cdot \text{Industry Q}_{i,t-1} + \beta_3 \cdot \log(\text{Industry GDP})_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}^*$ is the latent variable and the observed dependent variable, $y_{i,t} = \log(\text{IPO Activity})_{i,t}$, equals $y_{i,t}^*$ when positive and is censored at zero otherwise. The “IPO Activity” variable is either the number of IPOs or total IPO proceeds for industry i in year t . The main independent variable, $\text{PolicyFavor}_{i,t}$, is our measure of industry-level policy support, proxied by either a dummy variable (Favored) or a continuous measure (FavorIndex). Control variables include lagged industry Tobin’s Q and the logarithm of industry GDP. We include year fixed effects, γ_t , to absorb macroeconomic shocks common to all industries.

Table 4 reports the estimation results. Industries prioritized by industrial policy have significantly more IPO activity. In columns (1) and (2), where the dependent variable is $\log(\#\text{IPOs})$, the policy favor dummy (Favored) is positive and statistically significant at the 1% level. The continuous measure in column (2) yields a similar conclusion. Columns (3) and (4) show that this effect extends to the scale of capital raised: favored industries also raise significantly more capital via IPOs.

[INSERT TABLE 4 HERE]

The economic magnitude of these effects is large. Table IA3 in the Internet Appendix reports the marginal effects of our variables of interest. Panel A reports the total marginal effects. Panels B and C decompose the total effect into extensive and intensive margins following [McDonald and Moffitt \(1980\)](#).

The overall marginal effect of Favored on observed $\log(\#\text{IPOs})$ is 0.665, translating into 94% ($e^{0.665} - 1$) higher expected number of IPOs for favored industries. The policy favor affects both the likelihood and the intensity of IPO activity. At the extensive margin,

avored industries are 25 percentage points more likely to experience any IPO activity. At the intensive margin, conditional on having at least one IPO, they have approximately 64% ($e^{0.493} - 1$) more IPOs.

The policy effect on IPO proceeds is also large and primarily operates through the intensive margin. Favored industries are 15 percentage points more likely to generate any IPO proceeds. Conditional on positive proceeds, they raise approximately 8.7 times more capital. Overall, this translates into nearly a twenty-two increase in expected IPO proceeds. In other words, favored industries not only have more IPOs, but much larger IPOs. The continuous measure FavorIndex yields comparable magnitudes: a one-unit increase is associated with an overall marginal effect of 0.482 on $\log(\#IPOs)$ and 2.299 on $\log(\text{proceeds})$.

As a robustness check, we also estimate linear OLS regressions and report the results in the Internet Appendix. We find qualitatively similar results to Tobit regressions. Policy favor has significant and positive impact on the IPO activity. In addition, the marginal effects are of similar magnitude to those in Tobit regressions. For example, the coefficient on Favored in the regression of $\log(\#IPOs)$ is 0.683, which corresponds to roughly a 98% increase in the number of IPOs.

We next examine whether this relationship strengthens over time. Table 5 reports the same Tobit specification estimated separately by Five-Year Plan window. Table IA4 in the Internet Appendix reports the corresponding Tobit marginal effects by subperiod and shows the same monotonic pattern in total, extensive, and intensive margins. The pattern is monotonic. The effect of Favored is close to zero in the 10th FYP period (2002–2005) and rises steadily and significantly through the 11th, 12th, 13th, and 14th FYP (2021–2022). The continuous FavorIndex measure follows the same trajectory. Rather than relying only on separate subperiod regressions, we also estimate a pooled specification over 2002–2022 that interacts policy variables with FYP indicators. Figure 3 plots the implied policy effect on $\log(\#IPOs)$ relative to the 10th FYP and delivers the same conclusion: the policy effect

rises monotonically over time, and by the 14th FYP, the estimated policy effect is more than double the 11th FYP baseline. This trend is consistent with recent literature documenting the expanding scope and intensity of China’s industrial policy (Naughton, 2021; Heilmann and Shih, 2012). Our finding provides market-based evidence that the state’s influence over IPO allocation has strengthened over time.

[INSERT TABLE 5 HERE]

[INSERT FIGURE 3 HERE]

This time-series pattern also clarifies how unusual the China results are relative to a market-driven benchmark. In Table 6, we replicate the analysis using data from the U.S. IPO market. To construct a comparable U.S. policy favor measure (*Favored_US*), we employ a hybrid approach combining large language models with rigorous manual verification to identify 15 major U.S. industrial policies enacted between 2002 and 2022 (e.g., the America COMPETES Act, the CHIPS and Science Act, and the Inflation Reduction Act). We first use LLMs to process Congressional Research Service (CRS) reports and map policy texts to specific SIC codes. We then manually verify each AI-suggested mapping against official industry classifications and require direct, material evidence of support within the CRS reports before designating an industry as favored. We also manually exclude broad initiatives lacking specific industry-level funding or those that do not meet the strict OECD definition of industrial policy. Full details of this procedure and the final list of policies are provided in the Internet Appendix.

Using this rigorously verified measure, the coefficient on *Favored_US* in Table 6 is small and statistically insignificant. Instead, Industry Q is a strong and significant predictor of both the number of IPOs and proceeds raised. The effect is economically substantial given that the standard deviation of Industry Q is typically around 0.5–1.0. In contrast,

the coefficient on Industry Q in China is statistically insignificant across all specifications in Table 4. This comparison underscores the unique, policy-driven nature of capital allocation in China's IPO market, where government priorities appear to dominate market-based fundamentals.

[INSERT TABLE 6 HERE]

4.2 The Mechanism: The IPO Application and Approval Process

Having established that industrial policy is strongly associated with IPO activity, with favored industries having significantly more IPOs and raising more capital, we now investigate the mechanisms through which this influence operates.

As we discussed in Section 2, all IPOs in China must be approved by regulatory bodies. The approval process has two key features. First, it has historically imposed more rigid regulations concerning the profitability and size of pre-IPO companies compared to markets like the U.S. Second, there exists significant regulatory discretion, which leaves room for industrial policy to guide the IPO process, the main channel we argue for in this paper.

Against this institutional backdrop, the observation that favored industries have significantly more IPOs could arise from two non-mutually exclusive channels. First, the **approval channel**: the approval process could be more lenient for firms in favored industries, leading to a higher probability of success for any given application. Second, the **application channel**: there could simply be more firms in favored industries applying for IPOs. We now test these two channels empirically.

We first examine the approval channel. A natural hypothesis is that firms from favored industries enjoy a higher approval rate. However, the data do not support this hypothesis. We find no statistically significant difference in the overall approval rate between the two

groups (71.8% for favored vs. 72.3% for non-favored) as Table 7 shows. In fact, from 2014 to 2021, we find no single calendar year when the firms in favored industries have on average statistically higher approval rates than those in non-favored industries.

This leads us to investigate the application channel, which implies that significantly more firms in favored industries file for IPOs compared to non-favored industries. We test this channel formally by re-estimating our baseline specification with the logarithm of the number of IPO applications as the dependent variable. The results, presented in Panel B of Table 7, strongly support the application channel. The policy favor dummy (Favored) is positive and statistically significant at the 1% level. To provide a precise economic interpretation, we again decompose the Tobit marginal effects and report the results in Table IA5 in the Internet Appendix. The overall marginal effect of being favored on observed $\log(\#IPO \text{ applications})$ is 0.965. Decomposing this effect reveals that policy favor operates powerfully on both margins: it increases the probability of an industry having any IPO applications in a given year by 22.2 percentage points (the extensive margin), and, conditional on having applications, it raises $\log(\#IPO \text{ applications})$ by 0.745, which corresponds to roughly a 111% increase in $1 + \#IPO \text{ applications}$. This substantial effect indicates that industrial policy operates not by relaxing approval standards, but by inducing a significantly larger pool of firms in favored industries to enter the IPO pipeline.

[INSERT TABLE 7 HERE]

What drives so many more firms in favored industries to file for IPOs? One potential reason is that the government provides these firms with tangible advantages that encourage entry into the IPO process.

First, we find that the time between application and approval is significantly shorter for firms in favored industries. Panel A of Table 8 reports year-by-year summary statistics for approval duration. Favored industries experience an average of 486 days from

application to approval, compared to 561 days for non-favored industries, a difference of 75 days (significant at the 1% level). The median difference is 60 days (454 vs. 514 days). This pattern is particularly pronounced in recent years: from 2018 to 2021, favored industries consistently enjoyed significantly shorter waiting times.³ Panel B then shows that the same pattern survives controls for firm characteristics (SOE status, ROA, leverage, and firm size) and year fixed effects. The coefficient on Favored is -0.088 and statistically significant at the 1% level, implying that firms in favored industries experience approximately 8.4% shorter waiting times ($1 - e^{-0.088} \approx 0.084$). Applied to the non-favored baseline of 561 days, this translates to roughly 47 fewer days, consistent with the 75-day raw difference after accounting for firm-level controls. The Internet Appendix reports additional year-by-year and market-segment breakdowns for approval rates and approval duration.

[INSERT TABLE 8 HERE]

Besides, the Internet Appendix provides suggestive evidence that firms in favored industries receive more government subsidies after their IPOs, which may further encourage firms to pursue listing.⁴

Taken together, the evidence points to a clear mechanism: industrial policy primarily operates through the **application channel**. More firms in favored industries file for IPOs, and this larger pool of applicants drives the observed increase in IPO activity. Importantly, the rules governing IPO eligibility remain binding even for firms in favored industries: approval rates are similar across the two groups. We also find suggestive evidence that the government facilitates this process through faster approval times and post-IPO subsidies. These findings demonstrate that the government plays an active role

³More detailed summary statistics of the approval waiting times is provided in the Internet Appendix.

⁴We do not observe the data on subsidies before IPOs.

in facilitating capital market access for firms aligned with national strategic priorities, not by relaxing approval standards, but by encouraging applications and supporting firms through the process.

4.3 Identification: Isolating the Effects of Industrial Policy

An alternative interpretation of the results documented above is that industries prioritized by industrial policy are simply populated by better-performing firms with greater capital needs. If so, industrial policy would merely reflect endogenous supply and demand dynamics rather than act as an external force shaping market outcomes. We present three pieces of evidence against this interpretation.

4.3.1 Policy Evidence

Government and regulatory bodies explicitly state their intention to guide capital allocation through the IPO process. To document this systematically, we construct a document-level indicator from State Council policy texts issued between 2002 and 2022. We classify documents in two steps. First, we identify whether a document is an industrial-policy document, defined as one that provides targeted support, guidance, or regulatory facilitation for specific industries or economic activities. Second, among those industrial-policy documents, we identify whether the text explicitly mentions IPO-related facilitation, including references to firm listing, issuance review, or expanded access to direct financing. The resulting share therefore measures how often industrial policy documents explicitly mention IPO facilitation as part of the policy toolkit.

Figure 4 summarizes this measure by Five-Year Plan window from the Tenth to the Fourteenth. Of the 529 documents classified as industrial policy, about one third explicitly mention IPO support. The share remains broadly stable across planning cycles rather than concentrating in a single episode, which is consistent with IPO facilitation being a persistent policy tool rather than an isolated intervention. We manually reviewed rep-

representative positive cases to verify that the classification captures substantive references to listing support, review acceleration, or direct-financing access rather than incidental mentions of capital markets.

[INSERT FIGURE 4 HERE]

This pattern appears in explicit policy language as well. The 2020 State Council notice on integrated circuits and software called for “vigorously supporting” qualified firms to list and “accelerating the domestic listing review process.” The CSRC has been equally direct: a 2014 press release stated that IPO applicants in overcapacity industries that “do not comply with industrial policy will not be approved.” These are active commands, not passive reflections of market trends.

4.3.2 CN IPOs in HK and US

We next conduct placebo tests exploiting the fact that many Chinese firms list in the United States and Hong Kong, markets less directly impacted by mainland regulatory policy. If our results were driven by intrinsic firm quality, we should observe similar patterns overseas. Table 9, Panel A, presents results for Chinese firms listing in the United States. The coefficient on the policy favor dummy (Favored) is 0.239 for the number of IPOs and 1.327 for proceeds, neither statistically significant. The coefficient on FavorIndex is similarly small, at 0.165 for IPO counts and 0.848 for proceeds. The placebo null therefore survives in the U.S. market without the additional VIE control; the Internet Appendix shows that adding a proxy for industry-specific offshore-listing propensity, based on the prevalence of VIE structures in the same industry, does not change this conclusion.

[INSERT TABLE 9 HERE]

Table 9, Panel B, sharpens the Hong Kong placebo by contrasting IPOs by non-mainland

issuers with IPOs by mainland Chinese issuers. For non-mainland issuers, the coefficients on the policy favor dummy are small and statistically insignificant: 0.065 for the number of IPOs and 0.597 for proceeds. For mainland Chinese issuers listing in Hong Kong, the corresponding coefficients rise to 0.323 and 2.018, with the mainland count effect statistically significant. The coefficients on FavorIndex show the same pattern: 0.093 and 0.747 for non-mainland issuers versus 0.279 and 1.761 for mainland issuers. Even these mainland-in-Hong-Kong estimates remain far smaller than the mainland China estimates, indicating that policy-linked IPO access is strongest inside China's domestic regulatory environment and attenuates once firms list offshore.

Taken together, this evidence strongly rejects the alternative hypothesis that our results merely reflect better firms in favored industries. The overseas listings analysis shows that the IPO advantage enjoyed by favored industries disappears in the U.S., is absent for non-mainland issuers in Hong Kong, and is materially weaker for mainland Chinese issuers listing in Hong Kong than for firms listing domestically in mainland China. Combined with the baseline results and mechanism evidence, we conclude that industrial policy, operating through the IPO approval process, is a first-order determinant of which firms access China's equity markets.

5 Industrial Policy and IPO Pricing

The preceding sections establish that industrial policy shapes the quantity of capital flowing through China's IPO market. We now demonstrate that the capital market channel extends beyond quantity to affect the cost of capital, specifically, IPO valuations. If investors perceive policy-favored firms as having better growth prospects or lower risk due to implicit government support, these firms should command higher valuations at IPO.

We measure IPO valuation using Tobin's Q on the first trading day, calculated as the market value of equity plus book value of debt divided by book value of assets. Because

IPO prices in China are subject to regulatory caps and often hit daily price limits on the first trading day, we use the first “non-hit day” price, the first day when the stock does not hit its price limit, to compute market value (Qian et al., 2024). Q is winsorized at the 1st and 99th percentiles within each calendar year.

5.1 Industry-Level Policy Favor and IPO Valuation

We begin by examining whether firms in policy-favored industries receive higher valuations at IPO. We estimate the following regression:

$$Q_{i,t} = \alpha + \beta \cdot \text{PolicyFavor}_{j,t} + \gamma \cdot X_{i,t} + \delta_t + \varepsilon_{i,t} \quad (2)$$

where $Q_{i,t}$ is firm i 's first-day Tobin's Q, $\text{PolicyFavor}_{j,t}$ is our industry-level measure (either the dummy Favored or the continuous count), $X_{i,t}$ includes firm-level controls (SOE status, ROA, leverage, and log assets), and δ_t represents year fixed effects. Standard errors are clustered at the year and industry level.

Table 10 reports the results. The coefficient on the policy favor dummy (Favored) is 0.348 and statistically significant at the 1% level. Given that the mean first-day Q in our sample is 2.98 (Table 2), this coefficient implies that firms in policy-favored industries receive valuations that are 11.7% higher (0.348/2.98) than firms in non-favored industries. Using the continuous measure, each additional policy mention is associated with a 0.218 increase in Q (significant at 5%), representing a 7.3% valuation premium per mention.

To investigate whether the effect of industrial policy on valuation concentrates among firms of certain sizes and/or State-Owned Enterprises (SOEs), we include additional interaction terms in the regression. Column (3) shows the results after adding controls that interact the policy favor measure with indicator variables for firm size. Specifically, `Small` equals 1 if a firm's total assets rank in the bottom tercile of the IPO sample in a given year, and `Medium` equals 1 if the firm ranks in the middle tercile. The coefficient on the main

FavorIndex variable (which now captures the effect for the omitted “Large” tercile) rises to 0.406 and is highly significant. Conversely, the interaction terms for both small (−0.404) and medium (−0.291) firms are negative and statistically significant. This indicates that the valuation premium from policy alignment is concentrated almost entirely among the largest IPOs, consistent with large firms being better positioned to secure and benefit from actual government support, and being more visible to investors seeking policy-aligned investments.

