

Industrial Policy *via* the IPO Market*

Zhiguo He Yiming Qian Xi Sun Wang Renxuan

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Abstract

This paper studies how China uses access to public equity markets as an instrument of industrial policy. We find that policy-favored status, rather than industry Tobin's Q, predicts IPO activity, in contrast to the United States. The effect is economically large: our estimates imply that favored industries had 287% more IPOs and 148% higher IPO proceeds than non-favored industries over 2002 to 2022. We develop a framework to interpret these findings: the government shapes the number of listing opportunities available across industries, while market forces determine which firms obtain these opportunities based on firm fundamentals. Consistent with our framework, policy favor also predicts a valuation premium which persists after listing.

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*He is at Graduate School of Business, Stanford University and NBER (hezhg@stanford.edu). Qian is at the School of Business, University of Connecticut (yiming.qian@uconn.edu). Sun is at China Europe International Business School (sxi@ceibs.edu). Wang is at China Europe International Business School (rxwang@ceibs.edu). He acknowledges financial support from the Chai-Siriwatwechakul fellowship at Stanford GSB. All errors are our own.

1 Introduction

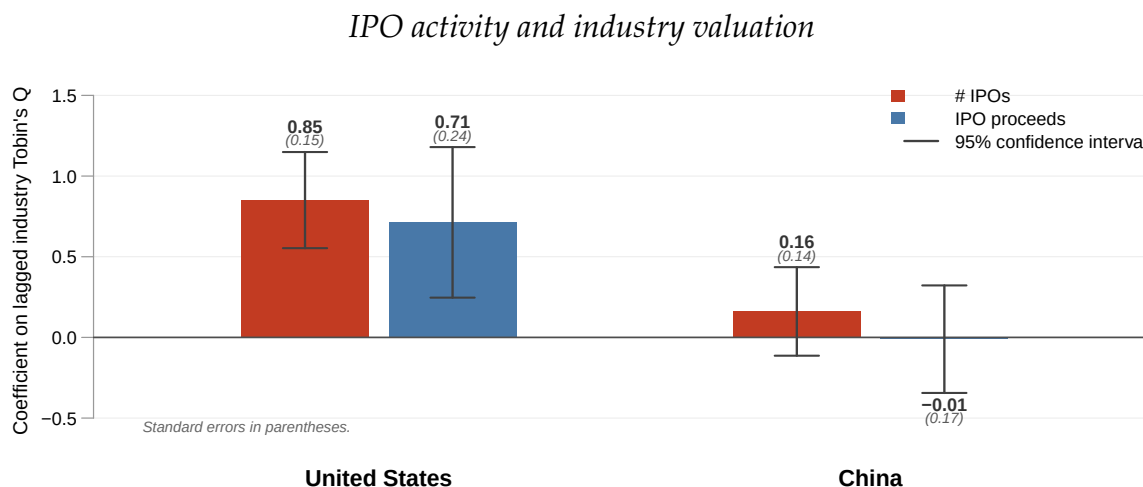
Industrial policy—targeted government interventions aimed at altering the sectoral composition of the economy—has moved from a once-taboo topic in mainstream economics to a central pillar of development strategy around the world ([Baldwin, 1969](#); [Krueger, 1990](#); [Rodrik, 2004, 2008](#)). Advanced 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 interest, the literature has focused on traditional tools: fiscal subsidies, tax incentives, and directed credit through state-owned banks. Far less is known about how it operates through public equity markets—even though equity plays a role that bank credit cannot. Equity is the patient, risk-bearing capital that innovation-driven development requires, funding the long-horizon, high-uncertainty projects that debt, with its fixed claims and collateral demands, systematically underserves. Debt powered the East Asian “miracle,” but equity markets are becoming the vital venue for allocation as China shifts from “high-speed” to “high-quality” growth.

Because the initial public offering (IPO) is the critical gateway to equity financing, this paper examines a novel form of state intervention: IPO-based industrial policy in China. We show that China’s IPO regulatory regime channels capital toward favored industries and firms aligned with national development priorities. Unlike traditional fiscal tools, it steers private capital toward priority sectors without eroding fiscal capacity. Although IPO proceeds are small relative to bank credit or bond issuance, their strategic weight is larger: a listing unlocks access to seasoned equity, cheaper bank credit, and bond markets, while the liquid equity it creates helps firms attract scarce talent. IPO exits also draw upstream venture capital and private equity.¹ Individual IPOs can now raise

¹The Chinese financial system is bank-dominated, though non-bank financing is growing fast ([He and](#)

Figure 1: Industry Tobin’s Q and Government Policy Direction Predict IPO Activity Differently in China and the United States



Notes: This figure plots the coefficient on lagged industry Tobin’s Q from PPML models of industry-year IPO activity—the number of IPOs (red bars) and IPO proceeds (blue bars)—estimated separately for the United States and China, controlling for $\log(\text{IndustryGDP})$ and year fixed effects. Each estimate is labeled with its coefficient and, in parentheses, its standard error, clustered by industry; whiskers are the corresponding 95% confidence intervals. Both samples cover 2002–2022; China excludes 2013 because IPOs were suspended. Full estimates are reported in Internet Appendix Table IA8. The residualized IPO-activity distributions are reported in Internet Appendix Figure IA2.

very large sums: ChangXin Memory Technologies (CXMT), China’s largest producer of DRAM memory chips, raised RMB 66.6 billion in its July 2026 listing on the STAR Market, the largest Asian IPO of the year. Its 466% first-day jump drew headlines in the Western financial press as well, and it is only one of many such listings.² IPO regulation therefore acts as a valve on the flow of both capital and talent toward favored sectors.

In a frictionless market, the “invisible hand” channels capital to sectors with the highest Tobin’s Q. In China, however, the state retains the ultimate prerogative to guide development. Figure 1 illustrates the contrast. It plots the estimated relationship between industry IPO activity (counts and proceeds) and lagged industry Tobin’s Q, the canonical

Wei, 2023). In 2022, IPOs on the Shanghai, Shenzhen, and Beijing exchanges raised RMB 0.6 trillion, against RMB 2 trillion in net corporate bond financing. This comparison nonetheless understates the role of IPO financing in China. The upstream VC/PE market it feeds is sizable: capital commitments to newly established funds totaled approximately RMB 4.6 trillion in 2022 (CVSource). Listed firms can also pledge their shares as collateral for bank loans, a market that peaked at about RMB 6 trillion in 2017 (He et al., 2024).

²The STAR Market, formally the Science and Technology Innovation Board of the Shanghai Stock Exchange, was launched in 2019 as a venue for firms in strategic technology sectors, and was the first Chinese board to adopt the registration-based listing system described in Section 2. On the listing, see, for example, ?.

measure of investment opportunities, separately for the U.S. and China. In the United States both coefficients are large and significant: IPO activity flows to the industries the market values highly. In China both are indistinguishable from zero, so the foundational relationship vanishes, suggesting a different rationale behind capital allocation in China's equity market. Consistent with this, policy texts repeatedly invoke IPO facilitation as an industrial-policy tool, and the 2021 "Double Reduction" policy shows the same logic in reverse: barring for-profit tutoring firms from listing terminated almost every education-related IPO application.

To establish industrial policy as a dominant driver of equity market access, we build a dataset of A-share IPOs from 2002 to 2022 and combine it with novel measures of policy intensity derived from a textual analysis of China's Five-Year Plan documents. We find that favored industries in our sample account for 64% of IPOs and 53% of IPO proceeds while representing about 31% of industry GDP, and the regressions confirm the tilt: they have roughly 287% more expected IPOs and 148% higher expected proceeds than otherwise comparable non-favored industries, with stronger effects at higher levels of policy favor. Lagged industry Q predicts neither, whereas in the U.S. the pattern reverses: industry Q predicts IPO activity and the United States' own industrial-policy measure does not. The policy effect also strengthens across planning cycles, rising from an increment of 0.870 in the 11th FYP to 1.753 in the 14th, relative to the 10th-FYP benchmark.

To interpret these patterns, we develop a simple framework with two forces acting on the IPO market: the Government's policy force G and firms' underlying fundamentals F . The policy force captures government support for industries designated as strategic; of the many instruments that deliver it, we focus on IPO access. Decomposing an industry's IPO proceeds into the number of listings and the average proceeds per listing, the framework posits that IPO entry responds to G alone, while proceeds per listing and valuations load on F and G jointly. The data suggest that the two forces are distinct: industries whose listing access expands most under a plan are statistically indistinguish-

able beforehand from those whose access does not, on profitability and growth alike. The decomposition then explains why IPO quantity and market valuation are disconnected in China. Policy moves the count margin, where prices play no role, whereas fundamentals surface only in the components that embed prices, and there in offsetting directions that roughly cancel.

Opening the gate shows how the policy actually operates. The favored-industry advantage originates upstream, in the applicant pool rather than at approval: favored industries file about 414% more expected applications, yet their realized approval rate is essentially identical to that of non-favored industries, 69.5% against 69.4%. Inside the gate, market forces are fully at work, since among applicants it is the larger, faster-growing, and more profitable firms that complete a listing. Policy thus sets how wide the gate opens for an industry while fundamentals select which of its firms pass through, an arrangement in which the invisible hand of the market operates inside the boundary that the visible hand of policy draws.

Industrial policy is also priced. Favored firms trade at a 14.4% higher Tobin's Q on their first trading day than comparable non-favored issuers, and the same holds within industries for firms whose disclosed business scope aligns more closely with the active plan. The premium does not fade: it equals 15.4% of mean Q one year after listing and 20.0% after three, and it concentrates among large firms, whose prices best reflect operating fundamentals. The market therefore treats policy alignment as a durable cash-flow fundamental rather than transient sentiment, a reading reinforced by the absence of any alignment-linked wedge between the A- and H-share prices of the same dual-listed firms. This estimate understates the full value of policy favor, since it conditions on firms that successfully listed and so omits the value of more likely access itself.

A central challenge is to distinguish these policy effects from purely market-driven forces, since sectors such as artificial intelligence attract both government support and private enthusiasm. Two pieces of evidence separate them. First, policy designation is

close to orthogonal to the fundamentals the market rewards: industries whose listing access expands most under a plan look no stronger beforehand on profitability or growth than those whose access does not, so policy favor selects industries on a dimension distinct from the one the market prices. Second, the policy–IPO link disappears once firms leave the CSRC’s jurisdiction: Chinese industrial policy does not predict Chinese firms’ IPO activity in the United States, and in Hong Kong the link is absent for non-mainland issuers and only partial for mainland issuers, whose offshore listings Beijing still partly oversees. Were the domestic advantage of favored industries a reflection of stronger fundamentals rather than policy, it should have reappeared in these venues; it does not.

The policy’s reach also extends beyond the main board. In the National Equities Exchange and Quotations (NEEQ), China’s over-the-counter venue for smaller firms, favored industries obtain about 313% more expected listings. Read alongside the offshore nulls, this locates the effect inside the boundary of the Chinese state’s regulatory authority: it operates wherever Beijing controls listing access, and fades where it does not.

This paper contributes to several literatures. First, we add to research on the new economics of industrial policy by identifying a distinct 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 better data and methods, documenting subtler effects and the importance of context and implementation ([Harrison and Rodríguez-Clare, 2010](#); [Lane, 2020](#); [Juhász et al., 2024](#); [Barwick et al., 2024a](#); [Aghion et al., 2015](#)). [Juhász et al. \(2025\)](#) 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 their global spillovers.

Many recent studies focus on China, whose 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 on millions of government documents to map policy objec-

tives, tools, and transmission across regions. Others examine specific tools: 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). We differ in focusing on IPO regulation, a capital-market-based instrument.

Second, we contribute to the literature on China’s financial markets, and its IPO market in particular. China’s financial system has historically been dominated by bank-based financing (He and Wei, 2023). As the economy matures, the stock market has become an increasingly important channel, particularly for innovation-driven firms (Song and Xiong, 2018; Cong et al., 2020). Qian et al. (2024) survey China’s IPO market, showing how the approval system and price caps produce persistent underpricing and a costly listing process. We show that IPO regulation is deployed with industrial-policy intent, skewing 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.

The remainder of the paper is organized as follows. Section 2 describes the institutional background and measure construction. Section 3 presents the main findings on industrial policy and IPO activity and shows they reflect policy rather than omitted industry fundamentals. Section 4 develops the framework, quantifies how policy and fundamentals shape IPO quantity and pricing, and opens the gate using application-level data. Section 5 extends the evidence to NEEQ listings and the Hong Kong market and weighs the advantages and limitations of IPO-based industrial policy. Section 6 concludes and considers implications beyond China.

2 Institutional Background and Data

This section describes the institutional setting, the data behind our analysis, and how we measure policy favor at the industry level and at the firm level.

2.1 IPO Listing Regulations in China

In China’s IPO market, the state exercises substantial control over firms’ access to public equity, a feature distinct from that of market-oriented economies such as the United States. In the U.S., IPO issuance operates under a disclosure-based registration regime: regulators review registration statements for compliance with disclosure requirements, while issuers and underwriters bring offerings to market and investors determine whether to participate and at what price.³ By contrast, China’s IPO process involves substantive regulatory review and administrative approval, turning public listing into a licensed entry process.

The China Securities Regulatory Commission (CSRC) has served as China’s central IPO regulator over the past three decades. Besides baseline requirements such as minimum firm size and profitability, the CSRC retained substantial discretion over IPO approval, taking into account broader considerations such as market conditions and the state’s strategic priorities (Qian et al., 2024). One prominent manifestation of this discretion was IPO suspensions: between the 1990s and mid-2010s, the CSRC periodically halted approvals for extended periods, during which no new firms could list (Cong and Howell, 2021). This approval-based regime made the listing process costly: review periods were long and uncertain, with the average interval between application and listing exceeding 400 days.⁴

³The SEC explicitly notes that the review “does not evaluate the merits of any transaction or determine whether an investment is appropriate for any investor.” See U.S. Securities and Exchange Commission, *Filing Review Process*, Division of Corporation Finance (Sept. 27, 2019).

⁴Among successful IPOs listed during 2014–2022, the average interval is 479 days for favored industries and 556 days for non-favored industries (Internet Appendix Table IA4).

Beginning in 2019, China transitioned to a registration-based IPO system, first on the STAR Market and extended to the whole market by 2023. The reform shifted the primary review of IPO applications from the CSRC to the stock exchanges and placed greater emphasis on information disclosure. It did not, however, eliminate substantive regulatory oversight. IPOs remain subject to a two-tier review process involving exchange review followed by CSRC registration, and both the exchanges and the CSRC retain authority to conduct substantive examinations under certain circumstances (Chen and Zhao, 2024). The current system continues to incorporate substantive regulatory criteria beyond disclosure. The CSRC explicitly requires that issuers’ business operations comply with national industrial policies, thereby introducing a policy-based criterion into the listing review framework.⁵

2.2 IPO Access as a Stated Policy Instrument

Beyond the listing regulations, a broad body of central-government policy texts explicitly names IPO access as a tool of industrial policy, showing that steering equity financing toward favored industries is a deliberate policy objective. To document this systematically, we code central-government policy texts issued between 2002 and 2022 using an LLM-assisted text-coding procedure. First, we classify document titles as industrial policy when they target specific industries or economic activities through long-run support, guidance, or regulatory facilitation. Second, within the documents classified as industrial

⁵Under 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>.

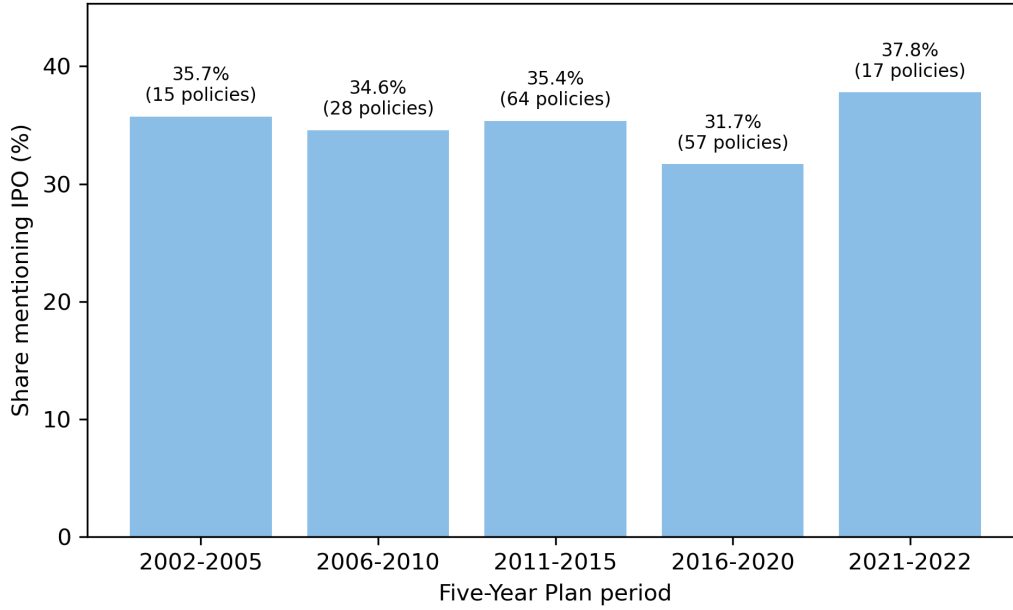
policy, we search the full text for IPO-related expressions, including the Chinese term for “listing” and “IPO,” and classify matched passages as IPO facilitation only when they explicitly promote firm listing, issuance review, or expanded access to direct financing.⁶ As an example, a passage that receives this label reads as follows: the 2020 State Council notice on integrated circuits and software calls for “vigorously supporting” qualified firms to list and for “accelerating the domestic listing review process.”

We define the IPO-facilitation share as the fraction of industrial-policy documents whose matched passages receive an IPO-facilitation label, so the measure captures how often industrial-policy documents explicitly invoke IPO facilitation as part of the policy toolkit. Figure 2 summarizes this measure by the Five-Year Plan window. Of the 529 documents classified as industrial policy, 34% explicitly mention IPO support. This share remains broadly stable across planning cycles rather than concentrating in a single episode.