Column (4) further explores whether this policy premium is driven by state ownership by adding an interaction between policy favor and the SOE indicator. The coefficient on the Favored × SOE interaction is negative (−0.125) and statistically insignificant. Meanwhile, the main FavorIndex coefficient remains large (0.438) and highly significant, and the size interactions remain stable. This result demonstrates that the valuation premium for policy-favored industries is not simply a proxy for state ownership; rather, industrial policy confers a significant pricing advantage to large, strategically aligned firms regardless of whether they are state-owned or privately held.

[INSERT TABLE 10 HERE]

5.2 Firm-Level Policy Alignment and IPO Valuation

We next examine whether, within the same industry, firms with closer alignment to government industrial policy receive higher valuations. We use our firm-level GPA measure, constructed from pre-IPO prospectus text, which captures how closely a firm’s business description matches the language of industrial policy documents. GPA is winsorized at the 1st and 99th percentiles.

We estimate the following regression:

$$Q_{i,t} = \alpha + \beta \cdot \text{GPA}_{i,t} + \gamma \cdot X_{i,t} + \delta_t + \mu_j + \varepsilon_{i,t} \quad (3)$$

where $Q_{i,t}$ is firm i 's first-day Tobin's Q, $GPA_{i,t}$ is the firm-level policy alignment measure, $X_{i,t}$ includes firm-level controls (SOE status, ROA, leverage, and log assets), δ_t represents year fixed effects, and μ_j represents industry fixed effects. The inclusion of industry fixed effects is critical: it ensures we are comparing firms within the same industry, isolating the effect of firm-specific policy alignment from industry-level policy favor. Standard errors are clustered at the year and industry level.

Table 11 presents results, progressively adding controls and fixed effects. The coefficient on GPA is 0.073 in the univariate specification (Column 1) and remains highly significant at 0.051–0.053 after adding firm controls and industry fixed effects (Columns 2–4). To interpret the economic magnitude: the standard deviation of GPA (scaled by 1000) is 5.81, so a one-standard-deviation increase in GPA is associated with a 0.30 increase in Q (0.051×5.81), or approximately 10% of the mean Q ($0.30/2.98$). In other words, moving from the 25th to the 75th percentile of GPA within an industry corresponds to roughly a 7% valuation premium.

As with the industry-level results, the GPA premium is concentrated among larger firms. The interactions with small and medium firm indicators are negative and significant, suggesting that the market rewards policy alignment primarily for firms with sufficient scale to credibly benefit from government support.

[INSERT TABLE 11 HERE]

5.3 Long-Run Effects

A natural question is whether the valuation premium for policy-aligned firms reflects rational expectations about future performance or temporary mispricing that subsequently reverses. We examine this question using buy-and-hold abnormal returns (BHAR) over 12, 24, and 36 months following the IPO. BHAR is calculated as the firm's cumulative return starting from the first non-hit day price, minus the return of a matched firm over

the same period.

Table 12 reports the results. Across all specifications, using the industry-level policy favor dummy, the continuous FavorIndex measure, and the firm-level GPA, we find no evidence of return reversal. Most coefficients on policy favor and GPA are statistically insignificant across horizons, and the only statistically significant estimate is a positive 36-month coefficient on FavorIndex. This pattern indicates that the valuation premium observed at IPO does not subsequently reverse, suggesting that the market's initial pricing of policy alignment reflects persistent expectations rather than temporary mispricing.

[INSERT TABLE 12 HERE]

We further examine the A-H premium for firms dual-listed in mainland China and Hong Kong. If the valuation premium for policy-aligned firms reflects China-specific factors, such as expectations of government support or preferential treatment, we would expect this premium to be larger in the A-share market than in Hong Kong. However, Table 13 shows that the coefficients on policy favor and GPA are not statistically significant, suggesting that both domestic and foreign investors recognize and price in the long-term benefits of policy alignment similarly across markets.

[INSERT TABLE 13 HERE]

The evidence in this section demonstrates that industrial policy affects not only the quantity of capital raised through IPOs but also the cost of capital. Firms in policy-favored industries receive an 11.7% valuation premium at IPO, which does not reverse over three years, suggesting investors recognize the long-term benefits of policy alignment. By reducing the cost of capital for policy-favored firms, industrial policy effectively subsidizes their access to equity markets. Together with evidence on IPO activity and approval speed, these findings suggest that China's industrial policy operates as a

comprehensive capital allocation mechanism, shaping which firms access public equity markets and the terms on which capital is raised.

6 Evidence from Broader Chinese Capital Markets

To demonstrate that the influence of industrial policy on capital allocation is not confined to the main board IPO market, we extend our analysis to two other important segments of China's capital markets: the National Equities Exchange and Quotations (NEEQ) market and the corporate bond market.

6.1 The NEEQ Market

The National Equities Exchange and Quotations (NEEQ) market, also known as the "New Third Board," is an over-the-counter market established in 2012. It was explicitly designed to serve as a financing platform for small and medium-sized enterprises (SMEs), particularly those in innovative and high-tech sectors, which often struggle to meet the stringent listing requirements of the main boards (Du et al., 2025). The focus on SMEs is critical, as a large body of literature has shown that SMEs are a primary engine of job creation and economic dynamism (e.g., Rajan and Zingales, 1998; Beck et al., 2008; Haltiwanger, 2012). The NEEQ market's institutional design and policy orientation make it a natural setting to test the influence of industrial policy. Given its explicit mandate to support strategic industries, we hypothesize that the effect of policy favor on capital allocation will be even more pronounced in this market.

We re-estimate our baseline specification from Equation (1), with the dependent variable being the logarithm of the number of NEEQ listings. The results, presented in Table 14, confirm this prediction. The policy favor dummy (Favored) is positive and statistically significant at the 1% level. To interpret the economic magnitude, we decompose the Tobit marginal effects in Table IA6 in the Internet Appendix. The overall marginal effect

of being favored on observed $\log(\#\text{NEEQ listings})$ is 1.062. This overall effect is driven by both a 17.3 percentage point increase in the probability of having any NEEQ listings (the extensive margin) and a conditional increase of 0.919 log points in listing volume, which corresponds to roughly a 151% increase in $1 + \#\text{NEEQ listings}$ among active industries. Notably, the overall marginal effect for NEEQ listings (1.062) is substantially larger than the corresponding effect for main-board IPOs (0.665). This finding underscores the pervasive role of industrial policy in guiding capital flows, particularly in markets explicitly designed to serve national strategic objectives.

[INSERT TABLE 14 HERE]

6.2 The Corporate Bond Market

Next, we turn to the corporate bond market. China's bond market has grown to become the second-largest in the world, with an outstanding value of over RMB 155 trillion (approximately USD 22 trillion) at the end of 2023 ([National Association of Financial Market Institutional Investors, 2024](#)). The market is characterized by two main segments: the exchange market and the larger, dominant interbank market, which accounts for the vast majority of trading volume ([Amstad and He, 2019](#)). Given its sheer size, the bond market is a crucial channel for capital allocation, and we test whether industrial policy also influences debt financing.

We estimate our baseline specification with the logarithm of the number of bond issuances and the logarithm of total bond proceeds as dependent variables. The results, presented in Table 15, show that the effect of industrial policy extends to the bond market. The policy favor dummy is positive and statistically significant at the 1% level for both the number of bond issuances and bond proceeds. Decomposing these Tobit marginal effects in Table IA7 in the Internet Appendix reveals that policy favor significantly boosts

debt financing across both margins. At the extensive margin, being favored increases the probability of issuing bonds by 6.5 percentage points. At the intensive margin, favored industries issue 84% more bonds ($e^{0.609} - 1$) and raise about 2.6 times as much debt capital ($e^{0.963}$) as non-favored industries. The overall marginal effects (0.687 for log issues and 1.071 for log proceeds) confirm that the influence of industrial policy is similarly powerful in the much larger debt market. Interestingly, we find that Industry Q has a significant *negative* relationship with bond issuance in China. This contrasts with the positive relationship typically observed in developed markets and further highlights the unique, policy-driven dynamics of China's capital markets.

[INSERT TABLE 15 HERE]

In summary, the evidence from both the NEEQ and corporate bond markets corroborates our main findings from the IPO market. Across different segments of China's capital markets, industrial policy appears to be a powerful determinant of capital allocation, often overshadowing traditional market-based fundamentals.

7 Conclusion

This paper establishes that public equity market regulation can function as a first-order industrial policy instrument, a channel that is distinct from, and potentially more powerful than, traditional fiscal tools. We show that in China, access to IPO financing is not primarily driven by market fundamentals, but is instead systematically directed toward industries aligned with national strategic priorities. This gatekeeping mechanism, explicitly confirmed by government and regulatory statements, channels capital on a scale comparable to the country's entire fiscal industrial policy apparatus, but does so by leveraging private capital and market-based valuations, making it a uniquely potent and non-

transparent tool of statecraft.

Our evidence demonstrates that this policy works through a powerful signaling channel. Firms in favored industries are substantially more likely to apply for IPOs, with policy favor increasing both the probability of any applications by 22.2 percentage points and the volume of applications conditional on activity by 111%. They are also processed faster and receive a persistent valuation premium. These findings, robust to a suite of identification strategies, reveal a comprehensive capital-market industrial policy that extends beyond IPOs to corporate bonds and other financing platforms. While the long-term welfare implications of prioritizing policy over market signals remain an open and critical question, our research makes one thing clear: the regulatory architecture of capital markets is not neutral infrastructure. It can be, and is, a core arena for industrial policy, with profound implications for corporate finance, economic development, and the global balance of economic power. As nations worldwide reconsider the role of the state in shaping economic outcomes, understanding this powerful, non-fiscal channel is more critical than ever.

The efficacy of this regulatory channel has profound implications for the design of industrial policy globally. As nations engage in increasingly costly “subsidy races,” with direct fiscal support often exceeding 1% of GDP in developed economies and 4% in China ([Garcia-Macia et al., 2025](#)), fiscal constraints become a binding limitation on state intervention. Our findings demonstrate that governments can successfully steer massive flows of capital and stimulate real economic activity purely through the regulation of market access. For developing countries with limited fiscal capacity, utilizing capital market gatekeeping as an industrial policy tool offers a potent alternative to debt-financed subsidies. However, this zero-fiscal-cost approach is not without its own shadow costs; it inherently distorts the allocative efficiency of public equity markets and effectively taxes the excluded, non-favored sectors by restricting their access to vital risk capital.

References

- Aghion, P., Cai, J., Dewatripont, M., Du, L., Harrison, A., and Legros, P. (2015). Industrial policy and competition. *American Economic Journal: Macroeconomics*, 7(4):1–32.
- Amsden, A. H. (1989). *Asia's Next Giant: South Korea and Late Industrialization*. Oxford University Press, New York.
- Amstad, M. and He, Z. (2019). Chinese bond market and interbank market. Working Paper 25549, National Bureau of Economic Research.
- Bai, J., Barwick, P. J., Cao, S., and Li, S. (2025). Quid pro quo, knowledge spillovers, and industrial quality upgrading: Evidence from the chinese auto industry. *American Economic Review*, 115(11):3825–3852.
- Baldwin, R. E. (1969). The case against infant-industry tariff protection. *Journal of Political Economy*, 77(3):295–305.
- Barwick, P. J., Kalouptsi, M., and Zahur, N. (2024a). Industrial policy: Lessons from shipbuilding. *Journal of Economic Perspectives*, 38(4):55–80.
- Barwick, P. J., Kwon, H., Li, S., Wang, Y., and Zahur, N. (2024b). Industrial policies and innovation: Evidence from the global automobile industry. Working Paper 33138, National Bureau of Economic Research.
- Beck, T., Demirgüç-Kunt, A., and Maksimovic, V. (2008). Financing patterns around the world: Are small firms different? *Journal of Financial Economics*, 89(3):467–487.
- Beraja, M., Peng, C., Yang, D. Y., and Yuchtman, N. (2025). Government as venture capitalists in artificial intelligence. *Entrepreneurship and Innovation Policy and the Economy*.
- Branstetter, L. and Li, G. (2024). The challenges of chinese industrial policy. *Entrepreneurship and Innovation Policy and the Economy*, 4:1–28.

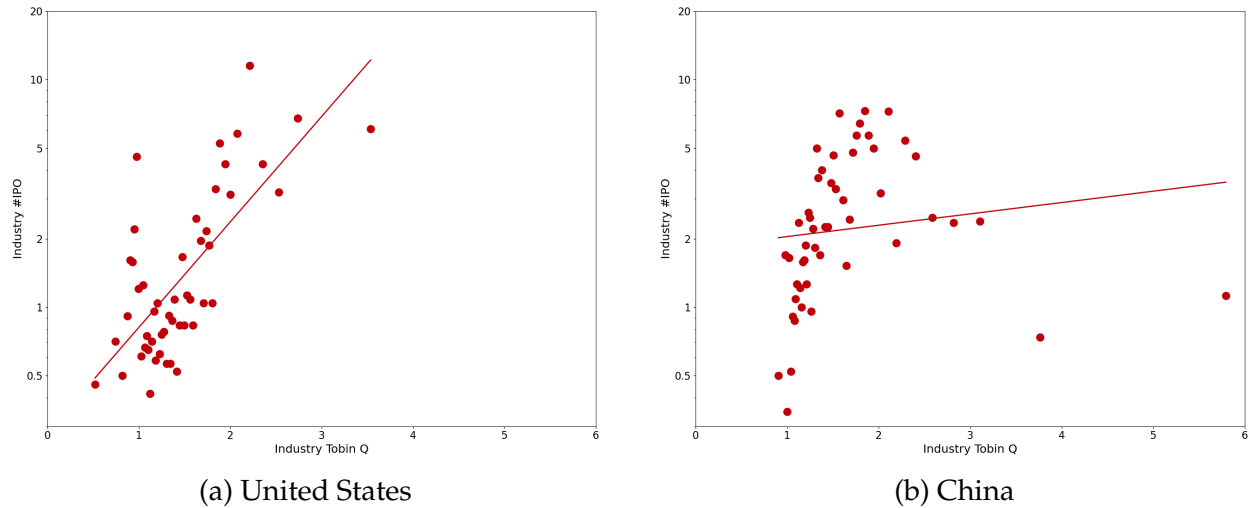
- Branstetter, L., Li, G., and Ren, S. (2023). Picking winners? government subsidies and firm productivity in china. *Journal of Comparative Economics*, 51(4):1186–1199.
- Cen, X., Fos, V., and Jiang, W. (2022). A Race to Lead: How Chinese Government Interventions Shape U.S.-China Production Competition.
- Chen, D., Li, O. Z., and Xin, F. (2017). Five-year plans, China finance and their consequences. *China Journal of Accounting Research*, 10(3):189–230.
- Chen, Z., Gong, J., and Li, P. (2026). Industrial policy in a new era: Government venture capital in the us–china trade war. *Journal of Development Economics*.
- Cong, L. W. and Howell, S. T. (2021). Policy uncertainty and innovation: Evidence from IPO interventions in china. *Management Science*, 67(11):7238–7261.
- Cong, L. W., Lee, B., Qu, Y., and Shen, D. (2020). Financing entrepreneurship and innovation in china. *Foundations and Trends in Entrepreneurship*, 16(1):1–64.
- Du, J. et al. (2025). Registration-based transfer listing system and high-tech sme innovation: Research on china’s specialized and sophisticated smes listed on the national equities exchange and quotations. *PLOS ONE*.
- Fan, J. P. H., Wong, T. J., and Zhang, T. (2007). Politically connected ceos, corporate governance, and post-ipo performance of china’s newly partially privatized firms. *Journal of Financial Economics*, 84(2):330–357.
- Fang, H., Li, M., and Lu, G. (2025). Decoding chinas industrial policies. NBER Working Paper 33814, National Bureau of Economic Research.
- Garcia-Macia, D., Gopinath, G., and Huang, Y. (2025). Industrial policy in china: Quantification and impact on misallocation. IMF Working Paper 2025/155, International Monetary Fund.