Just as policy support can open IPO access, its withdrawal can foreclose it. In July 2021, the “Double Reduction” policy barred for-profit K-12 tutoring firms from raising capital through IPOs, for explicitly social and political reasons—easing the education burden on households—rather than any deterioration in sectoral fundamentals. The sector had in fact been expanding rapidly, with leading firms still reporting strong growth in early 2021 and firms actively filing IPO applications. Yet after the policy, every education-related IPO applicant in our sample was terminated rather than listed. This policy-driven reversal, occurring despite strong pre-policy market momentum, shows directly that when the state withdraws policy support from a sector, access to equity markets can disappear.

⁶We use gpt-4o-mini model for classification. The classifier uses a consistent few-shot prompt across documents and returns a yes/no label with a short reason. As a quality check, we manually reviewed representative positive cases to confirm that the classification captures substantive references to listing support, review acceleration, or direct-financing access rather than incidental mentions of capital markets.

Figure 2: 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 source corpus restricts attention to national-level policy documents issued by central authorities, rather than routine administrative postings. The denominator is the number of documents classified as industrial policy in the period; the numerator is the subset of those documents with validated IPO-support language. The IPO-support indicator is constructed using LLM-based classification of document titles to identify industrial-policy documents, followed by full-text keyword search and LLM validation of IPO-related passages. Numbers in parentheses indicate the numerator in each period.

2.3 Measuring the Degree of Policy Favor

We measure the degree of policy favor at two levels. At the industry level, we construct two measures, which capture whether the national plan supports an industry and how intensively it does so. At the firm level, our measure captures the alignment of a firm's business scope with policy priorities.

Identifying favored industries. China's industrial policy operates through a hierarchy of plans, with the national Five-Year Plans (FYPs) at the top. Issued every five years by the central government, the national FYP sets strategic priorities across macroeconomic, industrial, technological, social, and environmental domains, and in particular designates the industries to be promoted, adjusted, or phased out.⁷ We build our measures on the na-

⁷These central directives cascade into provincial and sectoral plans that translate them into more granular targets and policy tools tailored to local conditions, which ministries and regulators then operationalize

tional plan for two reasons. First, it is the source from which the lower-level plans derive, so it records the government’s priorities before local implementation reshapes them. Second, IPO approval rests with a central regulator, the CSRC, so the central government’s priorities are the ones that bear on access to the IPO market.

We construct measures of policy support from the language of the national FYPs, following prior work (e.g., [Chen et al., 2017](#); [Cen et al., 2022](#)). Specifically, we draw on the structured policy-text database from the China Research Data Services Platform (CNRDS; www.cnrds.com). For each FYP, CNRDS identifies industry mentions, maps them to the CSRC 2001 industry classification, and assigns a policy attitude based on the surrounding language: *encouraging* mentions call for actively developing or promoting an industry, *neutral* mentions use adjustment-oriented language, and *restrictive* mentions signal 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 set our main indicator *Favored* equal to one when an industry receives at least one priority mention in the active FYP. We manually verify the pre-assigned labels by examining the context surrounding each mention and revise industry mappings where the initial assignment does not align with the best-matching industry.

As an industry may be discussed multiple times throughout the plan, we also construct a continuous measure of policy-favor intensity, *FavorIntensity*, defined as the number of times the industry is identified as a policy priority in the active FYP. Together, the two measures capture both margins of policy favor: *Favored* records whether the national plan designates an industry as a priority, and *FavorIntensity* records how strongly through concrete measures.

it does so. Additional details are provided in the Internet Appendix [I.1](#).

Table 1 lists the favored industries under each FYP window. Policy favor is neither universal nor fixed: while some broad strategic sectors persist across cycles, the set of favored industries rotates meaningfully from one FYP to the next, reflecting the evolving content of Chinese industrial policy. Biological-products manufacturing, for example, is absent in 2001–2005 but enters the favored list in later plans, mirroring the rising official priority assigned to biotechnology and other strategic emerging industries.

[INSERT TABLE 1 HERE]

For Chinese issuers listing overseas, we map the CSRC 2001 industries that underlie our policy-favor measures to the NAICS industry classification used in the overseas capital-market data, using a concordance between the two classification systems. For the U.S. benchmark analyses, we use the analogous U.S. industry-level measure of policy favor of [Ju et al. \(2026\)](#), which captures the number of U.S. industrial-policy actions in force at the ISIC four-digit industry level, averaged across child industries within each two-digit industry.

Identifying 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 (GPA) based on firms’ pre-IPO disclosures.

Specifically, we use business scope descriptions from IPO prospectuses filed on CN-INFO (www.cninfo.com.cn), an official securities information-disclosure platform, 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 re-

main relatively stable in the short run, they provide a suitable basis for measuring firms' alignment with prevailing policy priorities.

Intuitively, GPA should be high when a firm's business is close in meaning to the contemporaneous Five-Year Plan's industrial priorities. The construction of GPA proceeds in three steps. First, we extract business-related keywords from the IPO prospectus, producing a bag-of-words representation of the firm's stated business scope. Second, we compare each firm keyword with the policy-keyword vocabulary extracted from the contemporaneous Five-Year Plan using word-embedding cosine similarity, so that semantically related words can be matched even when the firm and policy documents do not use identical terms. Third, we aggregate these pairwise semantic proximities into a firm-level alignment index using normalized TF-IDF weights for the business-related terms. In this process, we calibrate the scoring parameters using only the industry-level policy labels defined above, choosing them to best distinguish firms in policy-favored industries from firms in non-favored industries. The aggregation yields a continuous firm-level measure of policy alignment, where higher values of GPA indicate closer alignment between a firm's stated business scope and prevailing government policy priorities. Detailed construction procedures are provided in the Internet Appendix [I.2](#).

2.4 IPO Activity and Pricing

We organize the outcome variables into two groups, following the IPO literature's distinction between the quantity and price sides of the market ([Ritter and Welch, 2002](#)): IPO activity covers realized issuance, measured by IPO counts and proceeds, and pricing covers firms' Tobin's Q at listing and one and three years after listing.

IPO activity. Our measures of IPO activity are the number of IPOs and IPO proceeds in an industry-year, the level at which policy favor is defined. We build both from firm-level offerings. For each completed China A-share IPO, the IPO-event data report the

issuing firm, its listing date, CSRC 2001 industry, board, offer proceeds, and accounting information. The number of IPOs is the count of firms in an industry that list in a given year, and IPO proceeds are the sum of their offer proceeds. Both the IPO-event records and the industry fundamentals we use as controls come from Wind. For the U.S. benchmark, we construct the same two measures from Refinitiv IPO data, classifying issuers into ISIC industries by their industry codes, aggregating to ISIC two-digit industry-years, and excluding REITs.

Pricing. We measure market pricing using Tobin’s Q , calculated as the market value of equity plus the book value of liabilities, divided by the book value of assets. The firm-level IPO pricing data provide market value, assets, liabilities, ownership, profitability, leverage, and offer proceeds. Because IPO offer prices in China are subject to regulatory caps and newly listed stocks often hit daily price limits over consecutive days, the first-day closing price need not reflect a market-clearing price; we therefore compute market value using the price on the first “non-hit” trading day, the first day on which the stock does not hit its price limit, following [Qian et al. \(2024\)](#). We also measure Q one and three years after listing for longer horizons.

2.5 Sample and Summary Statistics

Our main sample is China’s A-share IPO market from 2002 to 2022, which spans five FYP periods (the 10th through the 14th). We drop 2013, which falls inside the longest documented market-wide IPO suspension (October 2012 to January 2014) and so offers essentially no IPO activity or cross-industry variation to identify.⁸

Panel A of Table 2 reports summary statistics for the industry-year panel. Of the 1,432 baseline industry-year observations, 448 (31.3%) are policy-favored under the Favored

⁸Our baseline sample also excludes Beijing Stock Exchange listings, because the exchange is a distinct market segment that was initially populated primarily through transfers rather than the standard IPO application process. For more details on sample construction, see Internet Appendix Section II.

indicator, and `FavorIntensity` shows substantial dispersion, capturing variation in the intensity of policy support beyond the binary designation. IPO activity is far more concentrated in these industries than their footprint in the real economy: over 2002–2022, excluding the 2013 IPO suspension, policy-favored industries account for 64.0% of IPOs and 52.6% of IPO proceeds but an average of 30.8% of allocated industry GDP.⁹

Panel B reports the firm-level sample used for the pricing analysis. It consists of 3,817 IPO firms for which Tobin’s Q and the control variables are available at listing, one year after listing, and three years after listing. Table A1 provides detailed definitions of these variables.

[INSERT TABLE 2 HERE]

3 Empirical Results: Industrial Policy and IPO Activity

In this section, we present direct empirical evidence on `Favored` and `FavorIntensity`, the measures constructed in Section 2.3 to identify the industries that China’s industrial policy supports. Both strongly predict an industry’s IPO activity, measured by IPO counts and proceeds, while Tobin’s Q does not. This relationship strengthens across successive Five-Year Plans over the two decades our sample spans. We contrast our results with a similar analysis in the U.S., which finds that the measure of policy favor of Ju et al. (2026) has no predictive power for U.S. IPO activity. A placebo test on Chinese firms’ U.S. listings supports the interpretation that the policy effects do not stand in for omitted industry fundamentals.

Baseline specification. At the Chinese industry-year level, industry-years with no IPOs are common: 49.2% of industry-year observations (704 of 1,432) have no IPO activity. We therefore estimate the outcomes in levels using Poisson pseudo-maximum likelihood

⁹Internet Appendix Table IA10 reports the annual breakdown.

(PPML),¹⁰ which retains these zero observations and delivers coefficients that are semi-elasticities of the expected outcome. More specifically, the baseline model is

$$\mathbb{E}[Z_{j,t} \mid X_{j,t}] = \exp\left(\beta \text{PolicyVar}_{j,t} + \theta \text{IndustryQ}_{j,t-1} + \lambda \log(\text{IndustryGDP}_{j,t}) + \delta_t\right), \quad (1)$$

where $Z_{j,t}$ is the number of IPOs or total IPO proceeds of industry j in year t , and $X_{j,t}$ collects the right-hand-side variables: $\text{PolicyVar}_{j,t}$ is either *Favored* or *FavorIntensity*; IndustryQ , the asset-weighted average Tobin's Q of the industry's listed firms, lagged one year, is the industry's market valuation capturing forward-looking fundamentals like investment opportunities; $\log(\text{IndustryGDP})$ is the logarithm of the industry's annual GDP, absorbing the mechanical link between industry scale and IPO activity; and δ_t is a year fixed effect.

The key coefficient is β : favored industries have $100 \times (e^\beta - 1)\%$ more expected IPOs or proceeds than non-favored industries, with the same interpretation for both outcomes. A positive and significant β supports the hypothesis that industrial policy shapes IPO activity. On the other hand, the estimate of θ tests the classical benchmark: Tobin's Q is the standard measure of investment opportunities (Hayashi, 1982; Blundell et al., 1992), and industries with higher Q should attract more capital, including through IPOs (Pástor and Veronesi, 2005). Figure 1 in our introduction suggests that this relationship breaks down in China.

We estimate Equation (1) separately for China and the United States. The U.S. panel parallels the Chinese one at the ISIC two-digit industry-year level over 2002–2022, with *FavorIntensity_US*, the U.S. measure of policy favor of Ju et al. (2026), in place of the Chinese policy measures.¹¹

¹⁰PPML was proposed by Santos Silva and Tenreyro (2006) for settings with many zero observations and is now standard for nonnegative outcomes. Poisson-class estimators are also the workhorse for count outcomes in finance: Aghion et al. (2013) use fixed-effects Poisson for patent counts, and Cohn et al. (2022) recommend PPML in corporate finance, where log-based alternatives require an arbitrary added constant. PPML is consistent whenever the conditional mean in Equation (1) is correctly specified, whatever the outcome's distribution. The results are robust to log-linear OLS specifications, see Internet Appendix III.5.

¹¹Ju et al. (2026) document that the United States is itself an active industrial-policy nation and construct

Baseline results. Table 3 reports the estimates. Policy variables strongly predict IPO activity in China, while no such relationship appears in the U.S. For the number of IPOs (Panel A), the coefficient on *Favored* is 1.352, significant at the 1% level: favored industries have about 287% more expected IPOs than otherwise comparable non-favored industries. For IPO proceeds (Panel B), the coefficient is 0.910, implying about 148% higher expected proceeds. The continuous measure reveals a dose-response relationship: each additional encouraging industry reference flagged as key policy support is associated with about 110% more expected IPOs (coefficient 0.741) and 75% higher expected proceeds (0.560), both significant at the 1% level.¹² In contrast, the parallel design in the U.S. finds no policy effect. In column (3) of each panel, *FavorIntensity_US* predicts neither IPO counts (0.042) nor proceeds (−0.013).

We also find that *IndustryQ* strongly predicts IPO activity in the U.S., but not in China. In column (3) of Table 3, a one-unit increase in lagged *IndustryQ* in the U.S. raises expected IPO counts by about 136% (coefficient 0.857) and expected proceeds by about 104% (0.711), both significant at the 1% level—comparable to but smaller than the policy effects in China (287% and 148%). In China, by contrast, θ is insignificant throughout: for IPO counts the estimates imply at most a 17% increase per unit of *Q* (0.160 and 0.118 in columns (1) and (2)), and for proceeds they are close to zero (−0.044 and −0.062).¹³

The disconnect between *IndustryQ* and IPO activity does not simply arise because *IndustryQ* is an uninformative measure in China: Table IA9 in the Internet Appendix shows that it loads strongly on industry fundamentals, with industry profitability, leverage, and size explaining about half of its variation (an R^2 of 0.50, against 0.22 for a specification without them). *IndustryQ* thus carries information about fundamentals, yet IPO

an industry-level measure of this activity from federal policy documents: each industry’s score is the stock of industrial-policy actions in force that target it, at the ISIC four-digit level, which we average across child industries within each two-digit industry. Their measure is the U.S. analogue of our *FavorIntensity*: both are text-based counts of industry-directed policy attention.

¹²Section 4.2 relates the two effects, decomposing proceeds into the number of listings, the average size of the issuers, and the proceeds they raise per unit of assets.

¹³These estimates confirm the patterns in Figure 1.

activity in China does not respond to it. In Section 4, we provide a framework that explains this seemingly puzzling result.

[INSERT TABLE 3 HERE]

The dynamic policy effects on IPO across plans. The policy effect on IPO activity is not a fixed institutional feature: it strengthens sharply after the 10th Five-Year Plan and reaches its largest values in the most recent plan. To trace the effect across planning cycles, we augment the baseline specification in Equation (1) with interactions between the policy measure and Five-Year-Plan indicators:

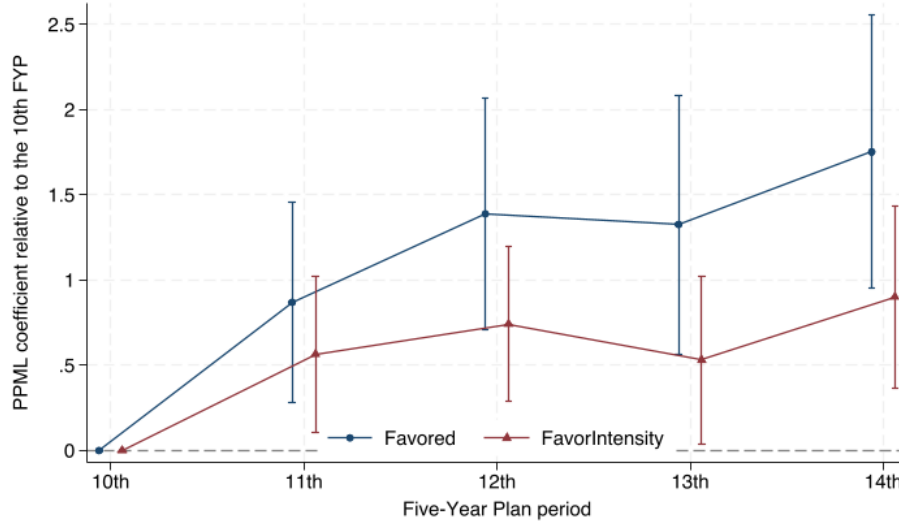
$$\begin{aligned} \mathbb{E}[Z_{j,t} \mid X_{j,t}] = \exp & \left(\beta \text{PolicyVar}_{j,t} + \sum_{k=11}^{14} \tau_k \text{PolicyVar}_{j,t} \times \mathbf{1}\{\text{FYP}_t = k\} \right. \\ & \left. + \theta \text{IndustryQ}_{j,t-1} + \lambda \log(\text{IndustryGDP}_{j,t}) + \delta_t \right). \end{aligned} \quad (2)$$

We take the 10th FYP as the benchmark, so each interaction coefficient τ_k measures how much the policy semi-elasticity during the k th plan exceeds that benchmark. Figure 3 plots the estimated τ_k for the number of IPOs with 95% confidence intervals. For Favored, the increment is 0.870 in the 11th FYP and 1.753 in the 14th, roughly double, with both estimates significant at the 1% level; the latter implies the favored-to-non-favored ratio of expected IPO counts was about $e^{1.753} \approx 5.8$ times higher than during the 10th plan. FavorIntensity traces the same path (0.565 to 0.902), and every post-10th increment is positive and significant, though both measures dip during the 13th-FYP window (2016–2020).¹⁴ The policy–IPO link has thus intensified as industrial policy itself has expanded since the mid-2000s (Naughton, 2021; Heilmann and Shih, 2012).

Policy effects vs. fundamentals: a placebo test. One concern of our baseline results is that policy favor merely proxies for unobserved industry fundamentals: favored indus-

¹⁴The separate-subperiod PPML coefficients for IPO counts and IPO proceeds, reported in Internet Appendix Table IA11, show a consistent pattern.

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



Notes: This figure plots the PPML interaction coefficients for the number of IPOs in each Five-Year Plan period from the 10th to the 14th FYP, normalized relative to the 10th FYP. The estimates come from the baseline PPML specification in Equation (1), augmented with interactions between the policy measure and Five-Year-Plan indicators, estimated over 2002–2022 with controls for lagged IndustryQ , $\log(\text{IndustryGDP})$, 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 *FavorIntensity*, the continuous policy-favor measure. Vertical bars show 95% confidence intervals for the difference relative to the 10th FYP; the 10th-FYP benchmark is normalized to zero.

tries may have more IPOs simply because they contain more firms with strong fundamentals. We therefore use IPO activity among Chinese firms listing in the United States as a placebo test. Fundamentals travel with the firm, whereas preferential access to A-share listings is specific to the domestic market. If such access drives our baseline results, the favored-industry advantage should not extend to Chinese firms' U.S. IPOs; otherwise, we would expect it to persist. We construct an industry-year panel of Chinese firms' U.S. IPOs from 2002 to 2022, map the Five-Year-Plan favor measures to NAICS industries using the concordance of Section 2.3, and estimate Equation (1) as in the domestic analysis.

Table 4 reports the estimates: the advantage disappears. The coefficient on *Favored* is 0.141 for the number of IPOs and 0.081 for proceeds, an order of magnitude below the domestic estimates of 1.352 and 0.910, and neither is statistically significant; *FavorIntensity* gives the same result (0.213 and 0.240, both insignificant).¹⁵ The null is not an artifact of a thin or narrow sample: the 310 U.S. listings come from 46 of the panel's 58 industries,

¹⁵Internet Appendix Table IA16 reports the corresponding OLS specifications.

no single industry supplies more than 11% of them, and favored industries account for 38.1% of the IPO events.

[INSERT TABLE 4 HERE]

We should note that this placebo may not fully rule out the fundamentals-driven explanation, because a firm’s choice of listing venue may itself depend on its fundamentals. Suppose Chinese firms prefer to list at home and turn to the United States only when a domestic listing is out of reach. The domestic market then takes the strongest candidates in every industry, and the firms that reach the United States are what remains. Any fundamentals advantage that favored industries enjoy would be absorbed at home, so it need not survive into the U.S. sample: favored industries would have more domestic IPOs but no more U.S. IPOs, even if policy favor merely proxies for latent fundamentals.

However, Chinese firms with strong fundamentals do not always end up listing domestically. ? find that firm fundamentals such as the P/E ratio have little explanatory power for Chinese firms’ choice between domestic and overseas listings—the sorting on which this alternative depends. A research report from the Shanghai Stock Exchange likewise notes that lengthy approval processes, together with other institutional constraints, may encourage financially eligible firms to list overseas instead (?).

4 Policy, Firm Fundamentals, and IPO Outcomes

To understand the mechanism behind the empirical results in Section 3, we develop a framework of China’s IPO market. The framework explains why IPO activity is disconnected from market valuation in China and yields further implications for IPO quantity and pricing, which we then test.

4.1 A Framework for the Chinese IPO Market

The setup: the government's policy force G and underlying fundamentals F . Our framework for China's IPO market features two forces: firms' underlying fundamentals F and the government's policy force G . F is a firm's underlying business fundamentals absent any government support. G is the state's support for the industries it designates as strategic, which reaches firms through many instruments, such as subsidies and credit extension. Our policy measures, built from the text of the Five-Year Plans, record which industries and firms the government designates, and so proxy for G as a whole.

In a market without policy intervention, F is the only force at work. Industries with stronger underlying fundamentals attract more capital and receive higher valuations. As a result, IPO proceeds Y and open-market valuation Q are strongly correlated at the industry level, a pattern we observe for the U.S. IPO market in Section 3.

China's approval-based IPO regime departs from this benchmark: it places a "gate" at market entry, the approval process described in Section 2, through which G operates. To see how each force operates, we decompose industry j 's realized IPO proceeds in a given year into two components:

$$Y_j = E_j \times M_j, \quad (3)$$

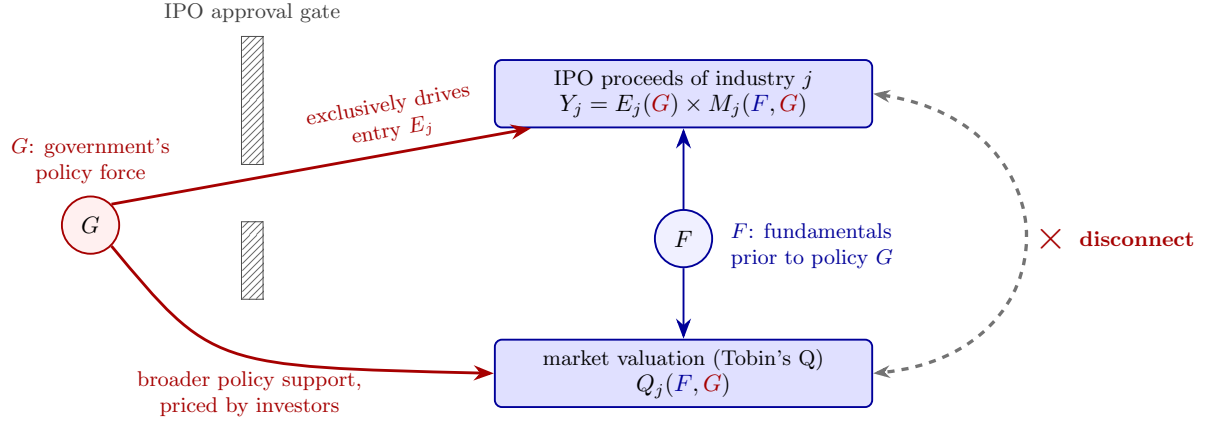
where E_j is the number of IPOs from industry j and M_j is the average proceeds per IPO. E_j is the extensive margin of IPO proceeds; M_j is the intensive margin, which embeds the market's valuation of the issuers. The two forces play different roles in shaping these two margins.

We posit that at the industry level, the extensive margin is governed exclusively by G , not by F :¹⁶

$$E_j = E_j(G). \quad (4)$$

¹⁶This is a claim about industries. At the firm level, F does affect which of an industry's firms list, as Section 4.4 shows; the closing paragraph of that subsection reconciles the two.

Figure 4: The Mechanism: China's IPO Market Gated by Industrial Policy



Notes: This figure summarizes the paper's industry-level framework. Two forces act on the IPO market: firms' underlying fundamentals F , absent any government support, and the government's policy force G , its support for the industries it designates as strategic. The hatched wall is the IPO approval gate. G acts through two channels: one passes through the gate and drives entry, the only arrow reaching the number of IPOs E_j ; the other runs around the gate as the broader policy support that investors price, reaching valuation Q_j and, through it, average proceeds per IPO M_j . F sits past the gate and feeds M_j and Q_j but never E_j . Total proceeds are $Y_j = E_j \times M_j$, the extensive and intensive margins. Because F moves valuation but not the entry component of proceeds, Y_j and Q_j need not move together: the disconnect marked on the right and documented in Section 3. Section 4.2 further decomposes M_j into issuer size and proceeds per unit of assets.

In contrast, the intensive margin M_j and IPO pricing Q_j , both of which embed market valuation, are shaped by the two forces jointly:

$$M_j = M_j(F, G), \quad (5)$$

$$Q_j = Q_j(F, G). \quad (6)$$

Underlying fundamentals F enter because they determine expected cash flows and risk; the policy force G enters because investors expect policy-supported firms to benefit from preferential access to capital and other forms of government support.¹⁷

Figure 4 assembles these relationships into the framework. The hatched wall is the IPO approval gate, and the two arrows leaving G are the two channels through which policy acts. The first passes through the gate's opening and drives entry: it is the only arrow that reaches the number of IPOs E_j . The second runs around the gate and carries

¹⁷Examples include cash subsidies (Branstetter et al., 2023), preferential credit (Cong et al., 2019), and government venture capital (Chen et al., 2026). Much of this support is hard to observe directly, which is why we proxy for G with the text of the plans rather than with measured transfers (Fang et al., 2025).

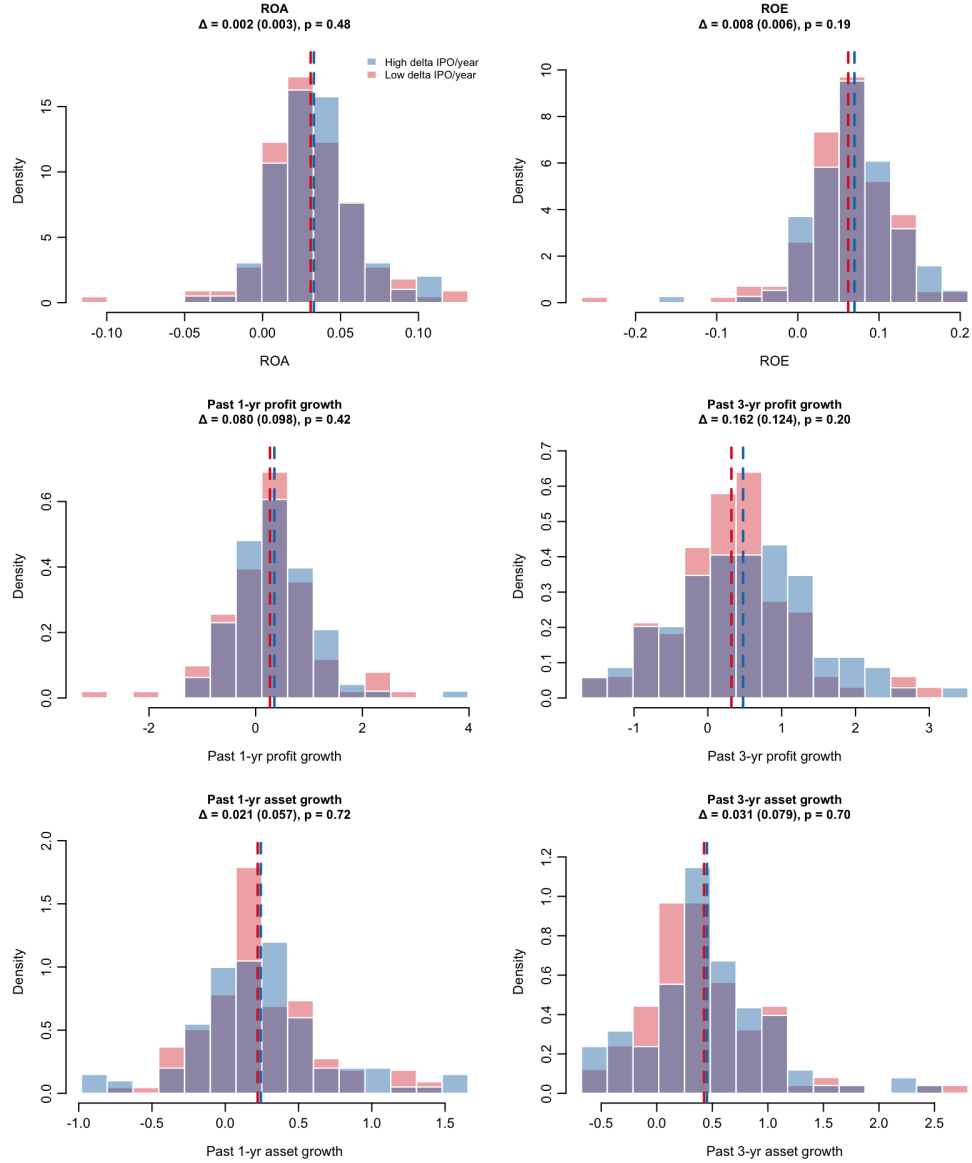
the broader policy support that investors price, so it reaches market valuation Q_j , and through valuation it also enters the average proceeds per IPO M_j . Underlying fundamentals F sit past the gate and feed both boxes directly, entering M_j and Q_j but never E_j . That asymmetry produces the disconnect marked on the right: underlying fundamentals move valuation Q_j , while the component of proceeds that policy controls, E_j , does not respond to them, so Y_j and Q_j need not move together.

The empirical independence of F and G . A crucial premise of the framework is that the two forces are distinct: in China over the past two decades, the policy force G that governs IPO entry has followed considerations quite different from an industry’s underlying fundamentals F . In fact, the data deliver a sharp version of this premise: on the commonly used proxies for underlying fundamentals, F and G are uncorrelated.

Figure 5 shows this. For each industry and Five-Year Plan, we measure how strongly G bears on the industry’s IPO access by the increase in its average annual number of IPOs relative to the preceding plan, and split industries by whether this increase in IPO access is above or below the median. If G simply captured stronger underlying fundamentals, the high-expansion industries should already have looked stronger before the plan began. They do not. Across pre-plan ROA, ROE, profit growth, and asset growth, the high-expansion group differs from the low-expansion group by 0.2 percentage points in ROA and 0.8 percentage points in ROE, and by at most 0.16 log points in the growth measures; no difference is statistically significant.

Explaining the empirical findings. The framework explains the two main findings of Section 3. First, it accounts for the contrasting patterns between the U.S. and China in the relation between policy and IPO activity. In the U.S. benchmark, where there is no gate—remove the wall from Figure 4, F is the only remaining force: it drives both Y and Q , leaving no role for G . This is consistent with Table 3, where IndustryQ positively predicts both IPO counts and proceeds in the U.S., while the U.S. policy measure predicts neither.

Figure 5: Industries Receiving More IPO Access Do Not Have Stronger Fundamentals



Notes: Each panel compares one pre-plan industry fundamental between industries receiving High versus Low increases in realized IPO access. For industry i and current Five-Year Plan p , the allocation change equals the annualized number of realized IPOs in plan p minus the corresponding annualized number in plan $p - 1$. Beijing Stock Exchange IPOs and IPO observations with missing proceeds are excluded. Fundamentals are measured in the year before the current plan starts and are winsorized at the 1st and 99th percentiles within year. ROA and ROE are constructed after firm-level winsorization and aggregated to the industry level using asset and positive-book-equity weights, respectively. Profit and asset growth are one- and three-year log changes in aggregate industry totals. Blue and red bars are density histograms on common bins, and dashed vertical lines mark group means. Each panel header reports Δ , the coefficient on the High indicator from a regression that includes Five-Year-Plan fixed effects, followed by its industry-clustered standard error in parentheses and the associated two-sided p -value.

In China, the gate transmits G directly into IPO proceeds, the upper arrow in the figure, so proceeds relate strongly to *Favored* and *FavorIntensity*.

Second, the framework also explains the disconnect between *IndustryQ* and IPO ac-

tivity in China, documented in Table 3. The explanation rests on two layers. Layer (i) concerns the number of IPOs. Conditional on the policy measures in regression (1), the coefficient on IndustryQ in Panel A mainly captures the impact of F , an interpretation that our premise of uncorrelated F and G makes clean; since Equation (4) leaves the extensive margin no role for F , that coefficient should be insignificant. Layer (ii) concerns total proceeds, where the prediction is ambiguous ex ante, because F does enter through the intensive margin M . We return to this issue in Section 4.2.

Guided by this framework, Section 4.2 decomposes IPO quantity into its margins and quantifies the role each force plays. Section 4.3 tests the pricing implication: policy favor should be priced at the IPO, and the premium should persist. Finally, the framework treats the gate as a policy instrument but is silent on how it operates; Section 4.4 opens it using application-level data, providing the micro-foundation.

4.2 Quantifying the Roles of Two Forces in Shaping IPO Quantity

We now use the framework of Section 4.1 to quantify the effects of G and F in the Chinese IPO market, sharpening our understanding of the disconnect between IPO proceeds and market valuation.

An empirical decomposition of IPO proceeds. Building on Equation (3), we further decompose the average proceeds per IPO, M_j , into two components:

$$Y_j = \underbrace{E_j}_{\text{extensive margin}} \times \underbrace{M_j}_{\text{intensive margin}} = \underbrace{E_j}_{\text{\#IPOs}} \times \underbrace{(A_j/E_j)}_{\text{avg. issuer size}} \times \underbrace{(Y_j/A_j)}_{\text{financing intensity}}. \quad (7)$$

Here, A_j denotes the total assets of industry j 's issuers, so A_j/E_j is their average size and Y_j/A_j the proceeds they raise per unit of assets, i.e., the financing intensity.¹⁸

¹⁸We measure these margins with realized IPO outcomes, as the data contain only firms that complete an IPO rather than the full underlying candidate pool: the extensive margin is whether an industry-year has any IPO activity and how many firms list, and the intensive components are computed from the completed

Splitting the intensive margin into issuer size and financing intensity isolates two opposing effects of the fundamental force F . First, in the context of China, F enters issuer size negatively: heavy-asset industries with high entry barriers list few but large issuers, while industries rich in growth opportunities list many young, small firms.¹⁹ Second, F enters financing intensity—proceeds raised per unit of assets—positively, since intensity embeds the market’s valuation of the issuers. How strongly is unclear ex ante: regulatory caps tied Chinese offer prices to accounting earnings for much of our sample (Qian et al., 2024), dampening the pass-through of valuations into proceeds, and G enters intensity alongside F if investors expect policy-supported firms to benefit. The net effect of F on average proceeds per IPO is therefore an empirical question, which we quantify next.

Taking logs of Equation (7) expresses total proceeds as the sum of the three margins,

$$\log Y_j = \log E_j + \log(A_j/E_j) + \log(Y_j/A_j),$$

so each margin can be examined with the same right-hand side as the baseline specification in Equation (1). For each margin outcome $Z_{j,t}$, we estimate

$$Z_{j,t} = \beta \text{PolicyVar}_{j,t} + \theta \text{IndustryQ}_{j,t-1} + \lambda \log(\text{IndustryGDP}_{j,t}) + \delta_t + \varepsilon_{j,t}, \quad (8)$$

where $Z_{j,t} \in \{\log E_{j,t}, \log(A/E)_{j,t}, \log(Y/A)_{j,t}, \log Y_{j,t}\}$. More specifically, we estimate Equation (8) separately for each component of the decomposition by OLS on the active sample—industry-years with at least one IPO, with issuers matched to total-asset data—with year fixed effects and standard errors clustered by industry. We also estimate the probability that an industry has any IPO, $\mathbf{1}\{E_{j,t} > 0\}$, with the same right-hand side as a linear probability model on the full industry-year panel.

deals. The industry is the natural unit of the decomposition because industrial policy mainly concerns how IPO access is tilted across industries.

¹⁹In the U.S., entry rates vary sharply across industries with entry barriers (Dunne et al., 1988), market-to-book ratios decline with firm age in the cross-section (Pástor and Veronesi, 2003), and new lists have accordingly skewed toward small, high-growth firms (Fama and French, 2004).