- Haltiwanger, J. (2012). Job creation and firm dynamics in the united states. In *Innovation Policy and the Economy*, volume 12, pages 17–38. University of Chicago Press.
- Harrison, A. E. and Rodríguez-Clare, A. (2010). Trade, foreign investment, and industrial policy for developing countries. In Rodrik, D. and Rosenzweig, M. R., editors, *Handbook of Development Economics, Volume 5*. Elsevier, Amsterdam. Survey of industrial policy tools and design; used for taxonomy.
- He, D. and Wei, S.-J. (2023). China’s financial system and economy: A review. *Annual Review of Economics*, 15(1):451–483.
- Heilmann, S. and Shih, L. (2012). The rise of industrial policy in china, 1978-2012. *Harvard-Yenching Institute Working Paper*.
- Johnson, C. (1982). *MITI and the Japanese Miracle: The Growth of Industrial Policy, 1925–1975*. Stanford University Press, Stanford, CA.
- Juhász, R., Lane, N., and Rodrik, D. (2023). The new economics of industrial policy. Working Paper 31538, National Bureau of Economic Research.
- Krueger, A. O. (1990). Government failures in development. *Journal of Economic Perspectives*, 4(3):9–23.
- Lane, N. (2020). The new empirics of industrial policy. *Journal of Industry, Competition and Trade*, 20(2):231–253.
- McDonald, J. F. and Moffitt, R. A. (1980). The uses of tobit analysis. *Review of Economics and Statistics*, 62(2):318–321.
- National Association of Financial Market Institutional Investors (2024). Reform and development of china’s bond market.
- Naughton, B. (2021). *The Rise of China’s Industrial Policy, 1978 to 2020*. Lynne Rienner Publishers / De Gruyter, Boulder, CO.

- Pack, H. and Saggi, K. (2006). Is there a case for industrial policy? a critical survey. *The World Bank Research Observer*, 21(2):267–297.
- Pan, Y., Shu, T., Yao, V., and Zhang, P. (2022). Market-based innovation policy: Evidence from high-tech incubators in china. SSRN Working Paper.
- Pástor, v. and Veronesi, P. (2005). Rational ipo waves. *The Journal of Finance*, 60(4):1713–1757.
- Piotroski, J. D. and Zhang, T. (2014). Politicians and the ipo decision: The impact of impending political promotions on ipo activity in china. *Journal of Financial Economics*, 111(1):111–136.
- Qian, Y., Ritter, J. R., and Shao, X. (2024). Initial public offerings: Chinese style. *Journal of Financial and Quantitative Analysis*, 59(1):1–38. First published online 2022.
- Rajan, R. G. and Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, 88(3):559–586.
- Rodrik, D. (2004). Industrial policy for the twenty-First century. Technical report, Harvard University. Working paper.
- Rodrik, D. (2008). *Normalizing Industrial Policy*. The World Bank, Washington, DC. Commission on Growth and Development.
- Song, Z. and Xiong, W. (2018). Risks in china’s financial system. *Annual Review of Financial Economics*, 10(1):261–286.
- Stiglitz, J. E., Lin, J. Y., and Monga, C. (2013). The rejuvenation of industrial policy. Policy Research Working Paper 6628, World Bank.
- Wade, R. (1990). *Governing the Market: Economic Theory and the Role of Government in East Asian Industrialization*. Princeton University Press, Princeton, NJ.

Figures and Tables

Figure 1: Industry IPO Counts vs. Industry Tobin's Q: U.S. vs. China



Notes: This figure plots binned scatter plots of industry-level IPO counts against industry Tobin's Q for the United States (Panel A) and China (Panel B). The plotted IPO counts are raw counts, shown on a logarithmic y-axis. The China sample covers 2002 to 2022, excluding 2013. The U.S. sample covers 2002 to 2022. Each panel groups industry-year observations into 50 bins by industry Tobin's Q and plots bin means with a fitted line. In the U.S., IPO counts are strongly positively correlated with Tobin's Q. In China, this relationship is weak.

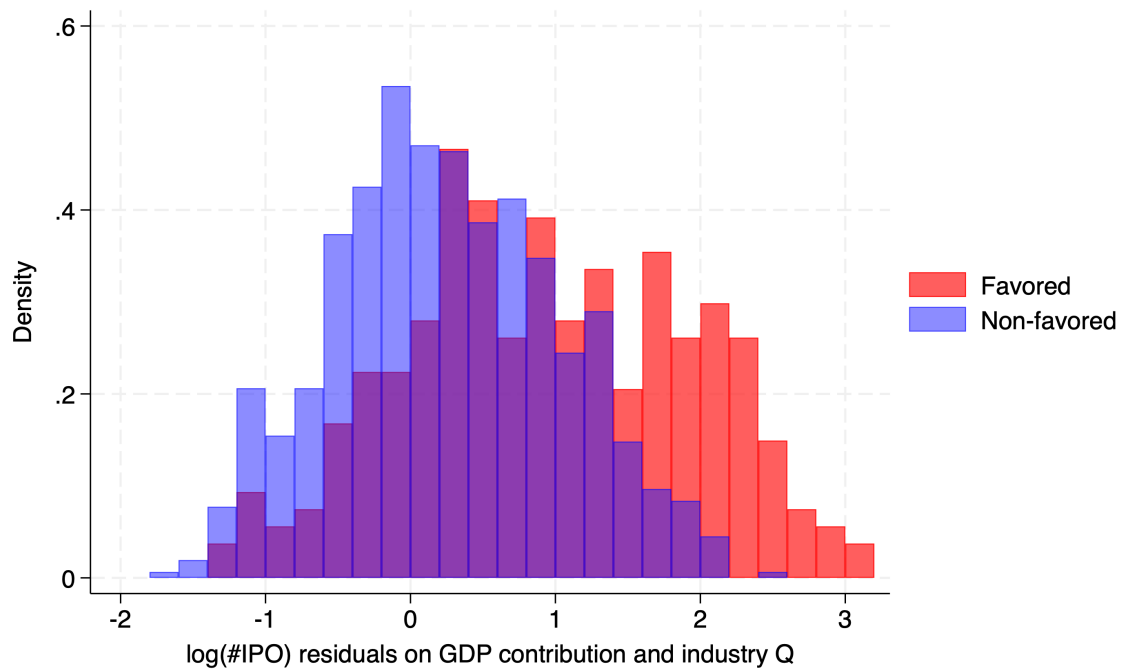


Figure 2: Residual IPO Activity Is Higher in Favored Industries

Notes: This figure plots the histogram of residuals from the corresponding Tobit regression reported in the Internet Appendix. The residuals are based on the log number of IPOs after controlling for industry GDP and lagged industry Q, and are shown separately for favored and non-favored industries. An industry is classified as favored when it receives positive policy emphasis in FavorIndex.

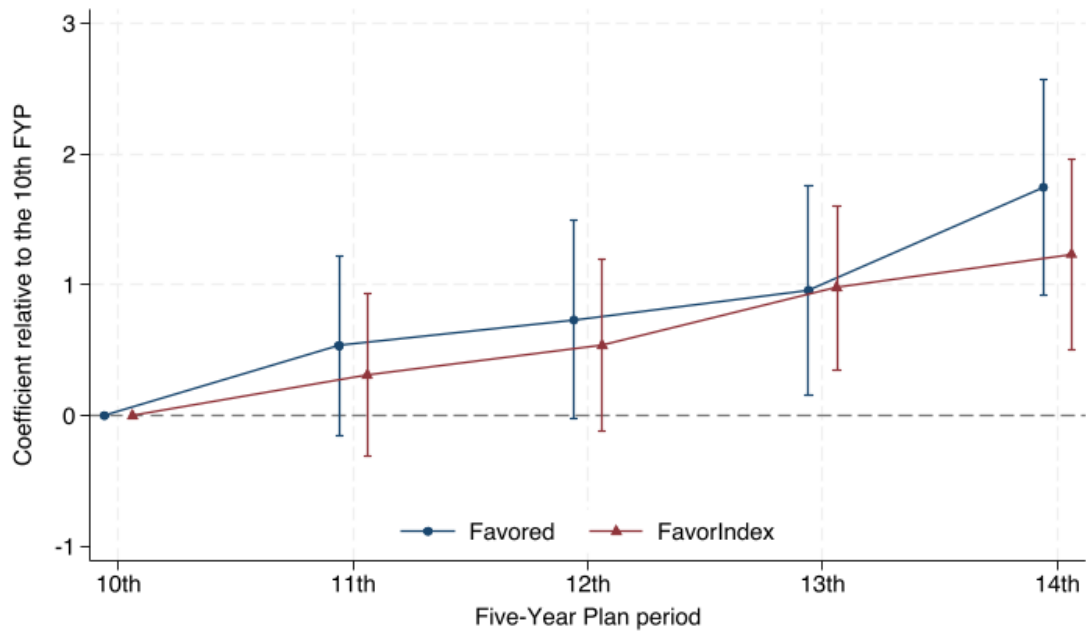


Figure 3: The Policy Effect on IPO Counts Strengthens Relative to the 10th FYP

Notes: This figure plots the implied effect of industrial policy on $\log(\#IPOs)$ for each Five-Year Plan period from the 10th to the 14th FYP, normalized relative to the 10th FYP. The estimates come from a single pooled Tobit regression over 2002–2022 that interacts the policy measure with FYP indicators while controlling for lagged Industry Q, $\log(\text{Industry GDP})$, and year fixed effects; standard errors are clustered by industry. Circles report the FYP-specific effect of *Favored*, the binary favored-industry indicator, relative to the 10th FYP. Triangles report the corresponding relative effect of *FavorIndex*, the continuous policy emphasis measure. Vertical bars show 95% confidence intervals for the difference relative to the 10th FYP; the 10th-FYP benchmark is normalized to zero.

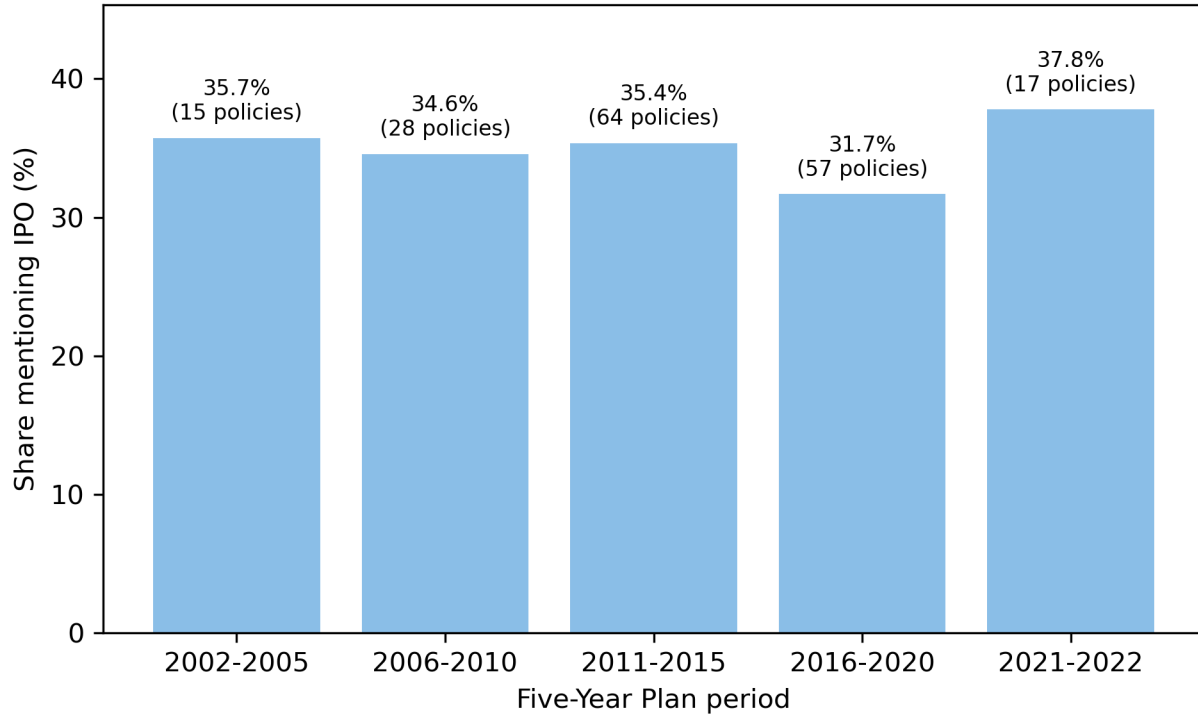


Figure 4: Share of Industrial Policies Mentioning IPO Support

Notes: This figure shows, for each Five-Year Plan period between 2002 and 2022, the share of industrial policy documents that explicitly mention IPO support. The IPO indicator is constructed using the LLM-based text classification approach described in the Internet Appendix. Numbers in parentheses indicate the number of industrial policy documents that mention IPO support in each period.

Table 1: Favored industries by Five-Year Plan

2001-2005	2006-2010	2011-2015	2016-2020	2021-2025
A01: Agriculture A03: Forestry A05: Animal Husbandry A07: Fishery A09: Agricultural and Related Servs. C51: Electronic Components Mfg. C55: Household Electronic Appliances Mfg. C57: Other Electronic Equip. Mfg. C71: General Machinery Mfg. C73: Special Equip. Mfg. C75: Transport Equip. Mfg. C76: Electrical Machinery and Equip. Mfg. C78: Instruments and Office Machinery Mfg. G81: Commun. Equip. Mfg. G83: Computer Equip. Mfg. G85: Telecommunications Servs. G87: Computer Application Servs. K34: Tourism L20: Information Transmission Servs.	A09: Agricultural and Related Servs. C01: Food Processing C03: Food Mfg. C05: Beverage Mfg. C51: Electronic Components Mfg. C57: Other Electronic Equip. Mfg. C71: General Machinery Mfg. C73: Special Equip. Mfg. C75: Transport Equip. Mfg. C76: Electrical Machinery and Equip. Mfg. C78: Instruments and Office Machinery Mfg. C81: Pharmaceutical Mfg. C85: Biological Products D01: Electric Power and Heat Supply F03: Road Transport F11: Transport Support Servs. F19: Other Transport Servs. F21: Warehousing G81: Commun. Equip. Mfg. G83: Computer Equip. Mfg. G85: Telecommunications Servs. G87: Computer Application Servs. K34: Tourism	A09: Agricultural and Related Servs. C01: Food Processing C35: Printing C43: Chemical Products Mfg. C47: Chemical Fiber Mfg. C51: Electronic Components Mfg. C57: Other Electronic Equip. Mfg. C71: General Machinery Mfg. C73: Special Equip. Mfg. C75: Transport Equip. Mfg. C81: Pharmaceutical Mfg. C85: Biological Products D01: Electric Power and Heat Supply F03: Road Transport F11: Transport Support Servs. F19: Other Transport Servs. F21: Warehousing G81: Commun. Equip. Mfg. G83: Computer Equip. Mfg. G85: Telecommunications Servs. G87: Computer Application Servs. K01: Public Utility Servs. K20: Professional and Scientific Servs. K99: Other Social Servs. L01: Publishing L05: Audiovisual Industry L10: Broadcasting, Film, and Television L99: Other Media and Cultural Services	A07: Fishery A09: Agricultural and Related Servs. C43: Chemical Products Mfg. C47: Chemical Fiber Mfg. C49: Plastics Mfg. C51: Electronic Components Mfg. C55: Household Electronic Appliances Mfg. C57: Other Electronic Equip. Mfg. C61: Non-Metallic Mineral Products C67: Non-Ferrous Metal Smelting and Rolling C73: Special Equip. Mfg. C75: Transport Equip. Mfg. C78: Instruments and Office Machinery Mfg. C81: Pharmaceutical Mfg. C85: Biological Products D01: Electric Power and Heat Supply F03: Road Transport F07: Water Transport F11: Transport Support Servs. F19: Other Transport Servs. F21: Warehousing G83: Computer Equip. Mfg. G85: Telecommunications Servs. G87: Computer Application Servs. K34: Tourism K99: Other Social Servs.	C43: Chemical Products Mfg. C47: Chemical Fiber Mfg. C48: Rubber Mfg. C49: Plastics Mfg. C51: Electronic Components Mfg. C55: Household Electronic Appliances Mfg. C57: Other Electronic Equip. Mfg. C59: Electronic Equip. Repair C61: Non-Metallic Mineral Products C65: Ferrous Metal Smelting and Rolling C67: Non-Ferrous Metal Smelting and Rolling C69: Metal Products Mfg. C71: General Machinery Mfg. C73: Special Equip. Mfg. C75: Transport Equip. Mfg. C76: Electrical Machinery and Equip. Mfg. C78: Instruments and Office Machinery Mfg. C81: Pharmaceutical Mfg. C85: Biological Products D01: Electric Power and Heat Supply F09: Air Transport G81: Commun. Equip. Mfg. G83: Computer Equip. Mfg. G85: Telecommunications Servs. G87: Computer Application Servs.