Lagged IndustryQ, unlike backward-looking accounting measures, reflects the market's expectation of an industry's future profitability. As discussed in Section 4.1, after controlling for the policy measures G , lagged IndustryQ proxies for F ; this interpretation becomes clean under our premise of uncorrelated F and G .

Table 5 reports the results. The coefficients of interest are β and θ , which capture how each outcome responds to policy favor and fundamentals, respectively. Because the outcomes are in logs, a coefficient β on Favored implies a $100 \times (e^\beta - 1)\%$ difference in the outcome, the same conversion as in Equation (1).

[INSERT TABLE 5 HERE]

G on the extensive margin. The framework's first implication is that entry responds to G alone, so θ should be zero at the count margins. Panel A confirms it. In columns (1)–(2), Favored raises the probability that an industry has any IPO in a given year by 16.9 percentage points (significant at the 1% level); against the 46% of non-favored industry-years with at least one IPO, that is about 37% ($0.169/0.46$) more likely to enter. FavorIntensity adds 11.2 percentage points per qualifying reference. Conditional on entry, columns (3)–(4) show that favored industries list about 93% more issuers (0.657, significant at the 1% level), while lagged IndustryQ is insignificant for both outcomes (-0.051 and 0.196). However highly the market values an industry, its firms do not list more often: at the industry level, policy alone opens the gate.

G on the intensive margin. Policy enters the two intensive components with opposite signs and nets out. On issuer size, the Favored coefficient in columns (1)–(2) of Panel B is -0.487 (significant at the 5% level): favored industry-years list smaller issuers—a natural outcome of the gate, since wider entry (Panel A's 93% more issuers, and the more-than-doubled applicant pool of Section 4.4) reaches deeper into the size distribution. On financing intensity, columns (3)–(4) show that favored issuers raise about 37% more per

unit of assets (0.316, significant at the 5% level), so policy favor does pass into offer proceeds. The two largely offset, leaving an insignificant -0.171 on average proceeds per IPO in Panel C.

***F* on the intensive margin.** The framework's second implication is that *F* moves the two intensive components in opposite directions: θ negative for issuer size, positive for financing intensity. Both appear. In columns (1)–(2) of Panel B, the coefficient on lagged IndustryQ is -0.592 (significant at the 1% level): higher-valuation industry-years list smaller, younger issuers, the pattern documented for U.S. listings ([Pástor and Veronesi, 2003](#); [Fama and French, 2004](#)). In columns (3)–(4), a one-unit increase raises proceeds per unit of assets by about 45% (0.372, significant at the 1% level), so the market's valuation of fundamentals does pass into offer proceeds despite the regulated pricing. Panel C reports the sum: -0.220 (significant at the 1% level), opposite in sign to *F*'s effect on valuation—precisely the condition under which the framework of Section 4.1 disconnects proceeds from valuation.

Total proceeds and the disconnect. Because the log decomposition holds exactly on the active sample, each regressor's component coefficients add up to its total effect on proceeds, which columns (1)–(2) of Panel C report. For Favored, the total is 0.486 (significant at the 5% level), the exact sum of $0.657 - 0.487 + 0.316$ and driven by the count margin; the FavorIntensity columns repeat the pattern, summing to 0.434 (significant at the 1% level). For lagged IndustryQ, the same aggregation yields an insignificant -0.023 —the disconnect of Section 3 in decomposed form. No new force produces this null: it is the zero count effect of Panel A combined with the offsetting intensive components above.

The deeper lesson of the decomposition is that aggregates conceal the forces at work: policy looks absent from average proceeds per IPO, fundamentals look absent from total proceeds, yet beneath each null lie significant components that offset. Policy operates

mainly through the extensive margin—its issuer-count component is 135% of its total proceeds effect (0.657 against 0.486), with the intensive components netting -35% —while fundamentals appear exactly where prices appear: the price-free extensive margin responds only to policy, and financing intensity, which embeds the offer price, responds to both.²⁰ How the market prices the policy force is the framework’s remaining implication, which the next subsection takes up.

4.3 Policy Favor Is Priced, and the Premium Persists

IPO entry determines which firms reach public equity markets; IPO pricing determines the cost at which they raise capital. For pricing, the framework of Section 4.1 carries a two-part implication: policy favor should be priced at listing—investors who expect policy-aligned firms to benefit capitalize those benefits into valuations—and, because the market prices G as a fundamental rather than as transient sentiment, the premium should not reverse as the firms trade. This subsection tests both parts and quantifies the premium.

We test both parts at the firm level: each IPO valuation is a firm outcome, so the natural unit is the IPO event rather than the industry-year, and firm-level data let us exploit within-industry variation through GPA. We estimate

$$Q_{i,j}^{(h)} = \beta^{(h)} \text{PolicyVar} + (\Gamma^{(h)})' X_i^{(h)} + \delta_{t_i}^{(h)} + \varepsilon_{i,j}^{(h)}, \quad (9)$$

where $h \in \{0, 1, 3\}$ indexes valuation at listing, one year after listing, and three years after listing, respectively, and $Q_{i,j}^{(h)}$ is Tobin’s Q for IPO firm i in industry j at horizon h . At $h = 0$, Q is computed at the first non-limit-up trading-day price (Section 2.4); t_i is firm i ’s IPO year; PolicyVar is the industry-level Favored or FavorIntensity, or the firm-level alignment measure GPA of Section 2.3; $X_i^{(h)}$ collects the firm controls (SOE, ROA, Leverage,

²⁰Estimating the issuer-count margin by PPML on the same sample yields a lagged- Q coefficient of 0.287 (standard error 0.111): the count margin’s Q sensitivity is stronger when industry-years are weighted by their activity, as PPML implicitly does.

and $\log(\text{Assets})$) at the corresponding horizon; and $\delta_{t_i}^{(h)}$ is an IPO-year fixed effect. We estimate each horizon separately. The GPA specification adds an industry fixed effect $\mu_j^{(h)}$.

The premium at listing. Columns (1)–(3) of Table 6, Panel A, confirm the first part of the implication: policy favor is priced at listing. The coefficient on Favored in column (1) is 0.682 (significant at the 1% level); relative to the mean first-day Q of 4.740 in the pricing sample, this estimate implies a 14.4% valuation premium for firms in policy-favored industries. The continuous FavorIntensity measure in column (2) yields a similar conclusion: one additional qualifying policy reference is associated with a 0.392 increase in Q (significant at the 5% level), or 8.3% of the sample mean. The premium is economically large: about 1.7 times the valuation effect of a one-standard-deviation difference in ROA in the same column (0.682 against $0.039 \times 10.2 \approx 0.40$; Table 2, Panel B).

Column (3) of Panel A shows that the premium holds even within industry, responding to the firm-level alignment measure. The coefficient on GPA is 0.076, significant at the 1% level. Because GPA is a continuous semantic-alignment index without natural units (Section 2.3), magnitudes are best read in standard deviations: a one-standard-deviation increase (6.027) is associated with a 0.46 increase in Q, or 9.7% of the mean first-day Q—within the same industry, firms whose stated business scope tracks the contemporaneous Five-Year Plan more closely command visibly higher valuations. Combining the two levels, policy alignment generates sizable valuation spreads across firms: moving from a non-favored industry to a favored one and, within it, from average to one-standard-deviation-higher GPA raises Q by about $0.682 + 0.46 \approx 1.14$, or 37% of the cross-sectional standard deviation of first-day Q (3.089) and 24% of its mean (Table 2, Panel B).

[INSERT TABLE 6 HERE]

The persistence of the premium. Columns (4)–(9) of Table 6 repeat the same specifications with Tobin’s Q measured one and three years after IPO, denoted $Q_{i,j}^{(1)}$ and $Q_{i,j}^{(3)}$.

The premium does not decay; if anything it widens. For *Favored*, the one- and three-year estimates equal 15.4% and 20.0% of the corresponding mean *Q*, against the 14.4% first-day premium; for *GPA*, a one-standard-deviation increase corresponds to 17.1% and 16.8%, and *FavorIntensity* shows the same pattern. Investors do not simply overprice policy-aligned firms at listing, at least over a three-year horizon; they expect the alignment to deliver long-lasting fundamental benefits. Section 5 provides a complementary cross-market check on this reading: for the same dual-listed firm, policy alignment does not command a larger premium in its mainland A-shares than in its Hong Kong H-shares, which likewise argues against a purely sentiment-driven interpretation.

Cross-sectional variation in the *G* premium. Panel B of Table 6 augments Equation (9) with interactions of each policy measure with firm size and state ownership. The premium is concentrated among large firms. *SME* indicates firms outside the top tercile of market capitalization, ranking each IPO firm against all listed stocks on its listing date, so the reported policy coefficients are the large-firm effects. Take *GPA* in column (3): the interaction implies an *SME* premium of 0.014 ($0.117 - 0.103$), about one-eighth of the large-firm premium of 0.117. *FavorIntensity* in column (2) gives the same ordering: the *SME* premium is 0.209 against the large-firm 0.685, less than a third as large. Splitting *SME* into its bottom and middle terciles (Internet Appendix Table IA12) shows the premium rising monotonically with size; for *GPA* it is absent in both lower terciles. This supports the fundamental interpretation, because valuations of small Chinese firms reflect speculative demand and shell value rather than operating fundamentals: the bottom tercile corresponds closely to the smallest 30% of listed stocks that Liu et al. (2019) identify as likely reverse-merger shells and exclude from factor construction. The *G* premium thus resides where prices are most informative.

Ownership status does not account for the premium. The industry-level premium is, if anything, smaller for SOEs: the *Favored* and *FavorIntensity* interactions with *SOE*

are negative, leaving state firms about half the premium of private firms in favored industries. Within industry, the GPA interaction with SOE is small at every horizon (-0.004 at listing, against a large-firm coefficient of 0.117), so alignment is priced almost identically for state and private firms. The market prices the alignment of a firm's business with industrial policy, not its state affiliation, which distinguishes the premium from the political-connection and state-ownership channels the literature has emphasized (Fan et al., 2007; Piotroski and Zhang, 2014).

In sum, Table 6 confirms both parts of the pricing implication: policy favor commands a 14.4% valuation premium at listing, across industries and within them, and the premium persists—if anything widens—over the three years after IPO, residing among the large firms whose prices best reflect fundamentals. The market prices policy alignment like a fundamental force: investors capitalize its expected benefits into prices, which lowers the cost of equity policy-favored firms face at listing. Policy and the market interact here rather than one overriding the other. The remaining question is how the gate itself operates; Section 4.4 turns to the applications and approvals behind it.

4.4 How the Gate Works: Applications and Approvals

Section 4.1 left open how the gate operates. This subsection examines the application-and-review process behind the gate, asking whether the entry pattern of Section 4.2 arises from firms' decisions to apply or from regulators' approval decisions.

The applicant pool, not the approval rate. The higher IPO activity in favored industries is already visible upstream, in a substantially larger applicant pool rather than a higher approval rate. We observe 3,559 IPO applications that reached a final outcome, listed or not, between 2014 and 2022, the period over which firm-level CSRC disclosures on application status and review progress are systematically available. Panel A of Table 7 shows that favored industries account for 2,460 of these applications, more than twice the

non-favored count and more in every year in which reviews concluded. Approval rates, however, are nearly identical: 69.5% for favored versus 69.4% for non-favored industries in the pooled sample.

A larger applicant pool. Columns (1)–(2) of Panel B estimate the baseline PPML specification in Equation (1) with the number of applications beginning in each industry-year as the outcome. The Favored coefficient of 1.636 implies about 414% more expected applications, and FavorIntensity implies about 116% more per qualifying policy reference. This oversized pool suggests that firms anticipate the advantages of listing in a policy-favored industry, many of which are hard to measure directly.²¹

Fundamental-based firm selection. Columns (3)–(4) ask whether observable application-time fundamentals predict which applications ultimately result in a listing. The linear-probability estimates use 3,140 applications with a final outcome. Fundamentals are measured in the fiscal year before the application began, and all specifications control for Favored. They do: larger applicants, faster-growing ones, and those with higher EBIT/assets are more likely to complete an IPO. Market forces are therefore at work inside the gate. Policy sets how wide the gate opens for an industry; within the industry, underlying fundamentals largely determine which firms pass through. This is the hybrid arrangement of Song and Xiong (2026), in which the state’s visible hand sets the direction and scale of economic activity while market forces allocate within the boundaries it draws. Here the boundary is the gate, and the sorting inside it is largely the market’s.²²

[INSERT TABLE 7 HERE]

²¹Among successful applicants, for instance, firms in favored industries reach listing roughly 49–77 days sooner, depending on the specification (Internet Appendix Tables IA4 and IA5).

²²Song and Xiong (2026) formalize China’s hybrid system through the career incentives of local officials, whose infrastructure investment raises firm productivity; their concern is the distortions those incentives generate, including the crowding out of private investment. We isolate a different instrument, the state’s control of entry into public equity markets, but share that division of labor. A parallel conditional runs through the industrial-policy literature: support raises productivity growth when it is directed to competitive sectors or preserves competition within them (Aghion et al., 2015), whereas subsidizing entry itself can draw in inefficient producers (Barwick et al., 2025); see Juhász et al. (2024) for a survey.

Column (4) allows the size, asset-growth, and EBIT/assets slopes to differ between favored and non-favored industry-years; the favored-industry slopes remain positive for all three.²³ In sum, the higher IPO activity in favored industries originates upstream, in a larger applicant pool rather than a higher approval rate, while observable underlying fundamentals sort which of an industry's applicants succeed.

Fundamentals thus appear to act on the extensive margin E_j , where the framework of Section 4.1 allowed only G : there, IPO entry is set entirely by G and is uncorrelated with F . But the framework, and the lack of correlation it posits, are claims about industries. The sorting established in this subsection operates at the firm level: given industry j 's policy G_j , the fundamental F_{ij} of firm i affects whether firm i lists. The two are consistent, as Appendix IV shows formally: the government sets the industry-level IPO quota, and the market selects which of the industry's firms pass through the gate. If the state directs capital through control of market access, the IPO market need not be the only place where it does so; the next section examines broader Chinese capital markets.

5 Additional Evidence and Discussion

The influence of IPO-based industrial policy on listing access is not confined to the main-board IPO market. The same policy tilt appears in NEEQ listings, while it weakens offshore, where the state's regulatory reach ends. This section documents both comparisons and then weighs the advantages of IPO-based industrial policy against its costs.

²³The favored/non-favored difference is insignificant for both the size and the EBIT/assets slopes. For asset-growth, in the non-favored industry its slope is slightly negative (-0.035), though insignificant from zero. The insignificance may reflect the proxy rather than the absence of sorting: asset growth ahead of an IPO can capture leverage-funded expansion that the review scrutinizes, making it a noisier firm-level signal of underlying fundamentals than size or profitability.

5.1 Additional Empirical Evidence

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 and Lu, 2025). SMEs are a primary engine of job creation and economic dynamism (e.g., Rajan and Zingales, 1998; Beck et al., 2008; Haltiwanger, 2012). Its explicit mandate to support strategic industries makes NEEQ a natural setting to test whether the policy tilt in listing access extends to smaller firms.

We re-estimate our baseline specification from Equation (1), with the dependent variable being the number of NEEQ listings over 2014 to 2022. The results, presented in Table 8, support this prediction. The policy favor dummy (Favored) is positive and statistically significant at the 1% level. Its coefficient of 1.419 implies about 313% more expected NEEQ listings in favored industries; the FavorIntensity coefficient of 0.766 implies about 115% more expected listings per additional qualifying policy reference. These estimates show the same positive association between policy favor and listing activity as the A-share results in Table 3. The policy tilt in listing access thus extends beyond the main boards to the NEEQ market for SMEs.

[INSERT TABLE 8 HERE]

Hong Kong Listings and the A–H Premium. The markets so far all lie inside China’s regulatory boundary. Hong Kong partially crosses that boundary. Beijing retains some regulatory hold over mainland firms’ listings there,²⁴ so it is not obvious ex ante whether

²⁴Chinese regulation reaches the overseas offerings of mainland firms, though its form has changed over time. Until 2023, mainland-incorporated issuers taking the H-share route needed prior CSRC approval to complete a Hong Kong listing, while firms listing through offshore holding companies (“red chips,” including VIE structures) largely fell outside that approval regime. The 2023 *Trial Administrative Measures for*

policy favor should show up in the Hong Kong market at all, or for which issuers.

Panel A of Table 9 estimates Hong Kong IPO activity separately for mainland and non-mainland issuers, whose listing access Beijing influences to different degrees. For non-mainland issuers, the Favored coefficients (-0.119 for counts, 0.234 for proceeds) are indistinguishable from zero. For mainland issuers, the corresponding coefficients are larger, at 0.400 and 0.497 , but neither is statistically significant. Only the coefficient on *FavorIntensity* for mainland IPO counts is significant at the 10% level. The effect is therefore much weaker than at home and establishes no broad Hong Kong listing advantage. Part of this is expected: the mainland issuers in our sample include both H-share issuers incorporated in mainland China, which needed CSRC approval to list offshore, and offshore-incorporated firms with mainland operations, which largely did not. It also fits Hong Kong's role as an international financial center: its issuers and investors are integrated with global markets and far less exposed to mainland policy, so favor loses much of its force even for the mainland issuers Beijing still partly oversees. Policy favor, in short, moves capital mainly within the reach of the Chinese state. The OLS estimates in Internet Appendix Table IA16 are similar.

Hong Kong also enables us to probe whether the IPO valuation premium of Section 4.3 partially reflects investor sentiment. The two markets have different investor clienteles. The Hong Kong market has substantially higher institutional and international investor participation.²⁵ If the higher Q of policy-aligned firms is partly due to hype from unsophisticated A-share investors, policy favor would command a larger premium in a firm's mainland A-shares than in its Hong Kong H-shares—an A–H wedge. Comparing the same firm's A- and H-share prices (differential valuation) tests for exactly such a wedge.

the Overseas Securities Offering and Listing by Domestic Companies replaced approval with a filing requirement and extended it to both routes. Beijing's gate thus touches mainland issuers' Hong Kong listings in a way it never touches non-mainland issuers.

²⁵ An et al. (2022) report that retail accounts contribute nearly 90% of trading volume in their Shanghai Stock Exchange sample. In Hong Kong, institutional and retail investors accounted for 53% and 23% of cash-market trading value in 2016, respectively, with exchange participants' principal trading accounting for the remaining 24%; overseas investors accounted for 40% of total trading value, including investors from mainland China (HKEX Cash Market Transaction Survey 2016).