Notes: The industry codes follow the *Guidelines on Industry Classification of Listed Companies* (2001 edition) issued by the CSRC. Industry names are concise English renderings of the original CSRC 2001 Chinese titles. Abbreviations include: Mfg. (Manufacturing), Servs. (Services), Equip. (Equipment), and Commun. (Communication). Each column reports industries with positive policy-emphasis mentions in the corresponding Five-Year Plan window.

Table 2: Summary Statistics

Panel A: Variables at the industry-year level

	N	Mean	Median	St. Dev.	Min	Max
Favored	1044	0.26	0.00	0.44	0.00	1.00
FavorIndex	1044	0.31	0.00	0.56	0.00	2.13
#IPOs	1044	2.95	1.00	6.69	0.00	74.00
log(#IPOs)	1044	0.81	0.69	0.91	0.00	4.32
IPO proceeds	1044	338091.18	45907.90	1057666.94	0.00	13867096.00
log(IPO proceeds)	1044	7.03	10.73	6.13	0.00	16.45
Industry Q	1044	1.66	1.41	0.78	0.91	5.53
Industry GDP	1044	8390.70	4777.85	9974.36	175.31	77215.87
log(Industry GDP)	1044	8.46	8.47	1.12	5.17	11.25

Panel B: Firm-level variables at the IPO event level

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Q First Day	3,504	2.975	2.142	1.588	2.296	3.575
GPA	3,504	33.391	5.805	28.774	33.483	37.567
SOE	3,504	0.205	0.403	0	0	0
log(Assets)	3,504	20.665	1.334	19.873	20.409	21.072
ROA	3,504	16.832	11.421	10.738	15.277	20.961
Leverage	3,504	1.126	1.705	0.423	0.758	1.289

Notes: The continuous measure FavorIndex may take non-integer values due to the aggregation of policy emphasis across multiple industry classifications when mapping policy texts to industries. In Panel A, Industry GDP is reported in levels and measured in RMB 100 million. In Panel B, Log(Total Assets) is the natural log of total assets denominated in RMB yuan. GPA is winsorized at 1% and 99%. Size terciles are determined for an IPO firm at its IPO date when compared among all stocks listed then based on their market capitalization of equity. See Table A1 in the Internet Appendix for variable definitions and units.

Table 3: IPO Activity and GDP Contribution by Policy Favor

IPOyear	#IPO	#IPO in Fav.Ind.	Ratio	Sum(proceeds)	Sum(proceeds) in Fav.Ind.	Ratio	GDP Contr. Ratio
2002	64	25	0.39	471.50	197.55	0.42	0.35
2003	64	22	0.34	465.39	78.37	0.17	0.27
2004	95	33	0.35	339.69	117.93	0.35	0.32
2005	14	6	0.43	52.73	13.65	0.26	0.30
2006	63	22	0.35	1337.37	99.72	0.07	0.26
2007	119	49	0.41	4762.75	179.04	0.04	0.26
2008	74	30	0.41	1029.31	177.13	0.17	0.26
2009	96	56	0.58	1732.86	551.82	0.32	0.26
2010	329	199	0.60	4776.77	2292.10	0.48	0.26
2011	270	182	0.67	2598.49	1472.36	0.57	0.26
2012	144	98	0.68	985.86	610.12	0.62	0.21
2014	120	81	0.68	650.08	341.96	0.53	0.20
2015	214	136	0.64	1556.46	762.13	0.49	0.20
2016	226	127	0.56	1493.85	565.60	0.38	0.20
2017	435	285	0.66	2296.48	1378.50	0.60	0.20
2018	105	69	0.66	1378.15	892.94	0.65	0.19
2019	201	141	0.70	2532.48	1479.56	0.58	0.19
2020	392	282	0.72	4685.36	3304.15	0.71	0.20
2021	481	348	0.72	5351.46	4089.52	0.76	0.23

Notes: This table summarizes annual IPO activity, proceeds, and GDP contributions across policy-favored and non-favored industries in China, where *Favored* denotes the binary favored-industry classification based on policy emphasis in China's Five-Year Plans. Columns include the IPO year, total IPO count and proceeds, the number and proportion of IPOs and proceeds from favored industries, and the ratio of GDP contribution from favored industries to the total.

Table 4: IPO Activity in Favored Industries

VARIABLES	(1) log(#IPOs)	(2) log(#IPOs)	(3) log(IPO proceeds)	(4) log(IPO proceeds)
Favored	0.973*** (0.263)		4.407*** (1.327)	
FavorIndex		0.784*** (0.202)		3.442*** (0.987)
Industry Q	-0.058 (0.114)	-0.048 (0.114)	-0.635 (0.824)	-0.589 (0.829)
log(Industry GDP)	0.211** (0.083)	0.202** (0.082)	1.019** (0.499)	0.987** (0.500)
Constant	-2.043*** (0.729)	-1.912*** (0.708)	-6.291 (4.402)	-5.783 (4.389)
Observations	1,044	1,044	1,044	1,044
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0955	0.0998	0.0304	0.0306

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics for the sample period from 2002 to 2022. The year 2013 is excluded due to the suspension of IPOs. The dependent variables are the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. Favored is a dummy variable indicating whether an industry is policy-favored. FavorIndex represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. Industry Q represents lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles. log(Industry GDP) measures the log of official industry GDP in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: log(#IPO) in Favored Industries: By Subperiod

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2002-2005		2006-2010		2011-2015		2016-2020		2021-2022	
Favored	0.033 (0.296)		0.702** (0.275)		0.941*** (0.338)		1.183*** (0.368)		2.030*** (0.306)	
FavorIndex		0.017 (0.269)		0.433* (0.240)		0.683** (0.263)		1.154*** (0.218)		1.450*** (0.282)
Industry Q	-0.743 (0.811)	-0.742 (0.810)	-0.230 (0.170)	-0.179 (0.177)	-0.261** (0.127)	-0.228* (0.124)	-0.034 (0.172)	-0.041 (0.161)	0.268** (0.115)	0.268** (0.117)
log(Industry GDP)	0.562*** (0.177)	0.564*** (0.178)	0.293*** (0.089)	0.304*** (0.094)	0.201* (0.113)	0.177* (0.106)	0.140 (0.113)	0.098 (0.105)	0.033 (0.130)	0.073 (0.134)
Constant	-3.417 (2.161)	-3.429 (2.165)	-2.216*** (0.717)	-2.324*** (0.755)	-0.551 (0.951)	-0.402 (0.901)	-0.894 (1.144)	-0.545 (1.032)	-0.172 (1.185)	-0.468 (1.234)
Observations	130	130	268	268	228	228	298	298	120	120
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.148	0.148	0.0916	0.0828	0.0717	0.0747	0.0760	0.106	0.169	0.139

Notes: This table presents Tobit regression results analyzing the relationship between IPO activity and industry characteristics over different subperiods, corresponding to China's Five-Year Plans, from 2002 to 2022 (excluding 2013 due to the suspension of IPOs). The dependent variable is the natural logarithm of the number of IPOs (log(#IPOs)). Favored is the binary favored-industry indicator, and FavorIndex is the cumulative policy emphasis score based on the frequency of priority terms in China's Five-Year Plans. Industry Q is lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles. log(Industry GDP) represents the industry GDP level in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: IPO Activity in Favored Industries: U.S.

VARIABLES	(1) log(#IPOs)	(2) log(IPO proceeds)
Favored_US	0.304 (0.267)	0.968 (0.890)
Industry Q	0.589*** (0.225)	1.686** (0.714)
log(Industry GDP)	0.648*** (0.115)	2.435*** (0.411)
Constant	-8.742*** (1.356)	-31.733*** (4.805)
Observations	1,188	1,188
Year FE	Yes	Yes
Pseudo R-squared	0.137	0.0669

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics for the sample period from 2002 to 2022. The dependent variables are the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. IPO proceeds are measured in USD million. Favored_US is the U.S. policy-favored industry indicator; technical details are provided in the Internet Appendix. Industry Q represents lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles. log(Industry GDP) measures the log of BEA industry GDP in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: IPO Applications in Favored Industries

Panel A: IPO Approval Rate by Year

Year	#App	Favored Mean rate	#App	Non-Favored Mean rate	Difference
2014	54	77.8%	44	75.0%	-2.8%
2015	149	85.2%	97	89.7%	4.5%
2016	166	78.3%	133	72.2%	-6.1%
2017	342	76.3%	218	79.8%	3.5%
2018	148	44.6%	104	37.5%	-7.1%
2019	187	74.9%	98	62.2%	-12.6%**
2020	325	77.8%	166	83.1%	5.3%
2021	533	65.3%	193	68.9%	3.6%
2014–2021	1,904	71.8%	1,053	72.3%	0.5%

Panel B: Tobit Regressions of log(#IPO Applications)

VARIABLES	(1) log(#IPO applications)	(2) log(#IPO applications)
Favored	1.156*** (0.128)	
FavorIndex		1.027*** (0.095)
Industry Q	-0.042 (0.069)	-0.039 (0.066)
log(Industry GDP)	0.184*** (0.054)	0.159*** (0.052)
Constant	-1.074** (0.523)	-0.907* (0.501)
Observations	476	476
Year FE	Yes	Yes
Pseudo R-squared	0.0777	0.0972

Notes: Panel A compares IPO approval rates between policy-favored and non-favored industries from 2014 to 2021. Mean approval rate is the fraction of IPO applications successfully approved; the difference in means is from a t-test. Panel B presents Tobit regression results where the dependent variable is log(#IPO applications) at the industry-year level. *Favored* is the binary favored-industry indicator; *FavorIndex* is the cumulative policy emphasis score based on China’s Five-Year Plans; Industry Q is lagged industry Tobin’s Q, winsorized at the 1st and 99th percentiles; log(Industry GDP) is the log of industry GDP. Year fixed effects are included; standard errors are clustered by industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: IPO Application Time in Favored Industries

Panel A: Year-by-Year Summary Statistics for IPO Approval Duration

Year	Favored			Non-favored			Difference	
	#IPO	Mean days	Median days	#IPO	Mean days	Median days	diff Mean	diff Median
2014	54	326	197	21	240	185	86	12
2015	136	389	362	78	391	365	-2	-3
2016	127	804	818	99	794	803	10	15
2017	285	622	613	150	649	653	-27	-40
2018	69	495	434	36	600	485	-105*	-51*
2019	141	414	441	60	615	553	-201***	-112***
2020	281	403	419	110	477	471	-74***	-52***
2021	348	415	376	133	475	424	-60***	-48***
2014–2021	1,441	486	454	687	561	514	-75***	-60***

Panel B: Approval Duration and Policy Favor

VARIABLES	(1) log(#Days to IPO)	(2) log(#Days to IPO)	(3) log(#Days to IPO)
Favored	-0.088*** (0.028)		
FavorIndex		-0.040** (0.017)	
GPA			-0.018*** (0.002)
SOE	-0.027 (0.036)	-0.026 (0.037)	-0.042 (0.040)
ROA	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)
leverage	0.013 (0.010)	0.015 (0.010)	-0.021 (0.017)
log(Assets)	0.026 (0.018)	0.027 (0.017)	0.005 (0.020)
Constant	4.881*** (0.367)	4.835*** (0.349)	5.802*** (0.420)
Observations	2,108	2,108	2,108
R-squared	0.337	0.335	0.390
year FE	Yes	Yes	Yes
Industry FE	No	No	yes

Notes: Panel A reports year-by-year summary statistics for IPO approval duration among successful IPOs, separately for favored and non-favored industries. *days* is the number of calendar days between application and listing, winsorized at the 1st and 99th percentiles; the table reports counts, mean days, median days, and favored-minus-non-favored differences. Panel B reports regressions of $\log(\#Days\ to\ IPO)$ on policy-favor measures and firm controls. $\log(\#Days\ to\ IPO)$ is constructed as $\ln(1 + days)$ using the same winsorized *days* variable. *Favored* is a dummy variable indicating whether an industry is policy-favored, and *FavorIndex* is the cumulative policy emphasis score based on priority terms in China's Five-Year Plans. Controls include *SOE*, *ROA*, *leverage*, and $\log(assets)$. Year fixed effects are included in all specifications; industry fixed effects are included in column (3). Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Chinese IPOs Outside Mainland China

<i>Panel A: Chinese IPOs in the U.S. Market</i>							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	log(#IPOs)		log(IPO proceeds)		IPO Occurrence		
Favored	0.239 (0.197)		1.327 (0.983)		0.264 (0.203)		
FavorIndex		0.165 (0.146)		0.848 (0.705)			0.163 (0.145)
Industry Q	0.391** (0.188)	0.391** (0.184)	1.979** (0.966)	1.988** (0.947)	0.373* (0.197)		0.374* (0.193)
Observations	1,193	1,193	1,193	1,193	1,193	1,193	1,193
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0837	0.0853	0.0561	0.0570	0.0762		0.0774

<i>Panel B: Chinese IPOs in the Hong Kong Market</i>								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(#IPOs)				log(IPO proceeds)			
	Non-mainland		Mainland		Non-mainland		Mainland	
Favored	0.065 (0.164)		0.323* (0.192)		0.597 (0.892)		2.018* (1.194)	
FavorIndex		0.093 (0.110)		0.279** (0.119)		0.747 (0.588)		1.761** (0.714)
Industry Q	-0.116 (0.115)	-0.117 (0.116)	0.006 (0.124)	0.001 (0.124)	-0.691 (0.631)	-0.702 (0.637)	0.169 (0.779)	0.143 (0.780)
Observations	1,325	1,325	1,325	1,325	1,325	1,325	1,325	1,325
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0645	0.0652	0.0250	0.0284	0.0339	0.0348	0.0133	0.0151

Notes: Panel A reports Tobit regressions for Chinese firms listing in the U.S. market during 2002 to 2022. The dependent variables are the natural logarithm of the number of IPOs ($\log(\#IPOs)$), IPO proceeds ($\log(IPO\ proceeds)$), and an IPO occurrence indicator equal to one if at least one IPO occurs in that industry-year. In Panel A, $\log(IPO\ proceeds)$ is $\ln(1 + \text{total IPO proceeds})$ in USD million. Panel B reports Tobit regressions for Chinese firms listing in the Hong Kong market during 2002 to 2024. $\log(\#IPOs)$ is $\ln(1 + \text{number of IPOs})$ at the NAICS 3-digit industry-year level, and $\log(IPO\ proceeds)$ is $\ln(1 + \text{total IPO proceeds})$ in HKD million. Columns (1)–(2) and (5)–(6) use non-mainland issuers; columns (3)–(4) and (7)–(8) use mainland Chinese issuers listing in Hong Kong. In both panels, *Favored* is the binary favored-industry indicator, *FavorIndex* is the cumulative policy emphasis score based on China’s Five-Year Plans, and *Industry Q* is the asset-weighted average Tobin’s Q within industry, winsorized at the 1st and 99th percentiles. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. The Internet Appendix adds *Industry VIE ratio* as a robustness control. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Government's Favored Industry and Firms' Q During IPO

	<i>Dependent variable: Q First Day</i>			
	(1)	(2)	(3)	(4)
Favored	0.348*** (0.094)			
FavorIndex		0.218** (0.078)	0.406*** (0.111)	0.438*** (0.143)
SOE	0.058 (0.053)	0.064 (0.052)	0.024 (0.115)	0.117* (0.057)
ROA	0.014** (0.006)	0.014** (0.006)	-0.008*** (0.003)	-0.008** (0.003)
Leverage	-0.038 (0.057)	-0.040 (0.056)	0.124** (0.044)	0.124** (0.043)
log(Assets)	-0.307*** (0.067)	-0.308*** (0.067)	-1.076*** (0.220)	-1.079*** (0.219)
Small			-3.151*** (0.437)	-3.134*** (0.453)
Medium			-2.167*** (0.296)	-2.151*** (0.311)
FavorIndex × Small			-0.404*** (0.089)	-0.422*** (0.107)
FavorIndex × Medium			-0.291*** (0.054)	-0.305*** (0.060)
FavorIndex × SOE				-0.125 (0.117)
Year FE	Yes	Yes	Yes	Yes
Observations	3,484	3,484	3,484	3,484
Adjusted R ²	0.301	0.302	0.505	0.505

Notes: Standard errors clustered at year and industry level in parentheses. *p<0.1; **p<0.05; ***p<0.01. "FavorIndex" is the number of times the firm's industry is marked as a major supportive industry. "Q First Day" is winsorized at 1% and 99% within each calendar year. "Small" and "Medium" indicate bottom and middle tercile of market capitalization at IPO.

Table 11: Firms' GPA Scores and Q During IPO

	<i>Dependent variable: Q First Day</i>			
	(1)	(2)	(3)	(4)
GPA	0.073*** (0.014)	0.051*** (0.010)	0.052*** (0.012)	0.053*** (0.014)
SOE		0.066 (0.038)	0.017 (0.090)	0.156 (0.306)
ROA		0.014** (0.005)	-0.008** (0.003)	-0.008** (0.004)
Leverage		-0.065 (0.077)	0.081* (0.042)	0.081* (0.043)
log(Assets)		-0.275*** (0.063)	-1.052*** (0.216)	-1.053*** (0.218)
Small			-1.912*** (0.598)	-1.894** (0.623)
Medium			-1.325** (0.577)	-1.309** (0.597)
GPA × Small			-0.045*** (0.012)	-0.046*** (0.012)
GPA × Medium			-0.030* (0.014)	-0.031* (0.015)
GPA × SOE				-0.004 (0.009)
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Observations	3,504	3,504	3,504	3,504
Adjusted R ²	0.269	0.319	0.508	0.507

Notes: Standard errors clustered at year and industry level in parentheses. *p<0.1; **p<0.05; ***p<0.01. "GPA" is scaled by 1000 and winsorized at 1% and 99%, calculated from pre-IPO prospectus. "Q First Day" is winsorized at 1% and 99% within each calendar year. "Small" and "Medium" indicate bottom and middle tercile of market capitalization at IPO.

Table 12: Industrial Policy and Long-Term Abnormal Returns Post IPO

	<i>Dependent variable: BHAR</i>		
	12-month (1)	24-month (2)	36-month (3)
<i>Panel A: Favored Industry (Favored)</i>			
Favored	−3.101 (2.345)	−0.055 (3.033)	6.417 (5.891)
<i>Panel B: Favored Industry (FavorIndex)</i>			
FavorIndex	−0.868 (1.067)	1.203 (1.544)	5.588* (3.171)
<i>Panel C: Firm-Level GPA</i>			
GPA	0.090 (0.248)	0.541 (0.396)	0.506 (0.408)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,005	3,005	3,003

Notes: Standard errors clustered at year level in parentheses. *p<0.1; **p<0.05; ***p<0.01. BHAR is buy-and-hold excess return starting from the first non-hit day price, minus matched firm returns. Controls include SOE, ROA, leverage, log(assets), and IPO Q. Each panel reports a separate regression with the indicated policy measure.

Table 13: AH Premium and Favored Industry and GPA

	AH_premium		
	(1)	(2)	(3)
Favored	-8.036 (9.644)		
FavorIndex		-2.846 (7.052)	
GPA			0.097 (1.079)
SOE	11.259 (12.344)	11.535 (12.557)	14.360 (12.431)
ROA	-4.839*** (0.989)	-4.899*** (1.006)	-3.889*** (0.995)
B/M	-66.898*** (17.882)	-65.965*** (17.933)	-63.895*** (18.089)
log(ME)	-39.087*** (4.820)	-38.582*** (4.958)	-45.347*** (5.202)
Date FE	Yes	Yes	Yes
Ind FE	Yes	No	No
Observations	14,127	14,127	14,127
R ²	0.462	0.461	0.493
Adjusted R ²	0.453	0.452	0.483
Residual Std. Error	77.073 (df = 13882)	77.133 (df = 13882)	74.886 (df = 13871)

Note:

*p<0.1; **p<0.05; ***p<0.01

"AH_premium" are monthly ratios between market capitalization of A-shares (listed in Shanghai or Shenzhen) and the H-shares (Listed in Hong Kong), subtracted by 1 and multiplied by 100. We further winsorize them at 1% and 99% each calendar year. Control variables include "SOE", or whether the firm is a state-owned enterprise, firm's return on assets (ROA), leverage, and the log of total market capitalization (A-shares + H-shares), "log(ME)" and the book-to-market ratios, where the market capitalization is the sum of both A-shares and H-shares. Standard errors are clustered at month and firm level.

Table 14: NEEQ in Favored Industries

VARIABLES	(1) log(#NEEQ)	(2) log(#NEEQ)
Favored	1.233*** (0.113)	
FavorIndex		1.008*** (0.086)
Industry Q	0.077 (0.060)	0.081 (0.059)
log(Industry GDP)	0.371*** (0.048)	0.354*** (0.047)
Constant	-1.756*** (0.465)	-1.630*** (0.457)
Observations	536	536
Year FE	Yes	Yes
Pseudo R-squared	0.235	0.243

Notes: This table presents the results of Tobit regressions analyzing the relationship between NEEQ listing and industry characteristics during 2014 to 2022. The dependent variable is the natural logarithm of the number of listing in the NEEQ market. Independent variables include Favored, a dummy variable indicating whether an industry is policy-favored, and FavorIndex, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles, and log(Industry GDP) measures the industry GDP level in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 15: Bond Issuance in Favored Industries

VARIABLES	(1) log(Bond proceeds)	(2) log(Bond proceeds)	(3) log(#Bond Issues)	(4) log(#Bond Issues)
Favored	1.145*** (0.420)		0.758*** (0.289)	
FavorIndex		0.900*** (0.311)		0.579** (0.225)
Industry Q	-1.315*** (0.298)	-1.304*** (0.297)	-0.859*** (0.196)	-0.852*** (0.196)
log(Industry GDP)	0.729*** (0.196)	0.712*** (0.196)	0.541*** (0.142)	0.530*** (0.143)
Constant	-2.758 (1.763)	-2.630 (1.752)	-2.785** (1.216)	-2.697** (1.213)
Observations	903	903	903	903
year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.112	0.113	0.162	0.161

Notes: This table presents the results of Tobit regressions analyzing the relationship between bond issuance activity and industry characteristics during 2014 to 2021. The dependent variables log(Bond proceeds) and log(#Bond Issues) are defined as $\ln(1 + \text{total corporate bond proceeds in RMB 100 million})$ and $\ln(1 + \text{the number of corporate bond issues})$, respectively. Independent variables include Favored, a dummy variable indicating whether an industry is policy-favored, and FavorIndex, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles, and log(Industry GDP) measures the industry GDP level in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1: Definitions of Variables

Variable	Definition
AH_premium	Monthly A/H market cap premium $(A/H - 1) \times 100$; winsorized at 1%/99% by calendar year.
Assets	Total assets in RMB yuan; level.
B/M	Book-to-market ratio.
BHAR	Buy-and-hold abnormal return from the first non-limit-up day over 12/24/36 months, minus matched benchmark returns; percent.
#Bond Issues	Number of corporate bond issues by industry-year; count.
Bond proceeds	Total corporate bond proceeds by industry-year; measured in RMB 100 million.
#Days to IPO	Calendar days from IPO application acceptance to listing; winsorized at 1%/99% within the sample in the approval-duration analysis.
Favored	Indicator for a policy-favored industry in a given year (industry-year); 1 if the industry receives positive policy emphasis, 0 otherwise. In the baseline implementation, a slightly stricter rule is applied in a small number of borderline mapped cases.
FavorIndex	Technical measure of industry-level policy emphasis constructed from Five-Year Plan texts using the CNRDS policy-text mapping to CSRC 2001 industries. For the plan in force in year t , the measure counts the number of supportive policy references and priority phrases mapped to an industry, with repeated mentions adding to the score. Higher values indicate stronger policy emphasis.
Favored_US	U.S. sample policy-favored industry indicator used in cross-country regressions; 1/0.
GPA	Firm-level policy alignment measure from pre-IPO prospectus text; level. The paper reports this variable uniformly as GPA; some appendix subsidy regressions additionally winsorize GPA at 1%/99% within the regression sample.
Industry GDP	Official industry GDP in year t ; level. Measured in RMB 100 million for China and USD million for the U.S. For China, the series comes from National Bureau of Statistics and provincial statistical yearbooks; for the U.S., from BEA industry accounts. Covers the full industry, not only listed firms.
Industry Q	Asset-weighted industry Tobins Q, lagged one year ($t-1$); winsorized at 1%/99% level.
#IPO applications	Annual number of IPO applications in an industry-year.
#IPOs	Annual number of IPOs in an industry-year.
IPO Occurrence	Indicator for whether at least one IPO occurs in the industry-year; 1/0.
IPO proceeds	Total annual IPO proceeds in an industry-year. It is measured in 10,000 RMB for the mainland China sample, USD million for Chinese firms listing in the U.S., and HKD million for Chinese firms listing in Hong Kong. Zero in industry-years with no IPOs.
Leverage	Total liabilities / shareholders' equity.
ME	Total market capitalization.
Medium	Indicator for middle tercile of market capitalization at IPO among then-listed firms; 1/0.
#NEEQ	Annual number of NEEQ listings in an industry-year; count.
Q First Day	Tobins Q using the first non-limit-up day IPO price; winsorized at 1%/99% within calendar year.
ROA	Return on assets.
SOE	State-owned enterprise indicator; 1 if SOE, else 0.
Small	Indicator for bottom tercile of market capitalization at IPO among then-listed firms; 1/0.

Notes: This table defines the underlying variables in levels. When regressions use logged specifications, the natural log is taken outside the variable definition. For count, proceeds, and duration variables, the logged form is $\ln(1 + x)$, including #Bond Issues, #Days to IPO, #IPO applications, #IPOs, #NEEQ, Bond proceeds, and IPO proceeds. For strictly positive scale variables, the logged form is $\ln(x)$, including Assets, Industry GDP, and ME. Unless otherwise noted, variables are winsorized at the 1st and 99th percentiles in the relevant regression sample.

Industrial Policy *via* the IPO Market

Internet Appendix

Zhiguo He Yiming Qian Xi Sun Wang Renxuan

April 12, 2026

I Industry Policy Measures

I.1 Policy favored industry

We construct two industry-level policy-favor measures: *Favored*, the baseline binary indicator for whether an industry is policy-favored in a given Five-Year Plan, and *FavorIndex*, the corresponding continuous measure of policy-emphasis intensity.

The measure construction begins with candidate industry mentions extracted from the Five-Year Plan text and mapped to CSRC 2001 industry codes. We then manually inspect these candidate mentions in the original policy text. This review first determines whether the mention reflects substantive policy support rather than a neutral, descriptive, or incidental reference, since not every industry mention is coded as favorable. It then verifies the industry mapping itself, because policy language often refers to products, technologies, or broad activity categories rather than formal industry labels, so the mapping to standardized industry codes is not one-to-one.

The underlying *FavorIndex* score is initially assigned to industries based on the CSRC 2001 industry code, which is used for market and regulatory purposes. However, the industry GDP measure is categorized by the GB/T 4754-2017 industry code, which is a different classification system used to categorize economic activities in China. The GB/T 4754-2017 classification system by the National Bureau of Statistics (GB classification hereafter) and the CSRC 2001 classification system do not perfectly match, which necessitates some adjustments to reconcile *FavorIndex* with the GB classification when doing regressions that include industry GDP.¹

For regressions under the GB classification, we then derive the binary variable *Favored* from the mapped

¹Because policy texts do not map one-to-one into industry classifications, the aggregated industry-year *FavorIndex* can occasionally take fractional values even though the underlying measure is discrete.

continuous measure. Specifically, *Favored* is set to 1 if the average *FavorIndex* score across all corresponding CSRC sub-industries exceeds 0.5. If the average score is 0.5 or below, *Favored* is set to 0.

I.2 GPA construction: Matching Time Line

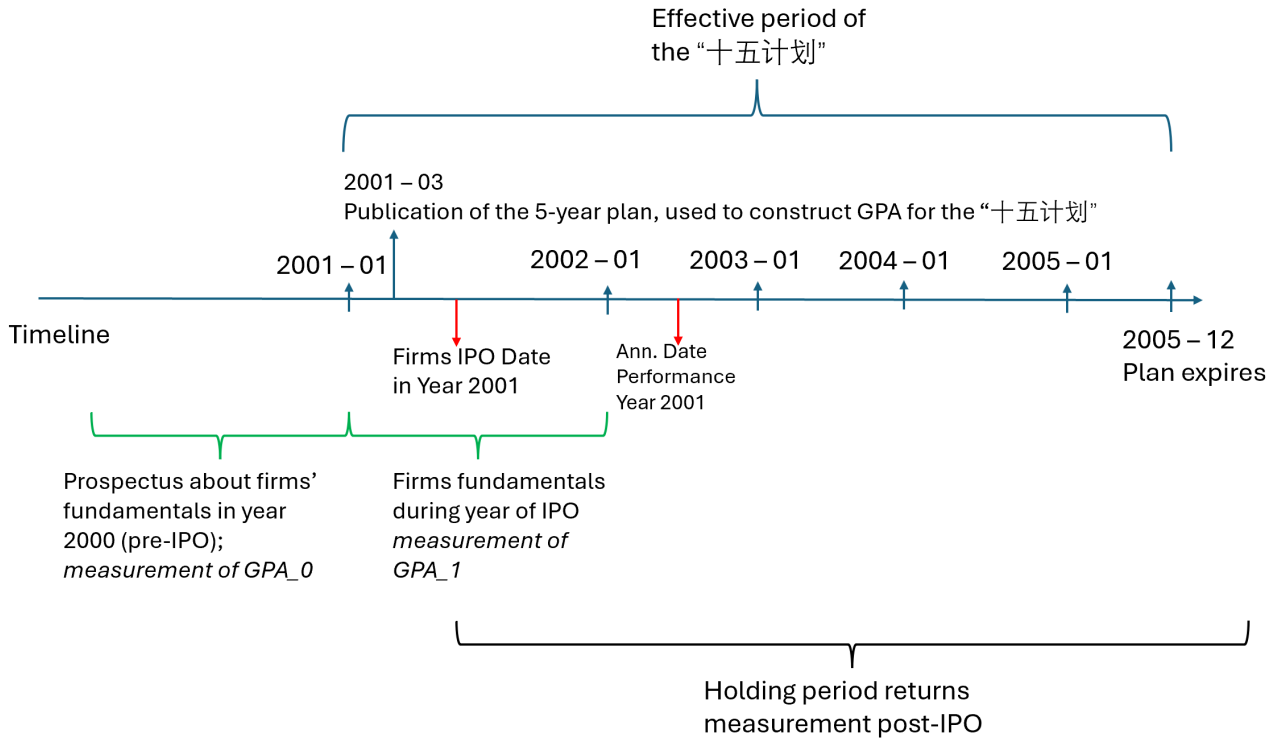


Figure IA1: Timeline Matching of Five-Year Plans, GPA Measurement, and IPO Dates

Two considerations when matching the three sources of data:

1. How do we match the Five-Year Plan with GPA and firm fundamentals? Here we consider two alternative versions.
 - In the baseline specification, we align the policy announcement year with firms whose IPOs occur in that same year; for example, the 2001 announcement of the Tenth Five-Year Plan is matched with firms' GPA and IPOs in 2001.
 - We also run a version in which we push forward the IPO and GPA by one year. In this case, we assume that the market only fully digests the implications of a new Five-Year Plan, and assesses firms' fundamentals accordingly, one year after the announcement.
2. How do we match the GPA measure with firms' IPO dates? Here we also consider two alternative versions.

- We construct firms' GPA measures based on firms' pre-IPO annual reports and examine how the GPA measures are priced during IPO, controlling for firm characteristics from the same pre-IPO annual reports;
- We construct firms' GPA measures based on the firms' IPO-year annual reports, which is announced in the calendar year after the IPO year, controlling for firm characteristics from the same IPO-year annual reports.

I.3 GPA construction

The pioneering work of Mikolov et al. (2013) first introduced this concept and proposed the Word2Vec model. Word embeddings have since become a standard tool for measuring semantic similarity in text and are now widely used in finance and economics research to analyze policy language, firm disclosures, and market sentiment.