Panel B performs this exercise on a 2002–2021 firm-month panel. The coefficients on *Favored*, *FavorIntensity*, and firm-level GPA are all insignificant (e.g., GPA of 0.180, standard error 1.412), so we find no alignment-linked A–H wedge. The premium therefore shows no sign of being A-share-specific sentiment, though the imprecision makes this suggestive rather than decisive.

[INSERT TABLE 9 HERE]

5.2 Advantages of IPO-Based Industrial Policy

Our evidence shows that modern industrial policy cannot be understood through fiscal transfers and state-owned banking alone: regulatory control over capital-market access offers states a further, and potentially more scalable, lever on development.

The limitations of such an instrument are fairly obvious. Gating access to public equity is neither costless nor necessarily welfare enhancing: picking “winners” inherently means penalizing “losers,” and by closing the market to non-favored sectors the state effectively “taxes” those industries, starving them of vital risk-sharing capital. Our pricing results quantify part of that tax, since the valuation premium of Section 4.3 implies a corresponding wedge in the cost of equity between favored and non-favored firms conditional on listing. Success also depends on the government’s ability to identify industries with genuine long-run economic or innovative potential, which leaves the tool exposed to the longstanding debate over whether states possess the information, incentives, and institutional capacity to make those selections efficiently (Baldwin, 1969; Krueger, 1990; Pack and Saggi, 2006). Less obvious are the advantages, which we take up in the rest of this subsection.

Preserving fiscal capacity. The IPO channel does not directly erode state fiscal capacity. Traditional instruments, such as subsidies, tax credits, government procurement, or state-backed lending, can impose large fiscal costs. Recent estimates put the fiscal cost

of industrial policy at roughly 4% of GDP per year in China, against about 1.5% of GDP of state aid in the European Union ([Garcia-Macia et al., 2025](#)). Such interventions can become difficult to sustain amid fiscal constraints, rising debt, and political resistance to large-scale subsidies. IPO regulation instead steers private capital toward favored firms without drawing on public funds.

Unlocking capital and talent beyond the offering. A listing delivers far more than the offering proceeds. Public firms gain access to seasoned equity, cheaper bank credit, and bond markets through greater disclosure, certification, and investor visibility ([Pagano et al., 1998](#); [Chemmanur and Fulghieri, 1999](#)), and their traded shares serve as acquisition currency and, in China and elsewhere, as loan collateral ([He et al., 2024](#)); acquisitions rise sharply after firms go public ([Celikyurt et al., 2010](#)). The effect also runs upstream: because venture capital depends on credible exits, above all IPOs ([Black and Gilson, 1998](#); [Gompers and Lerner, 2004](#)), preferential listing access draws venture and private-equity money into strategic industries long before firms list. Consistent with this, startups in policy-favored Chinese industries receive more venture and entrepreneurial financing ([Pan et al., 2022](#); [Ge et al., 2024](#); [Beraja et al., 2025](#); [Chen et al., 2026](#)).

Public listing also creates liquid equity that helps firms attract and retain scarce talent. Stock-based compensation becomes easier to value and monetize once a firm trades, which matters most in sectors such as semiconductors, biotechnology, and artificial intelligence, where human capital is the core input and individual productivity is hard to monitor ([Ittner et al., 2003](#); [Oyer and Schaefer, 2005](#); [Borisov et al., 2021](#)). IPO policy therefore shapes the allocation of talent as well as capital across industries.

Alleviating the “soft budget constraint.” Finally, IPO regulation may partially mitigate the classic “soft budget constraint” problem that often plagues state-directed industrial policy. [Kornai \(1986\)](#) famously argued that firms receiving repeated state support come to anticipate future bailouts, weakening incentives for efficiency and innovation. This con-

cern applies to both fiscal subsidies and directed credit (Cong et al., 2019; Branstetter et al., 2023). Listed firms, by contrast, remain subject to disclosure requirements, scrutiny from outside investors and analysts, stock-price feedback, and reputational or market-value losses when performance disappoints. Because stock markets help monitor managerial performance (Holmström and Tirole, 1993), IPO regulation combines state direction over initial market access with decentralized monitoring thereafter. Together these features make control of listing access an unusually economical instrument of industrial policy: the state directs private capital without spending its own, and the market it admits firms into keeps disciplining them afterward.

6 Conclusion

This paper shows that regulation of access to public equity markets can serve as an instrument of industrial policy, distinct from fiscal and credit tools. China’s policy documents name IPO access as such a tool, and the data bear this out. Policy-favored industries have substantially more IPOs and raise more proceeds, while industry valuation, which predicts IPO activity in the United States, does not in China. A simple framework explains this pattern: the government’s policy force alone governs entry through the approval gate, whereas fundamentals and policy jointly shape proceeds per IPO and valuation, so IPO quantity is disconnected from market valuation. Consistent with the framework, policy favor is priced. Favored firms trade at a persistent valuation premium, concentrated among large firms, whose prices best reflect fundamentals. Inside the gate, the favored-industry advantage arises from a larger applicant pool rather than a higher approval rate, and fundamentals sort which of an industry’s applicants list. Together, the evidence shows the state channeling private capital toward favored industries through listing regulation, while the market prices the value of that support.

The findings also speak to markets outside China. Western economies do not appear

to use IPO regulation as an explicit industrial-policy instrument, but state involvement in capital-market access may be more widespread than commonly recognized. Even under the disclosure-based U.S. regime, access has become entangled with national security: China Mobile, China Telecom, and China Unicom were delisted from the New York Stock Exchange following Executive Orders 13959 and 14032, which restricted U.S. investment in firms alleged to have military ties. Geopolitics can thus shape equity-market access even in formally market-oriented systems.

Listing review that goes beyond disclosure is also common outside the West. The Korea Exchange applies qualitative criteria and may inspect applicants on site; the Taiwan Stock Exchange assesses business quality, operational risk, and managerial integrity; Hong Kong's suitability review lets the Securities and Futures Commission object to listings in the public interest; and Saudi Arabia's Capital Market Authority and Tadawul exercise broad discretion over admission under the Vision 2030 strategy. In much of the world, then, IPO access runs through administrative review rather than market-based admission alone. Whether such review systematically reflects industrial-policy priorities remains an open question and a promising avenue for future research.

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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. C59: Electronic Equip. Repair 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. C59: Electronic Equip. Repair 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. C76: Electrical Machinery and 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 L20: Information Transmission Servs. 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. C61: Non-Metallic Mineral Products C67: Non-Ferrous Metal Smelting and Rolling 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 F07: Water 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 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 receiving at least one encouraging mention flagged as key policy support 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	1,432	0.313	0.000	0.464	0.000	1.000
FavorIntensity	1,432	0.392	0.000	0.646	0.000	3.000
#IPOs	1,432	2.578	1.000	6.233	0.000	74.000
#IPO applications	707	6.231	1.000	14.820	0.000	132.000
IPO proceeds	1,432	2,954.419	171.450	9,724.830	0.000	138,670.960
Any IPO	1,432	0.508	1.000	0.500	0.000	1.000
1[#IPO applications > 0]	707	0.605	1.000	0.489	0.000	1.000
Avg. proceeds	707	1,575.998	651.214	4,547.703	109.440	51,981.374
Avg. assets	707	35,320.845	1,082.835	308,647.627	96.622	5,600,022.500
Total proceeds / total assets	707	0.679	0.531	0.597	0.005	4.060
IndustryQ	1,432	1.655	1.415	0.726	0.918	4.794
log(IndustryGDP)	1,432	8.272	8.257	1.113	4.465	11.012

Panel B: Firm-Level Variables at the IPO Event Level

	N	Mean	Median	St. Dev.	Min	Max
First-day Q	3,817	4.740	3.867	3.089	0.999	27.833
1-Year Q	3,817	4.347	3.197	3.679	0.878	37.783
3-Year Q	3,817	3.040	2.341	2.277	0.886	21.918
GPA	3,817	33.870	34.004	6.027	21.292	48.408
SOE	3,817	0.203	0.000	0.402	0.000	1.000
Assets	3,817	18,232.928	713.376	273,239.249	68.516	9,516,211.000
ROA	3,817	16.828	15.436	10.230	-44.467	85.281
Leverage	3,817	1.110	0.751	1.663	0.062	25.744

Notes: Panel A reports the China CSRC 2001 industry-year sample over 2002–2022, excluding 2013 because IPOs were suspended. *Avg. proceeds*, *Avg. assets*, and *Total proceeds / total assets* use the same 707 industry-year observations and the same IPO issuers with positive proceeds and valid positive assets. The two averages divide matched issuer totals by the number of matched issuers; the ratio divides matched total proceeds by matched total assets. *IPO proceeds*, *Avg. proceeds*, and *Avg. assets* in Panel A are in RMB million and are not winsorized. The IPO-application rows cover 2014–2022 and count application processes by process-start year, defined by the public pre-disclosure date or, when unavailable, the submission or acceptance date. *FavorIntensity* is the integer count of encouraging industry references flagged as key policy support in China’s Five-Year Plans, and *log(IndustryGDP)* is the natural logarithm of official industry GDP allocated to CSRC 2001 industries. Panel B reports the China A-share IPO event sample over 2002–2022, the 3,817 firms used in every column of Table 6. *First-day Q*, *1-Year Q*, and *3-Year Q* are the winsorized outcomes of those regressions; the remaining firm characteristics are measured at the first-day horizon. *ROA* is in percent and winsorized at the 1st and 99th percentiles within each calendar year. In Panel B, *Assets* is total assets in RMB million; *log(Assets)* is the separate natural-log transformation used in the IPO valuation regressions. *GPA* is computed from pre-IPO prospectus text and winsorized at the 1st and 99th percentiles. *SME*, used in the IPO valuation regressions, indicates firms outside the top tercile of market capitalization of equity among all stocks listed at the firm’s IPO date. See Table A1 in the Internet Appendix for variable definitions and units.

Table 3: Policy Favor and IPO Activity in China vs. the U.S.

<i>Panel A: Number of IPOs</i>			
	China		U.S.
	(1)	(2)	(3)
Favored	1.352*** (0.256)		
FavorIntensity		0.741*** (0.111)	
FavorIntensity_US			0.042 (0.136)
IndustryQ	0.160 (0.137)	0.118 (0.126)	0.857*** (0.155)
log(IndustryGDP)	0.436*** (0.132)	0.395*** (0.128)	0.661*** (0.098)
Observations	1,432	1,432	1,680
Year FE	Yes	Yes	Yes
<i>Panel B: IPO Proceeds</i>			
	China		U.S.
	(1)	(2)	(3)
Favored	0.910*** (0.318)		
FavorIntensity		0.560*** (0.140)	
FavorIntensity_US			-0.013 (0.095)
IndustryQ	-0.044 (0.170)	-0.062 (0.158)	0.711*** (0.237)
log(IndustryGDP)	0.490*** (0.116)	0.460*** (0.112)	0.684*** (0.103)
Observations	1,432	1,432	1,680
Year FE	Yes	Yes	Yes

Notes: This table reports PPML estimates of industry-year capital-market activity in levels. Panel A reports the number of IPOs and Panel B reports IPO proceeds. In each panel, columns (1)–(2) use China samples and column (3) uses the U.S. benchmark. All columns cover 2002–2022, excluding 2013 from China because IPOs were suspended. Proceeds are measured in RMB 10,000 for China and USD million for the United States. *Favored* and *FavorIntensity* are China’s binary and continuous policy-favor measures, respectively. *FavorIntensity_US* is the average number of U.S. industrial-policy actions in force across ISIC four-digit child industries within each ISIC two-digit industry (Ju et al., 2026). *IndustryQ* is one-year lagged asset-weighted industry Tobin’s Q. *log(IndustryGDP)* uses official Chinese industry GDP and BEA gross output for the United States. Table 2 Panel A and Internet Appendix Table IA1 report China and the U.S. summary statistics, respectively. All specifications include year fixed effects; standard errors are clustered by industry. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 4: Chinese IPOs in the U.S. Market: A Placebo Test

	#IPOs		IPO proceeds		Any IPO	
	(1)	(2)	(3)	(4)	(5)	(6)
Favored	0.141 (0.277)		0.081 (0.412)		0.154 (0.209)	
FavorIntensity		0.213 (0.220)		0.240 (0.309)		0.149 (0.151)
IndustryQ	0.117 (0.124)	0.136 (0.126)	0.358** (0.182)	0.382** (0.183)	0.123 (0.112)	0.133 (0.112)
Observations	1,079	1,079	1,079	1,079	1,079	1,079
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports PPML estimates at the NAICS 3-digit industry-year level for Chinese firms listing in the United States during 2002–2022. Outcomes are IPO counts, proceeds in USD million, and an indicator for any IPO. **Favored** and **FavorIntensity** are the binary and continuous Chinese policy-favor measures. All columns control for lagged **IndustryQ**, winsorized at the 1st and 99th percentiles. Internet Appendix Table [IA2](#) reports sample summary statistics. All specifications include year fixed effects; standard errors are clustered by industry. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 5: Decomposing Policy and Market Effects on IPO Proceeds

<i>Panel A: Extensive Margin — Any IPO, and How Many</i>				
	Any IPO		log(#IPOs)	
	(1)	(2)	(3)	(4)
Favored	0.169*** (0.058)		0.657*** (0.182)	
FavorIntensity		0.112** (0.046)		0.540*** (0.102)
IndustryQ	-0.051 (0.037)	-0.052 (0.037)	0.196 (0.136)	0.192 (0.128)
log(IndustryGDP)	0.043 (0.028)	0.042 (0.028)	0.242*** (0.064)	0.226*** (0.061)
Year FE	Yes	Yes	Yes	Yes
Observations	1,432	1,432	707	707
R-squared	0.103	0.099	0.280	0.316
<i>Panel B: Intensive Margin — Issuer Size and Proceeds/Assets, Among IPO-Active Industry-Years</i>				
	log(Avg. Issuer Assets)		log(Proceeds / Assets)	
	(1)	(2)	(3)	(4)
Favored	-0.487** (0.219)		0.316** (0.134)	
FavorIntensity		-0.327** (0.141)		0.221** (0.085)
IndustryQ	-0.592*** (0.198)	-0.593*** (0.198)	0.372*** (0.129)	0.372*** (0.129)
log(IndustryGDP)	0.248** (0.099)	0.253** (0.100)	-0.192*** (0.064)	-0.197*** (0.065)
Year FE	Yes	Yes	Yes	Yes
Observations	707	707	707	707
R-squared	0.206	0.204	0.333	0.333
<i>Panel C: Combined Effects — Total Proceeds and Proceeds per IPO</i>				
	log(Total Proceeds)		log(Proceeds per IPO)	
	(1)	(2)	(3)	(4)
Favored	0.486** (0.193)		-0.171 (0.103)	
FavorIntensity		0.434*** (0.104)		-0.106 (0.066)
IndustryQ	-0.023 (0.135)	-0.029 (0.127)	-0.220*** (0.083)	-0.220*** (0.083)
log(IndustryGDP)	0.297*** (0.067)	0.282*** (0.064)	0.055 (0.044)	0.057 (0.045)
Year FE	Yes	Yes	Yes	Yes
Observations	707	707	707	707
R-squared	0.233	0.251	0.156	0.155

Notes: This table decomposes industry-year IPO proceeds into IPO entry, the number of issuers, average issuer size, and financing intensity; the estimating specification is Equation (8) in the paper. In Panel A, columns (1)–(2) report OLS linear probability models in which Any IPO equals one if an industry-year has at least one IPO; these columns use the full industry-year sample. Columns (3)–(4) report OLS estimates of the natural logarithm of the number of IPOs among IPO-active industry-years whose issuers match to IPO-year total assets. Panel B uses the same sample of IPO-active industry-years with matched issuer assets. Columns (1)–(2) report the natural logarithm of average issuer total assets, and columns (3)–(4) report the natural logarithm of total IPO proceeds divided by total issuer assets. Panel C reports the natural logarithms of total IPO proceeds in columns (1)–(2) and proceeds per IPO in columns (3)–(4), using the same sample of IPO-active industry-years with matched issuer assets. On this common sample, $\log(\text{total IPO proceeds}) = \log(\#IPOs) + \log(\text{proceeds per IPO})$, while $\log(\text{proceeds per IPO}) = \log(\text{average issuer assets}) + \log(\text{IPO proceeds/issuer assets})$. Consequently, for each regressor, the component coefficients add exactly to the corresponding Panel C coefficient. The sample covers Chinese A-share industry-years from 2002 to 2022, excludes 2013 because IPOs were suspended, and excludes Beijing Stock Exchange listings. Favored indicates whether an industry has at least one encouraging reference flagged as key policy support, and FavorIntensity counts those qualifying references in the active Five-Year Plan. IndustryQ is lagged industry Tobin's Q and is winsorized at the 1st and 99th percentiles; log(IndustryGDP) is the natural logarithm of official industry GDP. All specifications include year fixed effects. Standard errors are clustered by industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Policy-Aligned IPO Firms Receive Higher Valuations

Panel A: Baseline Regressions

	First-day Q			1-Year Q			3-Year Q		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Favored	0.682*** (0.235)			0.671** (0.257)			0.608*** (0.172)		
FavorIntensity		0.392** (0.166)			0.404** (0.174)			0.337** (0.139)	
GPA			0.076*** (0.020)			0.123*** (0.031)			0.084*** (0.023)
SOE	0.098 (0.081)	0.101 (0.080)	0.112 (0.090)	0.265** (0.108)	0.268** (0.106)	0.202 (0.129)	−0.142 (0.084)	−0.141 (0.085)	−0.087 (0.080)
ROA	0.039*** (0.012)	0.039*** (0.013)	0.031*** (0.009)	0.195*** (0.036)	0.196*** (0.036)	0.197*** (0.035)	0.091*** (0.022)	0.091*** (0.021)	0.099*** (0.020)
Leverage	−0.130 (0.084)	−0.135 (0.086)	−0.262** (0.117)	0.477*** (0.122)	0.470*** (0.119)	0.440** (0.210)	0.034 (0.065)	0.028 (0.068)	−0.082** (0.033)
log(Assets)	−0.488*** (0.105)	−0.492*** (0.103)	−0.464*** (0.108)	−0.980*** (0.176)	−0.980*** (0.174)	−1.046*** (0.194)	−0.429*** (0.087)	−0.434*** (0.089)	−0.420*** (0.086)
IPO-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817
Adjusted R ²	0.351	0.351	0.388	0.352	0.353	0.398	0.266	0.264	0.332

Notes: The sample consists of China A-share IPOs from 2002 through 2022; post-IPO Q outcomes are measured using market data through 2025. All nine columns use the same 3,817 firms, those with valuation and control data available at all three horizons. The dependent variables are First-day Q, 1-Year Q, and 3-Year Q; First-day Q uses the first non-limit-up trading-day price after listing, and Q is winsorized at the 1st and 99th percentiles within each calendar year. Favored is an indicator for policy-favored industries, FavorIntensity is the continuous policy-favor measure for the firm's industry, and GPA is computed from pre-IPO prospectus text and winsorized at the 1st and 99th percentiles. All specifications include IPO-year fixed effects and the firm controls SOE, ROA, Leverage, and log(Assets), whose coefficients are reported; ROA is in percent and winsorized at the 1st and 99th percentiles within each calendar year. For valuation at listing, accounting controls are measured using the most recent annual financial statements available before the IPO. For the one- and three-year valuation regressions, accounting controls are updated to the corresponding valuation horizon. Columns (3), (6), and (9) additionally include industry fixed effects at the unpooled CSRC-2012 level. Standard errors are two-way clustered by year and industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Panel B continues on the next page.

Table 6: Policy-Aligned IPO Firms Receive Higher Valuations (Continued)

Panel B: Regressions with Interaction Terms

	First-day Q			1-Year Q			3-Year Q		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Favored	1.151*** (0.370)			1.402*** (0.395)			0.791*** (0.223)		
× SME	−0.742*** (0.259)			−1.045** (0.376)			−0.471** (0.167)		
× SOE	−0.598* (0.303)			−0.863*** (0.273)			−0.497** (0.196)		
FavorIntensity		0.685** (0.271)			0.756** (0.265)			0.441** (0.175)	
× SME		−0.476** (0.180)			−0.586** (0.224)			−0.281** (0.116)	
× SOE		−0.351* (0.198)			−0.386** (0.156)			−0.277** (0.110)	
GPA			0.117*** (0.032)			0.170*** (0.027)			0.106*** (0.023)
× SME			−0.103*** (0.032)			−0.121*** (0.030)			−0.067*** (0.017)
× SOE			−0.004 (0.020)			−0.040* (0.019)			−0.022* (0.013)
IPO-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817
Adjusted R ²	0.482	0.483	0.509	0.515	0.514	0.543	0.473	0.473	0.511

Notes: Panel B augments the Panel A specifications with interactions of each policy measure with *SME* and *SOE*, where *SME* indicates firms outside the top tercile of market capitalization at IPO, i.e., the bottom two terciles; the *SME* and *SOE* main effects are included but not reported. The reported policy coefficients are therefore the large-firm, non-*SOE* effects. The remaining conventions—sample, outcomes, controls, fixed effects, clustering, and significance levels—are as in Panel A. Internet Appendix Table [IA12](#) repeats these specifications with *SME* split into separate bottom- and middle-tercile indicators.

Table 7: IPO Applicant Pools and IPO Selection

Panel A: Applications and Approval Rates by Process-Completion Year

Year	Favored		Non-favored		Difference in approval rate	t-statistic
	#App	Approval rate	#App	Approval rate		
2014	67	80.6%	31	67.7%	12.9%	1.40
2015	158	86.1%	88	88.6%	-2.6%	-0.57
2016	170	74.7%	129	76.7%	-2.0%	-0.41
2017	370	77.0%	190	78.9%	-1.9%	-0.52
2018	152	45.4%	100	36.0%	9.4%	1.48
2019	193	73.1%	92	65.2%	7.8%	1.36
2020	360	78.1%	131	84.0%	-5.9%	-1.44
2021	532	65.4%	194	68.6%	-3.1%	-0.79
2022	458	58.5%	144	52.8%	5.7%	1.21
2014–2022	2,460	69.5%	1,099	69.4%	0.0%	0.03

Panel B: Application Counts and Realized IPO Completion

	Industry level		Firm level	
	#IPO applications (1)	#IPO applications (2)	IPO success (3)	IPO success (4)
Favored	1.636*** (0.297)		0.021 (0.038)	-0.008 (0.581)
FavorIntensity		0.772*** (0.125)		
IndustryQ	0.212 (0.157)	0.144 (0.145)		
log(IndustryGDP)	0.443*** (0.143)	0.387*** (0.142)		
log(Assets)			0.069*** (0.014)	0.070*** (0.016)
× Non-favored				-0.001 (0.028)
Asset growth			0.069*** (0.024)	0.097*** (0.025)
× Non-favored				-0.132** (0.057)
EBIT / Assets			0.444*** (0.082)	0.416*** (0.088)
× Non-favored				0.173 (0.227)
Year FE	Yes	Yes		
Year × Board FE			Yes	Yes
Industry FE	No	No	Yes	Yes
Observations	707	707	3,140	3,140
R-squared			0.195	0.197

Notes: The table covers IPO applications in favored and non-favored industries over 2014–2022. Panel A groups terminal-outcome records by process-completion year and reports annual application counts and realized listing rates, favored-minus-non-favored rate differences, and two-sample *t*-statistics; the bottom row pools all years. Panel B columns (1)–(2) instead measure application inflows by process-start year, defined by the public pre-disclosure date or, when unavailable, the submission or acceptance date. These columns report industry-year PPML estimates of application counts, control for lagged IndustryQ and log(IndustryGDP), and include year fixed effects. Columns (3)–(4) report application-round OLS linear-probability estimates for 3,140 terminal-outcome, non-BSE applications with complete financial data; the dependent variable equals one when an application ultimately results in a listing. Financial variables precede the application process start date. *Asset growth* is the log change in total assets from T-2 to T-1; *EBIT/assets* is T-1 operating profit plus source-reviewed interest expense, divided by T-1 total assets. *Asset growth* and *EBIT/assets* are winsorized at the 1st and 99th percentiles; log assets is not winsorized. Columns (3)–(4) include Favored; column (4) additionally interacts a Non-favored indicator with all three fundamentals. The reported fundamental main effects in column (4) are therefore the slopes among favored-industry applicants, and each interaction is the non-favored-minus-favored slope difference. Columns (3)–(4) include CSRC 2001 industry and application-year-by-board fixed effects. Internet Appendix Table IA3 reports applicant-fundamentals summary statistics. Standard errors are reported in parentheses and clustered by CSRC 2001 industry. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Favored Industries Have More NEEQ Listings

	#NEEQ listings	
	(1)	(2)
Favored	1.419*** (0.323)	
FavorIntensity		0.766*** (0.151)
IndustryQ	0.360 (0.237)	0.301 (0.204)
log(IndustryGDP)	0.723*** (0.215)	0.683*** (0.206)
Observations	707	707
Year FE	Yes	Yes

Notes: This table presents PPML estimates for NEEQ listings and industry characteristics during 2014 to 2022. The dependent variable is the number of NEEQ listings. *Favored* indicates whether an industry has at least one encouraging reference flagged as key policy support, and *FavorIntensity* counts those qualifying references in the active Five-Year Plan. Controls are *IndustryQ*, lagged asset-weighted Tobin's Q within industry, and *log(IndustryGDP)*, the natural logarithm of official industry GDP. *IndustryQ* is winsorized at the 1st and 99th percentiles. All specifications include year fixed effects, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Policy Alignment in Hong Kong Capital Markets

Panel A: Hong Kong IPO Activity

	#IPOs				IPO proceeds			
	Non-mainland		Mainland		Non-mainland		Mainland	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Favored	-0.119 (0.261)		0.400 (0.271)		0.234 (0.322)		0.497 (0.389)	
FavorIntensity		-0.080 (0.183)		0.312* (0.164)		0.120 (0.173)		0.351 (0.233)
IndustryQ	-0.150 (0.180)	-0.156 (0.186)	-0.179 (0.194)	-0.149 (0.192)	0.136 (0.291)	0.144 (0.281)	-0.733 (0.664)	-0.653 (0.669)
Observations	1,206	1,206	1,206	1,206	1,206	1,206	1,206	1,206
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: A–H Premium

	A–H premium		
	(1)	(2)	(3)
Favored	-6.304 (10.186)		
FavorIntensity		-3.917 (6.576)	
GPA			0.180 (1.412)
Controls	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Industry FE	No	No	Yes
Observations	13,121	13,121	13,121
Adjusted R ²	0.530	0.530	0.622

Notes: Panel A. PPML estimates at the NAICS 3-digit industry-year level for Hong Kong listings during 2002–2022. Outcomes are IPO counts and proceeds in HKD million. Columns (1)–(2) and (5)–(6) use non-mainland issuers; columns (3)–(4) and (7)–(8) use mainland Chinese issuers. *Favored* and *FavorIntensity* are the binary and continuous Chinese policy-favor measures. All columns control for lagged *IndustryQ*, winsorized at the 1st and 99th percentiles, and include year fixed effects. Standard errors are clustered by industry. Panel B. OLS regressions for the 2002–2021 firm-month sample of firms dual-listed in mainland China and Hong Kong. A–H premium is the percentage by which a firm’s mainland A-share price exceeds its Hong Kong H-share price after converting prices to a common currency; a positive value means the A-shares trade at a premium. It is measured monthly and winsorized at the 1st and 99th percentiles within each calendar year. GPA is computed from annual-report text and winsorized at the 1st and 99th percentiles. The controls *SOE*, *ROA*, *book-to-market*, and $\log(\text{ME})$, the log of combined A- and H-share market capitalization, are included but their coefficients are not reported. *ROA* and *book-to-market* are winsorized at the 1st and 99th percentiles within each calendar year. All specifications include date fixed effects; column (3) additionally includes industry fixed effects. Standard errors are two-way clustered by month and firm and reported in parentheses. Internet Appendix Tables IA6 and IA7 report summary statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1: Definitions of Variables

	Definition
A-H premium	Monthly A-H cross-market price premium for dual-listed firms, defined as the percentage by which a firm's mainland A-share price exceeds the price of its Hong Kong H-shares after converting prices to a common currency; winsorized at the 1st and 99th percentiles by calendar year.
$\log(\text{Assets})$	Natural logarithm of total assets, measured in RMB 100 million before taking logs.
Asset growth	Log change in total assets from T-2 to T-1, where T is the IPO application process-start year; winsorized at the 1st and 99th percentiles.
B/M	Book-to-market ratio.
EBIT / Assets	T-1 operating profit plus interest expense, divided by T-1 total assets.
Favored	Indicator equal to one when a CSRC 2001 industry receives at least one encouraging mention flagged as key policy support in the Five-Year Plan active in year t , and zero otherwise.
FavorIntensity	Integer count of encouraging industry references flagged as key policy support in the Five-Year Plan active in year t , based on the CNRDS policy-text mapping to CSRC 2001 industries. Repeated qualifying references add to the score.
FavorIntensity_US	U.S. policy-favor intensity measure from Ju et al. (2026) . It is defined at the ISIC two-digit industry-year level as the average number of U.S. industrial-policy actions in force across the ISIC four-digit child industries within each ISIC two-digit industry. Higher values indicate greater U.S. industrial-policy exposure.
GPA	Firm-level policy-alignment score computed either from IPO prospectus text or annual-report text, depending on the empirical setting. IPO-related analyses use pre-IPO prospectus text, while secondary-market and A-H premium analyses use annual-report text. Winsorization follows each table note.
$\log(\text{IndustryGDP})$	Natural logarithm of official industry GDP in year t , measured in RMB 100 million for China and USD million for the U.S. before taking logs. For China, GDP reported under GB/T 4754 is allocated and mapped to CSRC 2001 industries; for the U.S., the series comes from BEA industry accounts. Covers the full industry, not only listed firms.
IndustryQ	Asset-weighted industry Tobin's Q, lagged one year ($t-1$); winsorized at the 1st and 99th percentiles.
#IPO applications	Number of IPO application processes beginning in an industry-year, dated by the public pre-disclosure date or, when unavailable, the submission or acceptance date.
#IPOs	Annual number of IPOs in an industry-year.
Any IPO	Indicator for whether at least one IPO occurs in the industry-year.
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.
$\log(\text{ME})$	Natural logarithm of total market capitalization; in the A-H premium regressions, market capitalization is the combined A- and H-share market capitalization.
#NEEQ	Annual number of NEEQ listings in an industry-year; count.
First-day Q	Tobin's Q using the first non-limit-up trading day price after listing, meaning the first trading day on which the stock does not hit its daily upper price limit; winsorized at the 1st and 99th percentiles within calendar year.
1-Year Q, 3-Year Q	Tobin's Q measured one and three years after IPO, respectively, that is, 365 and 1,095 calendar days after the listing date (the next trading day if that date is not one); winsorized at the 1st and 99th percentiles within each calendar year.
IPO success	Indicator equal to one when an IPO application ultimately results in a listing, and zero otherwise.
ROA	Return on assets, in percent: the data provider's primary return-on-assets series, with its net-income-based series used for the 2% of firms where the primary series is missing; winsorized at the 1st and 99th percentiles within each calendar year in the IPO valuation regressions.
SOE	State-owned enterprise indicator.
SME	Indicator for firms outside the top tercile of market capitalization at IPO among then-listed firms (the bottom two terciles).

Notes: This table defines the variables as they enter the main regression tables. Logged variables are reported directly as logged variables, with the underlying level, unit, and transformation described in the corresponding definition. All logged variables in the main-text tables use the natural logarithm, $\ln(x)$. The decomposition in Table 5 takes logs on its positive-value sample. 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

(Not for Publication)

Zhiguo He Yiming Qian Xi Sun Renxuan Wang

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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 *FavorIntensity*, the corresponding continuous measure of policy-favor 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.

We construct both policy measures directly at the CSRC 2001 industry-plan level. *FavorIntensity* is the integer count of encouraging industry references that CNRDS flags

as key policy support in the active FYP. We set Favored equal to one if this count is positive and zero otherwise; we do not average the policy measures across GB/T industries.

The industry GDP control originates from official statistics reported under the GB/T 4754 national classification. We first allocate broad-section GDP to GB/T two-digit industries using their shares of operating revenue among industrial enterprises above designated size, splitting equally where revenue data are unavailable. We then map those GDP amounts to CSRC 2001 industries and sum within each CSRC industry-year. Thus, the domestic regression panel, its policy measures, and its GDP control all use CSRC 2001 industries.

I.2 GPA construction

For the IPO analysis, we construct GPA from firms' IPO prospectuses, using the business-scope descriptions disclosed before listing. We match each IPO to the Five-Year Plan in effect at the time of listing, using the plan's announcement year as the policy-year anchor. Firm-level controls are taken from the most recent financial report available before the IPO, so both the text-based GPA measure and the accounting controls are determined prior to listing.

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 IPO prospectus $D_{i,t}$. Similarly, the government industrial preference is 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 are 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 alignments²⁶. 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:

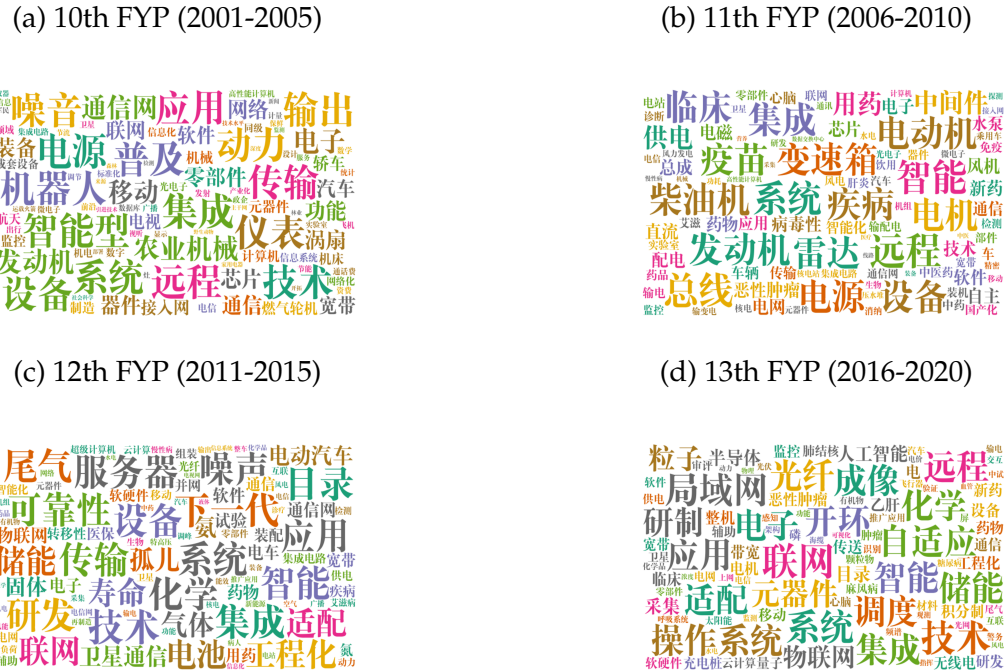
$$GPA_{i,t} = \sum_{b \in B_{i,t}} w_{b,i,t}^B \cdot \sum_{p \in P_{b,t}^{top10}} (\text{cossim}(b, p) \cdot w_{p,t}^P)$$

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.

²⁶Our results remain robust using alternative numbers of top words.

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.

Figure IA1: Word Clouds of Industrial Policy Keywords for Each Five-Year Plan



II Sample Construction

This section documents the samples used in the paper’s cross-market comparisons and broader capital-market tests. For each sample, we report the data source, sample window, exclusions, industry classification, and estimation level. The associated summary statistics are reported with the corresponding sample description.

II.1 China A-share IPO Sample

The main China sample contains A-share IPOs from 2002–2022. We exclude 2013 from the industry-year allocation sample because IPO issuance was suspended from October 2012 to January 2014. We also exclude Beijing Stock Exchange listings from the baseline sample because the exchange is a distinct market segment and was initially populated primarily through transfers rather than the standard IPO application process. Firm-level IPO-event records and issuer characteristics come from Wind; industry outcomes are aggregated to CSRC 2001 industry-year observations.