For each firm i in year t , we have a set of keywords, $B_{i,t}$, capturing its business scope derived from its annual report $D_{i,t}$. Similarly, the government industrial preference will also be represented by a set of policy words P_t from the corresponding Five-Year Plan. $GPA_{i,t}$ is then a function of $B_{i,t}$ and P_t , calculating the semantic relatedness of the two sets of words, $b \in B_{i,t}$ and $p \in P_t$. This alignment measure hinges on two key elements: the semantic relationship between b and p and the government policy preference, captured by the weights of words ($w_{p \in P_t}$).

To measure the semantic relationship between b and p , we use the cosine similarity of the word embeddings, denoted as $\text{cossim}(b, p)$. These embeddings are vector representations of words within a continuous vector space, designed to convey the meaning and context of words based on their use within a specific corpus. Our paper uses the pre-trained word embedding vectors from Li et al. (2018), which is trained on financial news collected from multiple news websites. Using these embeddings, we calculate the cosine similarity ($\text{cossim}(b, p)$) for each pair of words ($b \in B_{i,t}, p \in P_t$). This cosine similarity, bounded between 0 and 1, quantifies the similarity between the word embeddings of the two words. A higher cosine similarity indicates stronger semantic alignment between a firm's business scope and the policy language.

For each business keyword b , we identify its top alignment potentials by selecting the government policy word (p) that offers the top 10 semantic alignments². Ultimately, the $GPA_{i,t}$ metric is calculated as a weighted sum of these alignment scores, considering all keywords in the firm's business scope:

$$GPA_{i,t} = \sum_{b \in B_{i,t}} w_{b,i,t}^B \cdot \sum_{p \in P_{b,t}^{\text{top}10}} \left(\text{cossim}(b, p) \cdot w_{p,t}^P \right)$$

²Our results remain robust using alternative numbers of top words.

where $B_{i,t}$ is the set of business keywords for firm i at time t , $w_{b,i,t}^B$ is the weight of business keyword b , $P_{b,t}^{top10}$ represents the top 10 government policy words with the highest cosine similarity to business keyword b , $\text{cossim}(b, p)$ is the cosine similarity between business keyword b and government policy word p , $w_{p,t}^P$ is the weight of policy word p at time t . The weight ($w_{b,i,t}^B$) assigned to a business keyword (b) for firm i is determined through a classic Term Frequency-Inverse Document Frequency approach. TF-IDF values are calculated for each keyword and normalized by the sum of TF-IDF values for all keywords in the business scope ($B_{i,t}$) to ensure the weights sum to one.

The weight assigned to each policy word ($w_{p,t}^P$) is a dynamic parameter that is not predetermined. Instead of predefining specific word sets P_t and their associated weights using word frequency, we adaptively calibrate the weights through a supervised binary classification process. For each Five-Year Plan period, we use the industry label Favored to label firms and train a machine-learning model to back out $w_{p,t}^P$ so that it best distinguishes government-supported firms from non-supported ones based on their alignment metric $GPA_{i,t}(\hat{w}_{p,t}^P)$. Model optimization is conducted using the Adam optimizer, updating the estimated policy word weights ($\hat{w}_{p,t}^P$) through backpropagation. By doing so, we can then select the top 100 words from a pool of policy word candidates (P_t^0) consisting of all nouns mentioned in each policy document. We reweight $w_{p,t}^P \in \mathbb{R}^+$ to ensure the weights sum to one. More technical details are discussed in the Internet Appendix.

(a) 10th FYP (2001-2005)



(b) 11th FYP (2006-2010)



(c) 12th FYP (2011-2015)



(d) 13th FYP (2016-2020)



Figure IA2: Word clouds of industrial policy keywords for each Five-Year Plan

I.4 Identifying U.S. Industrial Policy

To construct our measure of U.S. industrial policy and identify policy-favored industries, we employ a hybrid approach combining Large Language Model (LLM) tools with rigorous manual verification.³ The data collection process follows a multi-step pipeline to identify the final list of policies and their corresponding affected industries.

Step 1: Initial Policy Compilation and Review

The data collection process began with establishing an initial, comprehensive list of U.S. industrial policies. We prompted advanced LLMs (ChatGPT-4o and o1, to ensure consistency) to generate a historical list of policies, grounding the models in the OECD definition of industrial policy. The initial prompt used was as follows:

“We define industrial policy based on the definition of OECD (following the link: <https://www.oecd.org/en/topics/policy-issues/industrial-policy.html>): ‘Industrial policy refers to government assistance to businesses to boost or reshape specific economic activities, especially to firms or types of firms based on their activity, technology, location, size or age...’ In your list, please output the following information, each taking up a specific column in a table... Policy Name, Policy Starting Date, Policy End Date, Policy Duration, The industries that are mostly affected, sector codes (NAICS-compatible) of these most affected, the reasons why these sectors are mostly affected, The industries that are least affected, sector codes (NAICS-compatible) of these least affected, the reasons why these sectors are least affected, A brief description of the policy.”

This initial sweep yielded a broad historical list, which was then compiled and further expanded by research assistants to ensure comprehensiveness. For example, we manually added the America COMPETES Act to the list, which the initial sweep didn’t include, because it directs government funding and strategic support to specific sectors, especially semiconductors and advanced manufacturing, in order to strengthen U.S. competitiveness and resilience, which aligns with the OECDs definition.

Subsequently, the coauthor team conducted a rigorous manual review of this expanded list. We excluded items that did not fit the strict definition of industrial policy, such as broad tax cuts (e.g., the Tax Cuts and Jobs Act), financial regulations that neither support nor discourage specific industries (e.g., the Dodd-Frank Act), and policies primarily focused on trade tariffs or regional development. We also restricted the sample to policies active during or relevant to our primary study period. This review process

³While we initially explored extending this analysis to other G7 countries, we ultimately restricted our focus to the U.S. due to the complexities of foreign language policy documents and the idiosyncrasies of individual national legislative frameworks.

established our finalized list of U.S. industrial policies.

Step 2: Identifying Affected Industries

For the finalized list of policies, we systematically identified the affected industries one by one. To ensure accuracy, we relied on Congressional Research Service (CRS) reports as our primary source for policy texts, collecting them from the official Congress website and the EveryCRSReport archive.

We processed these CRS reports using advanced LLMs (such as the DeepSeek model via AI platforms Perplexity and Tencent Yuanbao) to analyze the texts and identify the affected industries and corresponding Standard Industrial Classification (SIC) codes, based on the OSHA SIC Manual (<https://www.osha.gov/data/sic-manual>). The LLMs were employed not only to identify the relevant SIC codes but also to extract the underlying reasoning for why each industry was impacted. During our initial testing, we found that asking the AI to identify both most affected and least affected industries was inefficient, as the AI simply listed sectors unlikely to be affected at all, which was uninformative. Consequently, we refined our prompt to focus exclusively on significantly affected industries:

“According to the uploaded document, list SIC Industries (including their SIC code) are affected by [Policy Name] significantly and the corresponding selection reasons.”

Step 3: Manual Verification and Refinement

Recognizing that AI-generated outputs can sometimes hallucinate specific industry targets or miss relevant ones, we subjected the LLM outputs to a strict manual verification process that underwent approximately eight iterations of peer review among the research team.

First, we verified the policy dates. We used GPT models to cross-check policy start and end dates against official sources, leading to several critical corrections (e.g., refining the end dates for the American Recovery and Reinvestment Act). Specifically, a policy’s start date was defined as the date of final approval or its effective date. For the end date, since most acts do not have a clearly defined expiration, we determined it based on when the allocated budget was exhausted or when the act was superseded by an amended version; policies without a clear end date were treated as ongoing.

Second, we rigorously verified the industry mappings. We cross-referenced the AI-identified keywords and SIC codes with the original CRS reports to verify whether the policy genuinely affected the suggested industries, and to check if any industries mentioned in the document were missed by the AI. Every SIC name and code linked to a specific commodity or industry keyword (e.g., "solar cells") generated by AI or shown in the original CRS reports was manually verified against official industry classification databases

(such as SICCODE.com), as demonstrated in Figure IA4. An industry was only classified as policy-favored if we could verify direct, material support in the text. This rigorous standard required extracting specific, substantiating quotes directly from the CRS reports for each mapped industry. Figure IA3 illustrates an example of this manual verification spreadsheet, showing the cross-referencing of SIC codes with OSHA descriptions and these direct quotes from the CRS reports.

		systems engaged in the collection and disposal of garbage, sewage, and other wastes by means of destroying or processing materials, are also included.		
3674	Semiconductors and Related Devices	Establishments primarily engaged in manufacturing semiconductors and related solid-state devices. Important products of this industry are semiconductor diodes and stacks, including rectifiers, integrated microcircuits (semiconductor networks), transistors, solar cells, and light sensing and emitting semi-conductor (solid-state) devices.	https://www.osha.gov/sic-manual/3674	A member of the National Academies committee has provided two illustrations of what ARPA-E might fund. The first is a new class of inexpensive, efficient, and long lasting solar cells created using novel materials manufactured with thin-film technologies or nano-particle devices that convert sunlight.
3691	Storage Batteries	Establishments primarily engaged in manufacturing storage batteries.	https://www.osha.gov/sic-manual/3691	The bill also includes an additional \$5 million from the previous appropriation. The following statement is in the Consolidated Appropriations Act joint explanatory statement: "Of the amounts provided to ITS [Industrial Technology Services], \$65,200,000 is for the Technology Innovation Program as authorized by Public Law 110-49 [the America COMPETES Act]. TIP is structured to fund high-risk, high reward research focused on broad national needs such as advanced automotive batteries, aquaculture, novel lightweight materials, and other emerging technologies.
3761	Guided Missiles and Space Vehicles	Establishments primarily engaged in manufacturing complete guided missiles and space vehicles. This industry also includes establishments owned by guided missile and space vehicle manufacturers and primarily engaged in research and	https://www.osha.gov/sic-manual/3761	The Act also expresses the sense of the Congress that "robust" funding of NASA, at the levels authorized in the National Aeronautics and Space Act of 2005 (P.L. 109-55) and subsequent years, would allow NASA to contribute significantly to U.S. innovation and competitiveness, enable a fair balance of funding among its science, aeronautics, education, exploration, and human space flight

Figure IA3: Manual Verification Spreadsheet

Note: This figure shows the manual verification process for the America COMPETES Act (2007). It cross-references AI-suggested SIC codes (e.g., 3674 Semiconductors) with OSHA industry descriptions and specific, manually verified quotes from the corresponding CRS report.

(a) Keyword Search

The screenshot shows the SICCODE.com website with a search bar containing 'solar cells'. Below the search bar, there are two columns of results: 'Matching SIC Codes' and 'Matching NAICS Codes'. The SIC codes listed include 3674 - Semiconductors and Related Devices, 4911 - Electric Services, 2296 - Tire Cord and Fabrics, 2821 - Plastics Materials, Synthetic Resins, and Nonvulcanizable Elastomers, and 2823 - Cellulosic Manmade Fibers. The NAICS codes listed include 22114 - Solar Electric Power Generation, 334413 - Semiconductor and Related Device Manufacturing, 335910 - Battery Manufacturing, 238100 - Roofing Contractors, and 237130 - Power and Communication Line and Related Structures Construction.

(b) SIC Code Details

The screenshot shows the details for SIC Code 3674 - Semiconductors and Related Devices. It includes statistics for Total Companies (1,380) and Est. Employment (75,847). There are options to 'BUY BUSINESS LIST' and 'Use Data For' (Direct Mailing, Enabling, Calling, Research). A description states: 'Establishments primarily engaged in manufacturing semiconductors and related solid-state devices. Important products of this industry are semiconductor diodes and stacks, including rectifiers, integrated microcircuits (semiconductor networks), transistors, solar cells, and light sensing and emitting semiconductor (solid-state) devices.' It also notes that SIC Code 3674 is a final level code of the 'Manufacturing' Division.

Figure IA4: Industry Classification Verification

Note: These panels illustrate the manual verification of AI-generated keywords (e.g., "solar cells") against the official SIC classification system to confirm the appropriate 4-digit SIC codes.

During this manual review, we further refined the data in several key ways. First, we excluded broad or irrelevant initiatives that lacked specific industry support or did not meet the strict definition of an industrial policy. For example, while early AI-related policies were reviewed, both the American AI Initiative and the National AI Initiative Act of 2020 were ultimately excluded for lacking specific industry-level funding arrangements (see Figure IA5 for an illustration of the review process). The "21st Century Auto Plan" was removed because it was a company-specific plan rather than a federal policy, and the Cybersecurity Information Sharing Act was dropped for lacking sufficient industrial-policy relevance. Second, we manually dropped industries flagged by the AI as only marginally affected to ensure our measure captured economically meaningful policy support. Finally, when CRS reports provided explicit funding breakdowns (such

as the budget titles in the Agricultural Act of 2014, shown in Figure IA6), we prioritized the industries receiving the largest shares of mandatory program outlays.

American AI Initiative				An outlook of AI application on healthcare, agriculture, energy, etc, which were mentioned in previous policies. No material support for any industry.	https://www.whitehouse.gov/wp-content/uploads/2020/02/American-AI-Initiative-One-Year-Annual-Report.pdf
National AI Initiative Act of 2020			AT11 Motor Vehicles and Passenger Car Bodies	A comprehensive law about the coordination of AI-related departments. No specific arrangements of fund on various industries, but on these departments in following fiscal years.	https://www.congress.gov/116/bills/1/r6216/BILLS-116-6216-enr.pdf

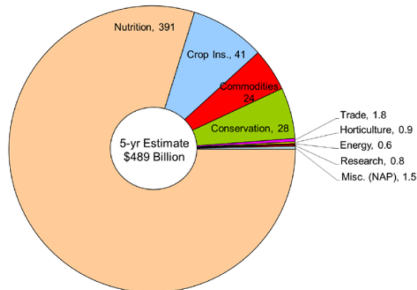
Figure IA5: Review and Exclusion of Broad Initiatives

Note: This excerpt from the verification spreadsheet illustrates the rigorous review process. Broad initiatives lacking specific industry-level funding, such as the American AI Initiative and the National AI Initiative Act of 2020, were ultimately excluded.

The overwhelming share (99%) of estimated total net outlays is anticipated for four farm bill titles: nutrition, crop insurance, conservation, and farm commodity support (Figure 1). Of the projected net outlays, about 80% is for the Supplemental Nutrition Assistance Program (SNAP). Farm commodity support and crop insurance are expected to account for 13% of mandatory program costs, with another 6% of costs in USDA conservation programs. Programs in all other farm bill titles are expected to account for about 1% of all mandatory expenditures.

CBO estimated that the total cost of mandatory programs in the 2014 farm bill would be \$489 billion over the next five years (FY2014-FY2018).

Figure 1. Share of Projected Outlays, 2014 Farm Bill (billions of dollars, FY2014-FY2018)



Source: CRS, using CBO's 2014 farm bill cost estimates.

Table 1. 2014 Farm Bill Budget, by Title (P.L. 113-79) (millions of dollars, FY2014-FY2018)

2014 Farm Bill Titles	CBO baseline FY2014-FY2018	CBO Score (chg. to baseline)	Projected Outlays (Baseline + Score)	Share
I Commodities	29,888	-6,332	23,556	4.8%
II Conservation	28,373	-208	28,165	5.8%
III Trade	1,718	+64	1,782	0.4%
IV Nutrition	393,930	-3,280	390,650	79.9%
V Credit	-1,011	+0	-1,011	-0.2%
VI Rural Dev.	13	+205	218	0.04%
VII Research	111	+689	800	0.2%
VIII Forestry	3	+5	8	<0.1%
IX Energy	84	+541	625	0.1%
X Horticulture	536	+338	874	0.2%
XI Crop Ins.	39,592	+1,828	41,420	8.5%
XII Misc. (NAP)	705	+839	1,544	0.3%
Total, Direct Spending	493,941	-5,310	488,631	100%

Source: CRS, using the CBO baseline and 2014 farm bill cost estimates (<http://www.cbo.gov/publication/45049>); CBO, "May 2013 Baseline for the 2008 Farm Bill Programs and Provisions, by Title," unpublished, May 2013; and "Updated Budget Projections: Fiscal Years 2013 to 2023," May 14, 2013 (<http://cbo.gov/publication/44172>). Reflects mandatory outlays in millions of dollars (FY2014-FY2018).

For more information, see CRS Report R43076, *The 2014*

Figure IA6: Prioritizing Industries by Funding Breakdown

Note: When available, explicit funding breakdowns in CRS reports (such as the 2014 Farm Bill budget shown here) were used to identify and prioritize the most heavily supported sectors.