II.2 U.S. IPO Benchmark from Refinitiv

The U.S. benchmark uses Refinitiv IPO data for 2002–2022. We retain IPOs listed on major U.S. exchanges, exclude REITs and Pink Sheet listings, classify issuers into ISIC industries, and aggregate IPO counts and proceeds to ISIC two-digit industry-year observations. Proceeds are measured in USD million.

Table IA1: U.S. IPO Benchmark Summary Statistics

	N	Mean	Median	St. Dev.	Min	Max
#IPOs	1,680	1.458	0.000	4.396	0.000	81.000
IPO proceeds	1,680	364.164	0.000	1,375.903	0.000	26,632.744
log(IndustryGDP)	1,680	11.604	11.918	1.969	0.362	15.427
IndustryQ	1,680	1.662	1.484	0.676	0.736	6.910
FavorIntensity_US	1,680	0.526	0.000	1.051	0.000	9.000

Notes: This table reports summary statistics for the 2002–2022 U.S. IPO benchmark sample at the ISIC two-digit industry-year level. IPO activity is measured using Refinitiv IPOs listed on major U.S. exchanges, excluding Pink Sheet listings and REITs. #IPOs is the number of IPOs, and IPO proceeds is total IPO proceeds in USD million. log(IndustryGDP) is the natural logarithm of BEA detailed-industry gross output allocated to ISIC industries. IndustryQ is lagged industry Tobin’s Q, and FavorIntensity_US is the U.S. policy-favor intensity measure from [Ju et al. \(2026\)](#).

II.3 Chinese Firms Listing in the United States

The overseas placebo sample contains Chinese firms listing in the United States during 2002–2022. We classify issuers at the NAICS three-digit level and aggregate IPO counts, proceeds, and IPO-occurrence indicators to industry-year observations. The sample is used to test whether Chinese policy favor predicts IPO activity outside the domestic regulatory environment. Its summary statistics are reported in Table [IA2](#).

Table IA2: Chinese IPOs Listing in the United States: Summary Statistics

	N	Mean	Median	St. Dev.	Min	Max
#IPOs	1,079	0.287	0.000	0.781	0.000	6.000
IPO proceeds	1,079	58.198	0.000	340.209	0.000	8,175.090
Any IPO	1,079	0.176	0.000	0.381	0.000	1.000
Favored	1,079	0.345	0.000	0.476	0.000	1.000
FavorIntensity	1,079	0.437	0.000	0.667	0.000	3.000
IndustryQ	1,079	1.625	1.420	0.652	0.920	4.603

Notes: This table reports Chinese firms listing in the U.S. market during 2002–2022 at the NAICS 3-digit industry-year level and uses the common 1,079-observation PPML estimation sample, which contains 310 IPOs spread across 46 of the panel’s 58 industries; the largest industry accounts for 11% of these IPOs. IPO proceeds are measured in USD million. Favored and FavorIntensity are the binary and continuous measures of Chinese policy favor.

II.4 IPO Application and Review Sample

The IPO application and review sample uses CSRC review disclosures from 2014–2022, the period in which application status and review progress become systematically available. The records contain application dates, review outcomes, industry classifications, listing boards, and the dates needed to construct review duration. We use these records to measure application counts, approval or completion outcomes, and the time from application acceptance to listing. The tables in this subsection report the complete-case applicant-fundamentals sample used in Table [7](#), annual approval-duration breakdowns, and regressions of review duration on policy alignment.

Table IA3: IPO Applicant Fundamentals: Summary Statistics

	N	Mean	Median	St. Dev.	Min	Max
IPO success	3,140	0.686	1.000	0.464	0.000	1.000
log(Assets)	3,140	20.574	20.340	1.201	17.995	29.882
Asset growth	3,140	0.260	0.191	0.297	-0.199	1.694
EBIT / Assets	3,140	0.132	0.121	0.092	-0.200	0.446
Favored	3,140	0.714	1.000	0.452	0.000	1.000
FavorIntensity	3,140	0.999	1.000	0.811	0.000	3.000

Notes: This table describes the 3,140 terminal-outcome, non-BSE IPO application records used in the application-round columns of Table 7. The application process start date falls between 2014 and 2022. **IPO success** equals one when the application ultimately results in a listing. Financial variables precede the application process start date. **Asset growth** is the log change in total assets from T-2 to T-1; **EBIT/assets** is T-1 operating profit plus source-reviewed interest expense, divided by T-1 total assets. **Asset growth** and **EBIT/assets** are winsorized at the 1st and 99th percentiles; log total assets is not winsorized. **Favored** and **FavorIntensity** are matched by CSRC 2001 industry and application year.

Table IA4: IPO Approval Duration by Year

Year	#IPO	Favored		#IPO	Non-favored		Difference	
		Mean days	Median days		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***
2022	268	443	424	76	508	446	-65***	-22
2014–2022	1,709	479	447	763	556	504	-77***	-57***

Notes: This table reports year-by-year summary statistics for IPO approval duration among successful IPOs listed during 2014–2022, 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.

Table IA5: Policy-Favored and More Policy-Aligned Applicants Complete IPO Review Faster

	log(#Days to IPO)		
	(1)	(2)	(3)
Favored	-0.093*** (0.028)		
FavorIntensity		-0.041** (0.016)	
GPA			-0.017*** (0.003)
SOE	-0.027 (0.035)	-0.025 (0.036)	-0.040 (0.038)
ROA	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)
Leverage	0.022* (0.011)	0.023** (0.011)	-0.015 (0.019)
log(Assets)	0.013 (0.019)	0.014 (0.018)	-0.003 (0.019)
Observations	2,429	2,429	2,429
R-squared	0.316	0.314	0.374
Year FE	Yes	Yes	Yes
Industry FE	No	No	Yes

Notes: This table reports OLS regressions of $\log(\#Days \text{ to IPO})$ among 2,429 successful China A-share IPO applications listed during 2014–2022. The dependent variable is the natural logarithm of the number of calendar days between application and listing; the underlying day count is winsorized at the 1st and 99th percentiles. *Favored* indicates at least one qualifying priority reference, *FavorIntensity* counts such references in the active Five-Year Plan, and *GPA* is computed from pre-IPO prospectus text. All columns control for *SOE*, *ROA*, *Leverage*, and *log(Assets)* and include year fixed effects; column (3) additionally includes CSRC 2001 industry fixed effects. The estimates are conditional on eventual listing and do not identify review speed for unsuccessful applications. Standard errors are clustered by CSRC 2001 industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

II.5 NEEQ Listings

The NEEQ sample covers industry-year listings on China’s National Equities Exchange and Quotations over the window used in the corresponding main-text tests. NEEQ outcomes are aggregated at the CSRC 2001 industry-year level, using the same policy-favor measures and industry controls as the A-share analysis. The sample excludes observations outside the NEEQ listing data coverage.

II.6 Hong Kong Listings

The Hong Kong sample covers Chinese and non-mainland issuers listed in Hong Kong over the window used in the boundary-market tests. We classify issuers at the NAICS

three-digit level and distinguish mainland Chinese issuers from non-mainland issuers. Its summary statistics are reported in Table [IA6](#).

Table IA6: Hong Kong IPOs by Issuer Origin: Summary Statistics

	N	Mean	Median	St. Dev.	Min	Max
#IPOs (non-mainland)	1,206	0.722	0.000	1.639	0.000	15.000
#IPOs (mainland)	1,206	0.737	0.000	1.573	0.000	20.000
IPO proceeds (non-mainland)	1,206	431.460	0.000	2,066.751	0.000	40,009.359
IPO proceeds (mainland)	1,206	1,572.545	0.000	6,173.007	0.000	92,791.570
Favored	1,206	0.274	0.000	0.446	0.000	1.000
FavorIntensity	1,206	0.356	0.000	0.638	0.000	3.000
IndustryQ	1,206	1.618	1.430	0.677	0.916	5.157

Notes: This table reports Hong Kong listings during 2002–2022 at the NAICS 3-digit industry-year level and uses the common 1,206-observation PPML estimation sample. Rows marked “non-mainland” cover non-mainland issuers, while rows marked “mainland” cover mainland Chinese issuers; neither group is the full Hong Kong market. IPO proceeds are measured in HKD million. Favored and FavorIntensity are the binary and continuous measures of Chinese policy favor.

A–H premium sample. The A–H premium analysis uses a 2002–2021 firm-month sample of dual-listed firms. Its summary statistics are reported in Table [IA7](#) because this sample is constructed from the Hong Kong-linked firm panel rather than from the IPO industry-year panel.

Table IA7: Firm-Level Summary Statistics for A-H Premium Analysis

	N	Mean	Median	St. Dev.	Min	Max
A–H premium	13,121	101.856	68.964	111.485	−26.454	863.880
SOE	13,121	0.720	1.000	0.449	0.000	1.000
ROA	13,121	3.502	2.832	5.137	−45.776	28.649
B/M	13,121	0.399	0.336	0.279	−0.244	2.052
log(ME)	13,121	25.010	25.083	1.488	20.862	29.757

Notes: This table reports summary statistics for the 2002–2021 A–H premium firm-month sample used in Table 9. A–H premium is measured monthly and winsorized at the 1st and 99th percentiles within each calendar year. The regression controls are SOE, ROA, book-to-market, and log(ME).

III Additional Results

III.1 Cross-Country Comparative Evidence

Table IA8 complements the cross-country comparison in the paper by estimating the association between IPO activity and industry fundamentals; Figure 1 in the paper visualizes its Q coefficients. Figure IA2 uses the OLS version of this residualization for IPO counts, while this table reports the corresponding PPML estimates for China and the United States. 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 IA8: IPO Activity across Industries

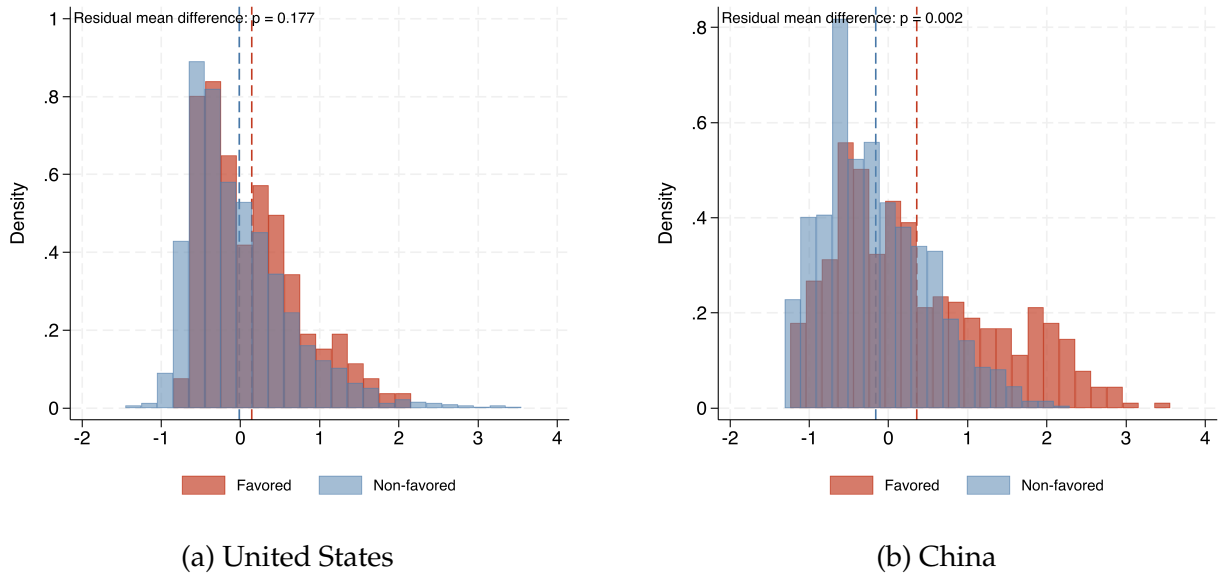
Outcome	China		U.S.	
	#IPOs (1)	IPO proceeds (2)	#IPOs (3)	IPO proceeds (4)
Industry Q	0.161 (0.140)	-0.011 (0.170)	0.851*** (0.152)	0.713*** (0.238)
$\log(\text{IndustryGDP})$	0.415*** (0.142)	0.480*** (0.116)	0.663*** (0.101)	0.683*** (0.101)
Observations	1,432	1,432	1,680	1,680
Year FE	Yes	Yes	Yes	Yes

Notes: This table presents PPML estimates of the relationship between IPO activity and industry characteristics for 2002–2022. The year 2013 is excluded from the China columns due to the suspension of IPOs in China; the U.S. columns retain 2002–2022. The dependent variables are the number of IPOs and IPO proceeds in levels. In the China columns, IPO proceeds are measured in RMB 10,000; in the U.S. columns, IPO proceeds are measured in USD million and industries are measured at the ISIC two-digit level. Industry Q represents lagged industry Tobin’s Q , defined as the asset-weighted average of firms’ Tobin’s Q ratios within an industry; it is winsorized at the 1st and 99th percentiles in the China specifications. $\log(\text{IndustryGDP})$ is the natural logarithm of official industry GDP for China and BEA detailed-industry gross output allocated to ISIC industries for the United States. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

III.2 Industry Q as a Summary of Fundamentals and Policy

Table IA9 characterizes the Industry Q variable that the industry-year analyses use as the market’s one-number summary of fundamentals. Regressing industry Q on industry-level analogues of the valuation-section controls shows that fundamentals dominate its cross-section—profitability, leverage, and size double the explained variation—while pol-

Figure IA2: Residual IPO Activity by Policy Favor in China and the United States



Notes: This figure plots the distribution of residuals from an OLS regression of $\log(1 + \text{\#IPOs})$ on $\log(\text{IndustryGDP})$, lagged industry Q , and year fixed effects. Dashed vertical lines mark group means. In the China panel, *Favored* equals one when *FavorIntensity* is positive. In the U.S. panel, *Favored* equals one when an industry receives a current-year policy mention in the U.S. industrial-policy measure of [Ju et al. \(2026\)](#). The China sample covers 2002–2022, excluding 2013; the U.S. sample covers 2002–2022 at the ISIC two-digit industry level. Reported p-values are from residual-mean comparisons with standard errors clustered by industry.

icy favor carries a positive premium conditional on them. Both forces of the framework in Section 4.1 are therefore visible in industry valuations before any IPO outcome is examined.

III.3 Supplementary Descriptive Tables for IPO Allocation and Approval Process

This subsection collects the descriptive table that complements the paper’s main estimation evidence on industry-level IPO activity. Table IA10 provides the annual breakdown underlying the full-sample descriptive contrast reported in the paper. It compares the share of IPO counts and IPO proceeds accruing to policy-favored industries with the corresponding GDP contribution share of those industries.

Table IA9: Industry Q Loads on Both Fundamentals and Policy Favor

	IndustryQ			
	(1)	(2)	(3)	(4)
Favored	0.183* (0.100)		0.138* (0.072)	
FavorIntensity				0.118** (0.051)
Industry ROA		6.412*** (1.746)	6.706*** (1.719)	6.851*** (1.711)
Asset growth (1y)		0.035 (0.044)	0.031 (0.044)	0.033 (0.044)
Book leverage		-0.828*** (0.302)	-0.642** (0.272)	-0.592** (0.259)
log(Total assets)		-0.112*** (0.033)	-0.121*** (0.033)	-0.125*** (0.033)
log(IndustryGDP)	-0.097* (0.054)	0.071 (0.047)	0.068 (0.046)	0.066 (0.045)
Year FE	Yes	Yes	Yes	Yes
Observations	1,101	1,101	1,101	1,101
R-squared	0.223	0.495	0.504	0.509

Notes: This table reports OLS regressions of industry Tobin's Q on industry fundamentals and policy favor. The dependent variable is industry Tobin's Q at the CSRC-2001 industry-year level (asset-weighted, winsorized at the 1st and 99th percentiles), 2002–2022 excluding 2013, for industries with at least three listed firms. The fundamentals block contains industry-level analogues of the firm controls in the valuation analysis, aggregated from the listed-firm universe: value-weighted ROA and book leverage, one-year log growth of aggregate assets, and the logarithm of aggregate total assets, each winsorized within year. *Favored* and *FavorIntensity* are the industry policy-favor measures. Standard errors are clustered by industry. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table IA10: IPO Activity and GDP Contribution by Policy Favor

Year	IPO Counts			IPO Proceeds			GDP
	Total	Favored	Share	Total	Favored	Share	Favored Share
2002	63	24	0.38	468.34	194.39	0.42	0.34
2003	64	22	0.34	465.39	78.37	0.17	0.34
2004	94	33	0.35	336.85	117.93	0.35	0.35
2005	14	6	0.43	52.73	13.65	0.26	0.33
2006	60	21	0.35	1328.50	98.19	0.07	0.32
2007	119	49	0.41	4762.75	179.04	0.04	0.30
2008	74	30	0.41	1029.31	177.13	0.17	0.29
2009	92	53	0.58	1706.30	533.35	0.31	0.28
2010	318	196	0.62	4656.99	2274.53	0.49	0.27
2011	266	179	0.67	2579.51	1461.37	0.57	0.29
2012	142	96	0.68	970.82	595.09	0.61	0.29
2014	119	81	0.68	640.65	341.96	0.53	0.28
2015	211	135	0.64	1540.92	756.03	0.49	0.28
2016	225	127	0.56	1485.65	565.60	0.38	0.30
2017	432	282	0.65	2286.55	1368.57	0.60	0.31
2018	104	68	0.65	1373.57	888.36	0.65	0.31
2019	200	140	0.70	2528.83	1475.91	0.58	0.32
2020	392	282	0.72	4685.36	3304.15	0.71	0.32
2021	479	348	0.73	5342.24	4089.52	0.77	0.32
2022	341	266	0.78	5704.08	4596.29	0.81	0.32

Notes: This table summarizes annual IPO activity, proceeds, and allocated GDP across CSRC2001 industries in China over 2002–2022, excluding the 2013 IPO suspension. Favored equals one when a CSRC 2001 industry receives at least one qualifying policy-support reference in the corresponding Five-Year Plan. IPO counts and proceeds use all CSRC2001 industries; proceeds are measured in RMB 100 million. GDP starts from official current-price one-digit industry GDP, is allocated to GB2017 two-digit industries using their shares of above-scale industrial-enterprise revenue (or equal shares when revenue weights are unavailable), and is then allocated equally across mapped CSRC2001 industries. The 2002–2003 GDP shares are rough backcasts: observed industries are subtracted from official secondary- and tertiary-sector GDP totals, and each residual is allocated across missing one-digit industries using their 2004 GDP shares before applying the standard crosswalk. Shares are rounded to two decimals.