Following this rigorous, multi-iteration procedure, the co-author team conducted a final, comprehensive manual review of the policies and their affected industries. This final review refined the list to ensure only the most robust and directly targeted policies were included, ultimately yielding a final sample of 15 major U.S. industrial policies. These policies, spanning technology, energy, agriculture, manufacturing, and infrastructure, are detailed in Table IA1. This rigorous process ensures that our Favored_US indicator accurately reflects targeted, material industrial policy interventions in the U.S. market.

Table IA1: Final List of U.S. Industrial Policies

Policy Name	Start	End	Affected SIC Industries
America COMPETES Act (2007)	2007-08	2010-09	49 (Electric, Gas, and Sanitary Services), 3674 (Semiconductors and Related Devices), 3691 (Storage Batteries), 3761 (Guided Missiles and Space Vehicles), 7371 (Computer Programming Services)
America COMPETES Act (2010)	2011-01	2013-09	7371 (Computer Programming Services), 8731 (Commercial Physical and Biological Research), 9661 (Space and Research and Technology), 49 (Electric, Gas, and Sanitary Services)
The American Recovery and Reinvestment Act	2009-02	2010	49 (Electric, Gas, and Sanitary Services), 16 (Heavy Construction Other Than Building Construction Contractors), 40 (Railroad Transportation), 41 (Local and Suburban Transit and Interurban Highway Passenger Transportation), 82 (Educational Services), 01 (Agricultural Production Crops), 80 (Health Services)
CHIPS and Science Act	2022-08	2027-09	3674 (Semiconductors and Related Devices), 3572 (Computer Storage Devices), 3571 (Electronic Computers), 4812 (Radiotelephone Communications)
Energy Independence and Security Act	2007-12	Ongoing	371 (Motor Vehicles and Motor Vehicle Equipment), 2911 (Petroleum Refining), 3632 (Household Refrigerators and Home and Farm Freezers)
Inflation Reduction Act	2022-08	Ongoing	4911 (Electric Services), 371 (Motor Vehicles and Motor Vehicle Equipment), 2834 (Pharmaceutical Preparations), 152 (General Building Contractors-Residential)
Energy Policy Act	2005-08	Ongoing	4911 (Electric Services), 4923 (Natural Gas Transmission and Distribution), 1311 (Crude Petroleum and Natural Gas), 2911 (Petroleum Refining), 12 (Coal Mining)
Advanced Manufacturing Partnership	2011-06	Ongoing	3691 (Storage Batteries), 3441 (Fabricated Structural Metal), 2836 (Biological Products, Except Diagnostic Substances), 3569 (General Industrial Machinery and Equipment, Not Elsewhere), 3339 (Primary Smelting and Refining of Nonferrous Metals, Except Copper and Aluminum)
Revitalize American Manufacturing and Innovation Act of 2014	2014-12	Ongoing	367 (Electronic Components and Accessories), 3571 (Electronic Computers), 3827 (Optical Instruments and Lenses), 2836 (Biological Products, Except Diagnostic Substances)
Federal Agriculture Improvement and Reform Act of 1996 (FAIR)	1996-04	2002-09	01 (Agricultural Production Crops), 0241 (Dairy Farms), 6351 (Surety Insurance)
Farm Security and Rural Investment Act of 2002	2002-05	2007-09	01 (Agricultural Production Crops), 0241 (Dairy Farms), 021 (Livestock, Except Dairy and Poultry), 0811 (Timber Tracts), 2869 (Industrial Organic Chemicals, Not Elsewhere Classified)
The Food, Conservation, and Energy Act of 2008	2008-06	2013-09	01 (Agricultural Production Crops), 0241 (Dairy Farms), 021 (Livestock, Except Dairy and Poultry), 2061 (Cane Sugar, Except Refining), 2869 (Industrial Organic Chemicals, Not Elsewhere Classified), 2879 (Pesticides and Agricultural Chemicals, Not Elsewhere Classified), 6351 (Surety Insurance)
Agricultural Act of 2014	2014-02	2018-09	01 (Agricultural Production Crops), 0241 (Dairy Farms), 2061 (Cane Sugar, Except Refining), 20 (Food and Kindred Products), 6351 (Surety Insurance)
The Agriculture Improvement Act of 2018	2018-12	2025-09	01 (Agricultural Production Crops), 2879 (Pesticides and Agricultural Chemicals, Not Elsewhere Classified), 0241 (Dairy Farms), 2899 (Chemicals and Chemical Preparations, Not Elsewhere Classified)
Infrastructure Investment and Jobs Act	2021-11	2026-09	4941 (Water Supply), 4952 (Sewerage Systems), 1623 (Water, Sewer, Pipeline, and Communications and Power Line Construction)

Note: This table lists the 15 major U.S. industrial policies identified through our LLM-assisted and manually verified procedure, finalized after a rigorous review by the co-author team. The affected SIC industries were mapped based on direct, verifiable evidence of support in Congressional Research Service (CRS) reports.

II Additional Results

II.1 Cross-Country Comparative Evidence

Table IA2 complements Figure 2 in the paper. In particular, column (1) of Table IA2 corresponds to the residualized China specification underlying Figure 2: the figure visualizes the residual distribution of $\log(\#IPOs)$ after controlling for industry Q , industry GDP, and year fixed effects. The remaining columns extend that same comparison to IPO proceeds in China and to the corresponding U.S. specifications. The role of this table is descriptive: it shows that U.S. IPO activity is much more tightly related to industry Q , whereas in China IPO activity is less tightly linked to standard market fundamentals.

Table IA2: IPO Activity across Industries

VARIABLES	China		U.S.	
	(1) log(#IPOs)	(2) log(IPO proceeds)	(3) log(#IPOs)	(4) log(IPO proceeds)
Industry Q	-0.038 (0.137)	-0.536 (0.903)	0.593*** (0.227)	1.698** (0.710)
log(Industry GDP)	0.260** (0.110)	1.229** (0.561)	0.672*** (0.118)	2.509*** (0.401)
Constant	-2.198** (0.964)	-6.799 (5.121)	-9.032*** (1.431)	-32.620*** (4.714)
Observations	1,044	1,044	1,188	1,188
year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0571	0.0225	0.134	0.0657

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics for the sample period from 2002 to 2022. The year 2013 is excluded due to the suspension of IPOs in China. The dependent variables are the natural logarithm of the number of IPOs ($\log(\#IPOs)$) and the natural logarithm of IPO proceeds ($\log(IPO\ proceeds)$) in the given year and industry. In the China columns, IPO proceeds are measured in RMB 10,000; in the U.S. columns, IPO proceeds are measured in USD million. Industry Q represents lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles. $\log(Industry\ GDP)$ measures the log of official industry GDP in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

II.2 Marginal Effects for Tobit Specifications

The baseline industry-level capital-allocation specifications in the paper use Tobit models because many industry-year cells have zero issuance or listing activity. The tables in this subsection therefore report marginal effects for the corresponding Tobit estimates rather than the latent-index coefficients themselves. In each table, Panel A reports average marginal effects on the observed outcome $E[y|x]$, Panel B reports average marginal effects on the probability of positive activity $Pr(y > 0|x)$, and Panel C reports average marginal effects on the conditional expectation among positive observations $E[y|y > 0, x]$.

Table IA4 complements Table 5 and Figure 3 in the paper. The paper uses separate-subperiod Tobit coefficients and a pooled interaction figure to show that the IPO effect of policy favor strengthens over

Table IA3: Marginal Effects for Baseline IPO Activity (Table 4 in the paper)

VARIABLES	(1) log(#IPOs)	(2) log(#IPOs)	(3) log(IPO proceeds)	(4) log(IPO proceeds)
<i>Panel A: $E[y x]$</i>				
Favored	0.665*** (0.199)		3.122*** (0.972)	
FavorIndex		0.482*** (0.126)		2.299*** (0.638)
Industry Q	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,044	1,044	1,044	1,044
<i>Panel B: $Pr(y>0 x)$</i>				
Favored	0.253*** (0.056)		0.152*** (0.044)	
FavorIndex		0.217*** (0.050)		0.125*** (0.036)
Industry Q	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,044	1,044	1,044	1,044
<i>Panel C: $E[y y>0,x]$</i>				
Favored	0.493*** (0.153)		2.276*** (0.722)	
FavorIndex		0.360*** (0.099)		1.673*** (0.474)
Industry Q	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,044	1,044	1,044	1,044

Notes: This table reports marginal effects implied by the baseline Tobit regressions in Table 4 in the paper. Panel A reports average marginal effects on the observed outcome $E[y|x]$. Panel B reports average marginal effects on the probability that the industry-year has positive IPO activity, $Pr(y > 0|x)$. Panel C reports average marginal effects on the expected outcome conditional on positive IPO activity, $E[y|y > 0, x]$. The dependent variables are $\log(1 + \#IPOs)$ and $\log(1 + IPO\ proceeds)$. Controls, sample window, fixed effects, and clustering follow the corresponding baseline Tobit specifications in the paper.

time. This appendix table reports the corresponding Tobit marginal effects by Five-Year Plan window. Its role is to show that the monotonic time pattern remains visible when the results are expressed as total, extensive, and intensive-margin effects rather than raw Tobit coefficients.

II.3 Robustness Checks

Table IA8 complements Figure 2 in the paper and Table IA2 in this appendix. While Figure 2 and Table IA2 rely on Tobit specifications because many industry-year cells have zero IPO activity, this table shows that the broad cross-country contrast is not driven solely by that censoring assumption. Its role is to verify that the stronger U.S. link between IPO activity and industry fundamentals also appears in a linear OLS specification.

Table IA9 corresponds to Table 4 in the paper. The paper presents the baseline favored-industry results

Table IA4: Marginal effects of policy favor on log(#IPOs): by subperiod

VARIABLES	2002–2005 log(#IPOs)	2006–2010 log(#IPOs)	2011–2015 log(#IPOs)	2016–2020 log(#IPOs)	2021–2022 log(#IPOs)
<i>Panel A: E[y x]</i>					
Favored	0.013 (0.116)	0.477** (0.204)	0.678** (0.268)	0.859*** (0.301)	1.736*** (0.267)
FavorIndex	0.006 (0.104)	0.268* (0.150)	0.447** (0.178)	0.749*** (0.141)	1.035*** (0.184)
Industry Q	Yes	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	130	268	228	298	120
<i>Panel B: Pr(y>0 x)</i>					
Favored	0.009 (0.083)	0.215*** (0.076)	0.254*** (0.077)	0.281*** (0.074)	0.358*** (0.062)
FavorIndex	0.005 (0.075)	0.138* (0.074)	0.201*** (0.076)	0.309*** (0.059)	0.360*** (0.068)
Industry Q	Yes	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	130	268	228	298	120
<i>Panel C: E[y y>0,x]</i>					
Favored	0.011 (0.095)	0.352** (0.154)	0.499** (0.207)	0.631*** (0.234)	1.405*** (0.242)
FavorIndex	0.005 (0.086)	0.198* (0.113)	0.329** (0.138)	0.564*** (0.116)	0.797*** (0.153)
Industry Q	Yes	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	130	268	228	298	120

Notes: This table reports Tobit marginal effects for IPO activity estimated separately by Five-Year Plan window. Panel A reports total effects, Panel B reports extensive-margin effects, and Panel C reports intensive-margin effects. The dependent variable is $\log(1 + \text{\#IPOs})$. *Favored* is the binary favored-industry indicator and is estimated as a 0-to-1 discrete change; *FavorIndex* is the continuous policy-emphasis measure and is reported as a marginal effect with respect to a one-unit increase. *Industry Q* is lagged industry Tobin's Q and is winsorized at the 1st and 99th percentiles. $\log(\text{Industry GDP})$ is the logarithm of industry GDP. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. The sample covers 2002 to 2022, excluding 2013. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

using Tobit to account for the mass of zeros in IPO activity; this appendix table asks whether the qualitative pattern survives in a linear specification. Its role is therefore a robustness check on the sign and relative magnitude of the policy-favor effects rather than a preferred replacement for the baseline estimator.

Table IA10 corresponds to Table 9 in the paper. The paper uses Chinese IPOs in the U.S. and Hong Kong markets as a placebo comparison, asking whether policy favor also predicts capital allocation outside the mainland IPO system. This appendix table adds *Industry VIE ratio* to that specification to absorb industry-specific offshore-listing propensity. Its role is to show that the placebo result is not driven by favored industries being mechanically more likely to list abroad through VIE-friendly structures.

Table IA11 complements Table 5 and Figure 3 in the paper. The paper focuses on the time pattern for IPO counts; this appendix table shows that the same monotonic strengthening also appears for IPO proceeds. Its role is to confirm that policy-favored industries not only list more frequently over time but also raise more capital over time.

Table IA12 extends Tables 10 and 11 in the paper. Those tables show that both industry-level policy favor and firm-level GPA are associated with higher IPO valuation; this appendix table asks whether that valuation effect varies across Five-Year Plan windows. Its role is to show when the valuation effect is

Table IA5: Marginal Effects for IPO Applications (Panel B of Table 7 in the paper)

VARIABLES	(1) log(#IPO applications)	(2) log(#IPO applications)
<i>Panel A: E[y x]</i>		
Favored	0.965*** (0.278)	
FavorIndex		0.790*** (0.157)
Industry Q	Yes	Yes
log(Industry GDP)	Yes	Yes
Year FE	Yes	Yes
Observations	476	476
<i>Panel B: Pr(y>0 x)</i>		
Favored	0.222*** (0.048)	
FavorIndex		0.243*** (0.050)
Industry Q	Yes	Yes
log(Industry GDP)	Yes	Yes
Year FE	Yes	Yes
Observations	476	476
<i>Panel C: E[y y>0, x]</i>		
Favored	0.745*** (0.232)	
FavorIndex		0.604*** (0.129)
Industry Q	Yes	Yes
log(Industry GDP)	Yes	Yes
Year FE	Yes	Yes
Observations	476	476

Notes: This table reports marginal effects implied by the Tobit regression in Panel B of Table 7 in the paper. The dependent variable is $\log(1 + \text{\#IPO applications})$ at the industry-year level. Panel A reports average marginal effects on $E[y|x]$, Panel B on $Pr(y > 0|x)$, and Panel C on $E[y|y > 0, x]$. Controls, sample window, fixed effects, and clustering follow the corresponding Tobit specification in the paper.

Table IA6: Marginal Effects for NEEQ Listings (Table 14 in the paper)

VARIABLES	(1) log(#NEEQ)	(2) log(#NEEQ)
<i>Panel A: $E[y x]$</i>		
Favored	1.062*** (0.233)	
FavorIndex		0.814*** (0.145)
Industry Q	Yes	Yes
log(Industry GDP)	Yes	Yes
Year FE	Yes	Yes
Observations	536	536
<i>Panel B: $Pr(y > 0 x)$</i>		
Favored	0.173*** (0.031)	
FavorIndex		0.166*** (0.031)
Industry Q	Yes	Yes
log(Industry GDP)	Yes	Yes
Year FE	Yes	Yes
Observations	536	536
<i>Panel C: $E[y y > 0, x]$</i>		
Favored	0.919*** (0.209)	
FavorIndex		0.700*** (0.128)
Industry Q	Yes	Yes
log(Industry GDP)	Yes	Yes
Year FE	Yes	Yes
Observations	536	536

Notes: This table reports marginal effects implied by the Tobit regressions in Table 14 in the paper. The dependent variable is $\log(1 + \text{\#NEEQ listings})$ at the industry-year level. Panel A reports average marginal effects on $E[y|x]$, Panel B on $Pr(y > 0|x)$, and Panel C on $E[y|y > 0, x]$. Controls, sample window, fixed effects, and clustering follow the corresponding Tobit specification in the paper.

Table IA7: Marginal Effects for Bond Issuance (Table 15 in the paper)

VARIABLES	(1)	(2)	(3)	(4)
	log(Bond proceeds)	log(Bond proceeds)	log(#Bond Issues)	log(#Bond Issues)
<i>Panel A: E[y x]</i>				
Favored	1.071*** (0.392)		0.687*** (0.264)	
FavorIndex		0.830*** (0.280)		0.514*** (0.197)
Industry Q	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	903	903	903	903
<i>Panel B: Pr(y>0 x)</i>				
Favored	0.049** (0.020)		0.065*** (0.024)	
FavorIndex		0.045** (0.020)		0.056** (0.024)
Industry Q	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	903	903	903	903
<i>Panel C: E[y y>0, x]</i>				
Favored	0.963*** (0.354)		0.609*** (0.236)	
FavorIndex		0.735*** (0.245)		0.450*** (0.171)
Industry Q	Yes	Yes	Yes	Yes
log(Industry GDP)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	903	903	903	903

Notes: This table reports marginal effects implied by the Tobit regressions in Table 15 in the paper. The dependent variables are log(1 + Bond proceeds) and log(1 + #Bond issues). Panel A reports average marginal effects on $E[y|x]$, Panel B on $Pr(y > 0|x)$, and Panel C on $E[y|y > 0, x]$. Controls, sample window, fixed effects, and clustering follow the corresponding Tobit specification in the paper.

Table IA8: IPO activity and industry GDP – OLS

VARIABLES	China		U.S.	
	(1) log(IPO proceeds)	(2) log(#IPOs)	(3) log(IPO proceeds)	(4) log(#IPOs)
Industry Q	-0.330 (0.522)	-0.013 (0.083)	0.941** (0.427)	0.373** (0.156)
log(Industry GDP)	0.724** (0.349)	0.168** (0.074)	1.246*** (0.210)	0.343*** (0.068)
Constant	0.296 (3.024)	-0.938 (0.604)	-13.859*** (2.389)	-4.132*** (0.816)
Observations	1,044	1,044	1,188	1,188
R-squared	0.106	0.149	0.231	0.294
year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of OLS regressions analyzing the relationship between IPO activity and industry characteristics in China and the U.S. IPO activity is proxied by the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. In the China columns, IPO proceeds are measured in RMB 10,000; in the U.S. columns, IPO proceeds are measured in USD million. log(Industry GDP) measures official industry GDP in that year. Industry Q is lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles. Columns (1) and (2) present the regression results for China, while columns (3) and (4) present the results for the U.S. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IA9: IPO activity in favored industries – OLS

VARIABLES	(1)	(2)	(3)	(4)
	log(#IPOs)	log(#IPOs)	log(IPO proceeds)	log(IPO proceeds)
Favored	0.683*** (0.232)		2.512** (1.021)	
FavorIndex		0.566*** (0.185)		2.022** (0.779)
Industry Q	0.014 (0.101)	0.023 (0.100)	0.142 (0.690)	0.182 (0.686)
log(Industry GDP)	0.146** (0.061)	0.142** (0.061)	0.998** (0.423)	0.986** (0.425)
Constant	-1.054* (0.512)	-0.993* (0.512)	-3.522 (3.250)	-3.310 (3.280)
Observations	848	848	848	848
R-squared	0.264	0.275	0.155	0.157
Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of OLS regressions analyzing the relationship between IPO activity and industry characteristics for the sample period from 2002 to 2021. The year 2013 is excluded due to the suspension of IPOs. The dependent variables are the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. Favored is the binary favored-industry indicator. FavorIndex represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. Industry Q represents lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles, and log(Industry GDP) measures the industry GDP level in that year. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

strongest and whether the time variation differs across the industry-level and firm-level policy measures.

Table IA13 corresponds to Table 13 in the paper. The paper shows that policy-aligned firms command a different cross-market valuation in the A-H sample on average; this appendix table splits that evidence by subperiod. Its role is to show whether the A-H premium effect is concentrated in earlier policy regimes or persists into later periods.

Table IA10: Chinese IPOs Outside Mainland China: Controlling for Industry VIE Ratio

<i>Panel A: Chinese IPOs in the U.S. Market</i>							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(6)
	log(#IPOs)		log(IPO proceeds)		IPO Occurrence		
Favored	0.239 (0.184)		1.327 (0.904)		0.264 (0.190)		
FavorIndex		0.203 (0.139)		1.040 (0.660)			0.209 (0.137)
Industry Q	0.247 (0.180)	0.249 (0.177)	1.219 (0.875)	1.240 (0.865)	0.229 (0.186)		0.233 (0.184)
Industry VIE ratio	2.841*** (0.729)	2.843*** (0.720)	14.879*** (3.432)	14.869*** (3.380)	3.037*** (0.727)		3.036*** (0.716)
Observations	1,158	1,158	1,158	1,158	1,158		1,158
Year FE	Yes	Yes	Yes	Yes	Yes		Yes
Pseudo R-squared	0.126	0.127	0.0858	0.0866	0.115		0.116

<i>Panel B: Chinese IPOs in the Hong Kong Market</i>								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(#IPOs)		log(IPO proceeds)		log(IPO proceeds)			
	Non-mainland	Mainland	Non-mainland	Mainland	Non-mainland	Mainland		
Favored	0.050 (0.162)		0.326* (0.193)		0.503 (0.881)		2.028* (1.199)	
FavorIndex		0.085 (0.109)		0.277** (0.120)		0.700 (0.579)		1.744** (0.723)
Industry Q	-0.086 (0.115)	-0.087 (0.116)	-0.009 (0.136)	-0.013 (0.135)	-0.529 (0.635)	-0.539 (0.641)	0.092 (0.860)	0.067 (0.858)
Industry VIE ratio	-0.680 (0.595)	-0.693 (0.618)	1.391*** (0.432)	1.369*** (0.426)	-3.987 (3.288)	-4.099 (3.458)	8.727*** (3.176)	8.596*** (3.050)
Observations	1,307	1,307	1,307	1,307	1,307	1,307	1,307	1,307
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0660	0.0667	0.0276	0.0309	0.0347	0.0355	0.0146	0.0164

Notes: This table re-estimates the overseas IPO placebo regressions with Industry VIE ratio included as an additional control. Panel A reports Tobit regressions for Chinese firms listing in the U.S. market during 2002 to 2022, where $\log(\text{IPO proceeds})$ is $\ln(1 + \text{total IPO proceeds})$ in USD million. Panel B reports Tobit regressions for Chinese firms listing in the Hong Kong market during 2002 to 2024, with columns (1)–(2) and (5)–(6) using non-mainland issuers and columns (3)–(4) and (7)–(8) using mainland Chinese issuers listing in Hong Kong; in Panel B, $\log(\text{IPO proceeds})$ is $\ln(1 + \text{total IPO proceeds})$ in HKD million. Industry VIE ratio is constructed at the year \times NAICS 3-digit industry level using the stock of already listed Chinese firms. Its numerator is the number of already listed Chinese firms in that cell that use VIE structures, and its denominator is the total number of already listed Chinese firms in the same cell, so the measure is a ratio in $[0, 1]$. We merge this ratio to the overseas-listing industry-year panel by year and NAICS code and use it as a proxy for industry-specific offshore-listing propensity. Industry Q continues to be winsorized at the 1st and 99th percentiles. Other variable definitions, fixed effects, and standard errors follow Table 9. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IA11: $\log(\text{IPO proceeds})$ in favored industries: by subperiod

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2002-2005	2002-2005	2006-2010	2006-2010	2011-2015	2011-2015	2016-2021	2016-2021
Favored	1.815 (3.596)		4.098** (1.812)		3.782 (3.081)		4.948*** (1.848)	
FavorIndex		1.406 (2.827)		3.201** (1.370)		2.345 (2.156)		4.356*** (1.227)
Industry Q	-15.289 (18.416)	-15.392 (18.497)	-1.845 (1.398)	-1.623 (1.252)	-1.103 (1.759)	-0.891 (1.715)	1.771* (0.970)	1.736* (0.965)
$\log(\text{Industry GDP})$	5.188*** (0.416) (0.503)	5.296*** (0.454) (0.509)	1.132** (0.564) (0.091)	1.108* (0.588) (0.091)	1.091 (0.665) (0.724)	1.020 (0.642) (5.905)	1.979*** (0.631) (0.190)	1.929*** (0.625) (6.298)
Observations	117	117	229	229	197	197	305	305
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents Tobit regression results analyzing the relationship between IPO activity and industry characteristics over different subperiods, corresponding to China's Five-Year Plans, from 2002 to 2021 (excluding 2013 due to the suspension of IPOs). The dependent variable is the natural logarithm of IPO proceeds ($\log(\text{IPO proceeds})$). Favored is the binary favored-industry indicator, and FavorIndex is the cumulative policy emphasis score based on the frequency of priority terms in China's Five-Year Plans. $\log(\text{Industry GDP})$ represents the industry GDP level in that year, and Industry Q is lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry and is winsorized at the 1st and 99th percentiles. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IA12: Sub-period Analysis: Industrial Policy and IPO Valuation

	<i>Dependent variable: Q First Day</i>				
	Full Sample (1)	2002–05 (2)	2006–10 (3)	2011–15 (4)	2016–21 (5)
<i>Panel A: Favored</i>					
Favored	0.744*** (0.130)	0.112 (0.134)	−0.372 (0.376)	0.439 (0.627)	0.896*** (0.100)
Favored × Small	−0.679*** (0.066)	−0.106 (0.067)	0.351 (0.296)	−0.397 (0.551)	−0.799*** (0.105)
Favored × Medium	−0.559*** (0.052)	−0.102 (0.072)	0.437 (0.208)	−0.195 (0.360)	−0.819*** (0.117)
<i>Panel B: FavorIndex (continuous)</i>					
FavorIndex	0.438*** (0.143)	0.152* (0.049)	−0.270 (0.231)	0.292 (0.441)	0.396*** (0.043)
FavorIndex × Small	−0.422*** (0.107)	−0.152 (0.081)	0.266 (0.177)	−0.279 (0.411)	−0.369*** (0.057)
FavorIndex × Medium	−0.305*** (0.060)	−0.146* (0.059)	0.202 (0.163)	−0.102 (0.252)	−0.315*** (0.039)
<i>Panel C: GPA (firm-level)</i>					
GPA	0.052*** (0.012)	0.030** (0.009)	−0.010 (0.017)	−0.010 (0.039)	0.068*** (0.012)
GPA × Small	−0.045*** (0.012)	−0.017 (0.020)	0.030** (0.008)	0.026 (0.040)	−0.065*** (0.013)
GPA × Medium	−0.030* (0.014)	−0.037** (0.007)	0.030* (0.013)	0.043 (0.045)	−0.053*** (0.010)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE (Panel C)	Yes	Yes	Yes	Yes	Yes
Observations	3,484	188	694	774	1,828

Notes: Standard errors clustered at year and industry level in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Each panel reports a separate set of regressions with the indicated policy measure. Controls include SOE, ROA, leverage, $\log(\text{assets})$, and size tercile indicators. Q First Day is winsorized at 1% and 99% within each calendar year.

Table IA13: Sub-period Analysis: A-H Premium and Industrial Policy

	2006–2010			2011–2015			2016–2021		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Favored	−43.60*			−20.79*			−1.44		
	(22.85)			(12.07)			(8.43)		
FavorIndex		−22.87*			−2.27			−0.51	
		(12.96)			(8.12)			(6.56)	
GPA			−3.28*			−0.09			1.38
			(1.91)			(1.90)			(0.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	No	No	Yes	No	No	Yes	No	No	Yes
Obs.	2,371	2,371	2,371	3,660	3,660	3,660	7,364	7,364	7,364
Adj. R ²	0.471	0.465	0.524	0.508	0.501	0.546	0.378	0.378	0.426

Notes: Standard errors clustered at month and firm level in parentheses. *p<0.1; **p<0.05; ***p<0.01. Dependent variable is A-H premium (ratio of A-share to H-share market cap, minus 1, times 100), winsorized at 1% and 99%. Controls include SOE, ROA, book-to-market, and log(market cap).

II.4 Additional summary statistics

Table IA14 corresponds to Table 6 in the paper. The paper uses the U.S. benchmark regressions to show that policy favor does not predict IPO activity once standard market fundamentals are taken into account; this summary-statistics table documents the underlying U.S. industry-year sample. Its role is to make the scale and dispersion of the benchmark variables transparent before readers interpret the null policy coefficients.

Table IA14: U.S. IPO Benchmark Summary Statistics

	count	mean	p50	sd	min	max
n_cusip_log	1188	0.61	0.00	0.81	0.00	4.49
proceeds_log	1188	2.85	0.00	3.15	-2.70	10.20
industry GDP	1188	396615.65	233332.00	478401.49	16952.00	3969098.00
log(industry GDP)	1188	12.37	12.36	1.04	9.74	15.19
lag_avg_q	1188	1.44	1.34	0.53	0.00	4.47
policy_favor	1188	0.19	0.00	0.39	0.00	1.00

Notes: This table reports summary statistics for the U.S. IPO benchmark sample at the SIC 3-digit industry-year level. n_cusip_log and proceeds_log are the log number of IPOs and log IPO proceeds. industry GDP is BEA industry GDP in levels, measured in USD million; log(industry GDP) is its natural logarithm. lag_avg_q is lagged industry Tobin's Q, and policy_favor is the U.S. favored-industry indicator constructed from the policy classification described in the appendix.

Table IA15 corresponds to Table 9 in the paper. The paper uses overseas-listing regressions as a placebo comparison for Chinese firms raising capital outside the mainland IPO system; this appendix table summarizes the U.S. and Hong Kong samples underlying those tests. Its role is to clarify how the overseas samples differ in scale, issuance frequency, and policy-favor measures before the placebo results are interpreted.

Table 13 in the paper reports the baseline A-H premium regressions; the summary-statistics table below documents the firm-month sample used for that analysis. Its role is descriptive: it shows the distribution

Table IA15: Chinese IPOs Outside Mainland China: Summary Statistics

Panel A: Chinese IPOs in the U.S. Market

	count	mean	p50	sd	min	max
n_ipo_log	1193	0.14	0.00	0.36	0.00	1.95
proceeds_musd_log	1193	0.74	0.00	1.82	0.00	9.01
ipo_dummy	1193	0.16	0.00	0.37	0.00	1.00
lag_avg_q	1193	1.50	1.42	0.55	0.61	3.57
ind_plcyfavor_emph	1193	0.33	0.00	0.47	0.00	1.00
ind_n_emphasize	1193	0.42	0.00	0.65	0.00	3.00

Panel B: Chinese IPOs in the Hong Kong Market

	count	mean	p50	sd	min	max
n_ipo_log	1325	0.32	0.00	0.52	0.00	2.77
n_ipo_log_CN	1325	0.35	0.00	0.54	0.00	3.04
proceeds_mhkd_log	1325	1.90	0.00	2.85	0.00	10.60
proceeds_mhkd_CN_log	1325	2.45	0.00	3.48	0.00	11.34
lag_avg_q	1325	1.26	1.12	0.55	0.45	3.31
ind_plcyfavor_emph	1325	0.26	0.00	0.44	0.00	1.00
ind_n_emphasize	1325	0.34	0.00	0.63	0.00	3.00

Notes: This table reports summary statistics for the overseas IPO samples underlying the table “Chinese IPOs Outside Mainland China” in the paper. Panel A reports summary statistics for Chinese firms listing in the U.S. market at the NAICS 3-digit industry-year level. *n_ipo_log*, *proceeds_musd_log*, and *ipo_dummy* are the log number of IPOs, log IPO proceeds in USD million, and an indicator for any IPO activity in a given industry-year. Panel B reports summary statistics for Chinese firms listing in the Hong Kong market at the NAICS 3-digit industry-year level. *n_ipo_log* and *proceeds_mhkd_log* refer to the full Hong Kong market, while *n_ipo_log_CN* and *proceeds_mhkd_CN_log* restrict the sample to mainland Chinese issuers listing in Hong Kong. In both panels, *lag_avg_q* is lagged industry Tobin’s Q, and *ind_plcyfavor_emph* and *ind_n_emphasize* are the binary and continuous measures of Chinese policy favor.

of the A-H premium outcome and the firm characteristics entering the valuation regressions, which helps interpret the magnitude of the cross-market valuation wedge.

Table IA16: Firm-Level Summary Statistics for A-H Premium Analysis

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
AH Premium	14,127	97.604	104.197	29.429	68.130	133.921
SOE	14,127	0.705	0.456	0	1	1
ROA	14,127	3.495	5.061	1.231	2.811	5.451
B/M	14,127	0.422	0.308	0.213	0.348	0.562
log(ME)	14,127	25.061	1.473	24.033	25.131	25.948

References

- Li, S., Zhao, Z., Hu, R., Li, W., Liu, T., and Du, X. (2018). Analogical reasoning on Chinese morphological and semantic relations. In Gurevych, I. and Miyao, Y., editors, *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 138–143, Melbourne, Australia. Association for Computational Linguistics.
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in neural information processing systems*, 26.