III.4 Subperiod Analysis

Table [IA11](#) reports the separate-subperiod PPML coefficients for IPO counts and IPO proceeds by Five-Year Plan window. The two panels correspond to the time-pattern discussion summarized by Figure [3](#) in the paper and show the underlying coefficient estimates directly.

Table IA11: IPO Activity in Favored Industries: By Subperiod

Panel A: IPO counts

	2002–2005		2006–2010		2011–2015		2016–2020		2021–2022	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Favored	0.023 (0.313)		0.963*** (0.272)		1.476*** (0.303)		1.387*** (0.334)		1.825*** (0.355)	
FavorIntensity		0.083 (0.252)		0.658*** (0.193)		0.844*** (0.116)		0.640*** (0.150)		0.995*** (0.167)
IndustryQ	-1.082* (0.636)	-1.115* (0.643)	-0.075 (0.138)	-0.008 (0.138)	0.054 (0.168)	0.079 (0.141)	0.145 (0.185)	0.058 (0.173)	0.334* (0.172)	0.226 (0.159)
log(IndustryGDP)	0.537** (0.252)	0.527** (0.249)	0.505*** (0.169)	0.451*** (0.162)	0.537*** (0.141)	0.412*** (0.143)	0.370** (0.162)	0.364** (0.165)	0.399** (0.157)	0.333** (0.131)
Observations	192	192	376	376	313	313	393	393	158	158
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: IPO proceeds

	2002–2005		2006–2010		2011–2015		2016–2020		2021–2022	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Favored	-0.122 (0.355)		-0.167 (0.363)		1.016*** (0.309)		1.165*** (0.398)		2.023*** (0.371)	
FavorIntensity		-0.060 (0.311)		-0.098 (0.269)		0.622*** (0.145)		0.559*** (0.148)		1.080*** (0.177)
IndustryQ	-5.132*** (1.677)	-5.156*** (1.689)	-0.751 (0.557)	-0.765 (0.574)	-0.142 (0.152)	-0.133 (0.145)	-0.021 (0.210)	-0.101 (0.195)	0.239 (0.203)	0.127 (0.195)
log(IndustryGDP)	0.313 (0.212)	0.303 (0.211)	0.521*** (0.170)	0.526*** (0.173)	0.639*** (0.127)	0.576*** (0.149)	0.423*** (0.148)	0.415*** (0.150)	0.425** (0.170)	0.338** (0.140)
Observations	192	192	376	376	313	313	393	393	158	158
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents PPML estimates of IPO activity in levels over different subperiods, corresponding to China's Five-Year Plans, from 2002 to 2022, excluding 2013 due to the suspension of IPOs. Panel A uses IPO counts as the dependent variable; Panel B uses IPO proceeds, measured in RMB 10,000. **Favored** is the binary favored-industry indicator, and **FavorIntensity** is the integer count of encouraging industry references flagged as key policy support in China's Five-Year Plans. **IndustryQ** is lagged industry Tobin's Q, defined as the asset-weighted average of firms' Tobin's Q ratios within an industry and winsorized at the 1st and 99th percentiles. **log(IndustryGDP)** is the natural logarithm of industry GDP. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table IA12 repeats the interaction specifications of Panel B of Table 6 in the paper with the SME indicator split into its two components, *Small* and *Medium*, the bottom and middle terciles of market capitalization at IPO. Its role is to document the size gradient behind the main-text statement that the valuation premium concentrates among large firms.

Table IA12: IPO Valuation Interaction Specifications: Size Terciles

	First-day Q			1-Year Q			3-Year Q		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Small</i>	−3.568*** (0.672)	−3.572*** (0.711)	−0.613 (0.921)	−4.319*** (0.537)	−4.470*** (0.604)	0.413 (0.901)	−3.342*** (0.425)	−3.397*** (0.423)	−0.699 (0.620)
<i>Medium</i>	−2.217*** (0.436)	−2.298*** (0.501)	0.840 (0.737)	−3.065*** (0.408)	−3.175*** (0.450)	0.181 (0.739)	−2.299*** (0.315)	−2.361*** (0.321)	−0.217 (0.501)
<i>SOE</i>	0.458** (0.197)	0.398** (0.188)	0.185 (0.708)	0.738*** (0.215)	0.576*** (0.158)	1.443** (0.626)	0.183 (0.108)	0.125 (0.088)	0.686 (0.454)
<i>Favored</i>	1.062*** (0.351)			1.334*** (0.386)			0.717*** (0.210)		
× <i>Small</i>	−0.785** (0.285)			−1.277*** (0.397)			−0.541*** (0.180)		
× <i>Medium</i>	−0.649** (0.276)			−0.792** (0.368)			−0.395** (0.156)		
× <i>SOE</i>	−0.589* (0.305)			−0.882*** (0.289)			−0.512** (0.197)		
<i>FavorIntensity</i>		0.633** (0.258)			0.721** (0.254)			0.402** (0.159)	
× <i>Small</i>		−0.555*** (0.176)			−0.745*** (0.244)			−0.337*** (0.115)	
× <i>Medium</i>		−0.372* (0.205)			−0.440** (0.208)			−0.221** (0.101)	
× <i>SOE</i>		−0.337 (0.196)			−0.430** (0.159)			−0.297** (0.112)	
<i>GPA</i>			0.111*** (0.030)			0.164*** (0.025)			0.101*** (0.022)
× <i>Small</i>			−0.099*** (0.034)			−0.161*** (0.035)			−0.083*** (0.019)
× <i>Medium</i>			−0.098*** (0.030)			−0.106*** (0.029)			−0.065*** (0.016)
× <i>SOE</i>			−0.002 (0.022)			−0.038* (0.019)			−0.024* (0.013)
IPO-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817
Adjusted R ²	0.516	0.517	0.544	0.543	0.542	0.574	0.511	0.511	0.544

Notes: This table repeats the interaction specifications in Panel B of Table 6 in the paper, replacing *SME* with *Small* and *Medium*, indicators for the bottom and middle terciles of market capitalization at IPO among then-listed firms, and also reports the *Small*, *Medium*, and *SOE* main effects, which the main-text table suppresses. See that table's notes for the remaining variable definitions, sample, controls, fixed effects, and clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table IA13 extends the IPO-valuation evidence in Table 6 by estimating the Panel B specifications—each policy measure interacted with *SME* and *SOE*—within Five-Year Plan windows. The main table shows 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 strongest and whether the time variation differs across the industry-level and firm-level policy measures.

Table IA13: Sub-Period Analysis: Industrial Policy and IPO Valuation

	First-day Q				
	Full Sample (1)	2002–05 (2)	2006–10 (3)	2011–15 (4)	2016–22 (5)
<i>Panel A: Favored</i>					
Favored	1.151*** (0.370)	0.397*** (0.065)	0.104 (0.187)	1.029 (0.596)	1.146* (0.531)
× SME	−0.742*** (0.259)	−0.010 (0.185)	0.207 (0.164)	−0.610 (0.307)	−0.742* (0.376)
× SOE	−0.598* (0.303)	−0.122 (0.312)	−0.169 (0.112)	−0.559 (0.394)	−0.537 (0.674)
Observations	3,817	188	693	772	2,164
<i>Panel B: FavorIntensity (continuous)</i>					
FavorIntensity	0.685** (0.271)	0.280** (0.064)	−0.093 (0.141)	0.834 (0.437)	0.556 (0.300)
× SME	−0.476** (0.180)	0.002 (0.131)	0.193 (0.116)	−0.729 (0.351)	−0.313 (0.204)
× SOE	−0.351* (0.198)	−0.051 (0.294)	−0.071 (0.059)	−0.252 (0.134)	−0.339 (0.426)
Observations	3,817	188	693	772	2,164
<i>Panel C: GPA (firm-level)</i>					
GPA	0.117*** (0.032)	0.074 (0.033)	0.027** (0.009)	0.088 (0.069)	0.106* (0.050)
× SME	−0.103*** (0.032)	−0.027 (0.022)	−0.027* (0.012)	−0.078 (0.073)	−0.106 (0.055)
× SOE	−0.004 (0.020)	−0.005 (0.025)	0.004 (0.015)	0.043 (0.042)	0.031 (0.038)
Observations	3,817	188	693	772	2,164
Controls	Yes	Yes	Yes	Yes	Yes
IPO-year FE	Yes	Yes	Yes	Yes	Yes
Industry FE (Panel C)	Yes	Yes	Yes	Yes	Yes

Notes: The full-sample column covers China A-share IPOs from 2002–2022 and reproduces columns (1)–(3) of Table 6, Panel B; the subperiod columns split the same sample into 2002–2005, 2006–2010, 2011–2015, and 2016–2022, the windows of the 10th through 13th Five-Year Plans with the first two years of the 14th Plan appended to the last window. Each panel reports the indicated policy measure and its interactions with SME, an indicator for firms outside the top tercile of market capitalization at IPO, and SOE; the SME and SOE main effects and the controls ROA (winsorized at the 1st and 99th percentiles within each calendar year), Leverage, and log(Assets) are included but not reported. GPA is computed from pre-IPO prospectus text and winsorized at the 1st and 99th percentiles. First-day Q is winsorized at the 1st and 99th percentiles within each calendar year. All specifications include IPO-year fixed effects; Panel C additionally includes industry fixed effects. Standard errors are two-way clustered by year and industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

III.5 Robustness Checks

Table IA14 provides an OLS robustness check for the cross-country contrast shown in Figure 1 and Internet Appendix Table IA8. The stronger association between industry Tobin's Q and IPO activity in the United States also appears in linear regressions of log IPO outcomes.

Table IA14: IPO Activity and Industry GDP – OLS

	China		U.S.	
	log(1+IPO proceeds) (1)	log(1+#IPOs) (2)	log(1+IPO proceeds) (3)	log(1+#IPOs) (4)
IndustryQ	-0.536 (0.479)	0.010 (0.082)	0.941** (0.427)	0.373** (0.156)
log(IndustryGDP)	0.728** (0.365)	0.156** (0.062)	1.246*** (0.210)	0.343*** (0.068)
Observations	1,432	1,432	1,188	1,188
R-squared	0.095	0.120	0.231	0.294
Year FE	Yes	Yes	Yes	Yes

Notes: This table presents OLS regressions analyzing the relationship between IPO activity and industry characteristics in China and the U.S. China columns use 2002–2022 excluding 2013; U.S. columns use 2002–2022. IPO activity is proxied by log(1 + IPO proceeds) and log(1 + #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(IndustryGDP) is the natural logarithm of official industry GDP in that year. IndustryQ is lagged industry Tobin's Q, defined as the asset-weighted average of firms' Tobin's Q ratios within an industry; it is winsorized at the 1st and 99th percentiles in the China specifications. 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 significance at the 1%, 5%, and 10% levels, respectively.

Table IA15 corresponds to the China baseline specifications in columns (1)–(2) of each panel of Table 3 in the paper. The paper presents the baseline favored-industry results using PPML for nonnegative level outcomes with many zero industry-years; this appendix table asks whether the qualitative pattern survives in a linear log-outcome 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 IA16 reports the corresponding OLS versions of the overseas placebo specifications. The estimates provide a log-outcome robustness check for the PPML overseas specifications: policy favor does not predict U.S. IPO activity, remains weak for non-mainland issuers in Hong Kong, and is stronger for mainland Chinese issuers listing in Hong Kong.

Table IA15: IPO Activity in Favored Industries – OLS

	log(1+#IPOs)		log(1+IPO proceeds)	
	(1)	(2)	(3)	(4)
Favored	0.523*** (0.161)		2.325*** (0.777)	
FavorIntensity		0.406*** (0.126)		1.617** (0.615)
IndustryQ	-0.012 (0.074)	-0.018 (0.073)	-0.631 (0.461)	-0.645 (0.460)
log(IndustryGDP)	0.138** (0.055)	0.130** (0.054)	0.648* (0.356)	0.626* (0.354)
Observations	1,432	1,432	1,432	1,432
R-squared	0.192	0.204	0.125	0.123
Year FE	Yes	Yes	Yes	Yes

Notes: This table presents OLS regressions analyzing the relationship between IPO activity and industry characteristics for China industry-years from 2002 to 2022, excluding 2013 due to the suspension of IPOs. The dependent variables are log(1 + #IPOs) and log(1 + IPO proceeds). IPO proceeds are measured in RMB 10,000. Favored is the binary favored-industry indicator. FavorIntensity is the integer count of encouraging industry references flagged as key policy support in China's Five-Year Plans. IndustryQ is lagged industry Tobin's Q, defined as the asset-weighted average of firms' Tobin's Q ratios within an industry and winsorized at the 1st and 99th percentiles. log(IndustryGDP) is the natural logarithm of industry GDP. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table IA16: Chinese IPOs Outside Mainland China: OLS Robustness

Panel A: Chinese IPOs in the U.S. Market								
	log(1+#IPOs)		log(1+IPO proceeds)		Any IPO			
	(1)	(2)	(3)	(4)	(5)	(6)		
Favored	0.024 (0.040)		0.171 (0.193)		0.027 (0.038)			
FavorIntensity		0.033 (0.036)		0.174 (0.159)		0.028 (0.031)		
IndustryQ	0.021 (0.023)	0.023 (0.023)	0.184 (0.130)	0.195 (0.130)	0.025 (0.025)	0.027 (0.025)		
Observations	1,124	1,124	1,124	1,124	1,124	1,124		
R-squared	0.081	0.084	0.078	0.080	0.074	0.075		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes		
Panel B: Chinese IPOs in the Hong Kong Market								
	log(1+#IPOs)				log(1+IPO proceeds)			
	Non-mainland		Mainland		Non-mainland		Mainland	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Favored	-0.001 (0.064)		0.131 (0.088)		0.164 (0.336)		0.764 (0.517)	
FavorIntensity		0.007 (0.046)		0.121* (0.062)		0.219 (0.235)		0.731** (0.346)
IndustryQ	-0.024 (0.034)	-0.024 (0.035)	-0.050 (0.048)	-0.044 (0.048)	-0.078 (0.171)	-0.068 (0.175)	-0.360 (0.301)	-0.324 (0.301)
Observations	1,206	1,206	1,206	1,206	1,206	1,206	1,206	1,206
R-squared	0.101	0.101	0.054	0.062	0.067	0.069	0.050	0.058
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS versions of the overseas IPO placebo regressions. Panel A uses Chinese firms listing in the U.S. market during 2002 to 2022. Panel B uses Hong Kong listings during 2002 to 2022, separating non-mainland issuers from mainland Chinese issuers. The dependent variables are $\log(1 + \#\text{IPOs})$, $\log(1 + \text{IPO proceeds})$, and, for Panel A, an IPO occurrence indicator. All columns control for lagged IndustryQ, 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 significance at the 1%, 5%, and 10% levels, respectively.

IV Firm-Level Foundation of the Extensive Margin

Section 4.1 posits that the industry-level extensive margin is governed by the policy force alone, $E_j = E_j(G)$, while Section 4.4 shows that firm fundamentals predict which applicants complete an IPO. This appendix reconciles the two: sorting on F among the firms of an industry is compatible with an industry-level IPO count that depends only on G .

Setup. Index firms by i and industries by j , with $i \in I_j$ and $N_j = |I_j|$ the number of firms in industry j . Write firm i 's realized IPO proceeds as

$$y_{ij} = (\tilde{e}_j \cdot \tilde{e}_{ij}) \times \hat{m}_{ij}, \quad (\text{IA1})$$

where $\tilde{e}_j \in \{0, 1\}$ indicates whether the government opens the gate to industry j , and is therefore common to every firm $i \in I_j$; $\tilde{e}_{ij} \in \{0, 1\}$ indicates whether firm i lists, given that the gate is open; and $\hat{m}_{ij}$ is the proceeds firm i raises conditional on listing. Equation (IA1) makes listing require *both* policy favor and the firm's own passage through the gate: $y_{ij} > 0$ only if $\tilde{e}_j = \tilde{e}_{ij} = 1$.

Collecting the two firm-specific terms makes the separation transparent. Define $m_{ij} \equiv \tilde{e}_{ij} \cdot \hat{m}_{ij}$, so that

$$y_{ij} = (\tilde{e}_j \cdot \tilde{e}_{ij}) \times \hat{m}_{ij} = \tilde{e}_j \times \underbrace{\tilde{e}_{ij} \cdot \hat{m}_{ij}}_{m_{ij}},$$

where m_{ij} is firm i 's expected IPO proceeds conditional on belonging to industry j and on its own fundamental F_{ij} . The firm-level outcome thus factors into a pure policy term, $\tilde{e}_j$, and a term carrying everything the firm and the market contribute, m_{ij} . The subscripts carry the economics. The policy term is indexed by j alone: it is an *industry-level* object, identical for every firm in industry j and varying only across industries, which is what makes G incapable of selecting among an industry's firms. The market term m_{ij} is indexed by both i and j , and so varies within an industry. The government decides whether an

industry's firms may raise public equity at all; the market decides what firm i raises if they may. This is the framework of Section 4.1 read at the firm level.

The two indicators carry the two forces. The gate is a policy object,

$$\Pr(\tilde{e}_j = 1) = e(G_j) \equiv e_j \in [0, 1],$$

a function of G_j alone, with G_j unrelated to $F_j \equiv \mathbb{E}[F_{ij} | j]$, the expected fundamental of industry j —the premise verified in Section 4.1. Firm-level selection, by contrast, is left unrestricted:

$$\Pr(\tilde{e}_{ij} = 1) = E_{ij}(F_{ij}, G_j),$$

which may depend on firm i 's own fundamental as well as on industry policy. The sorting evidence of Section 4.4 says precisely that F_{ij} enters E_{ij} .

Aggregation. The number of IPOs and total proceeds in industry j are

$$E_j = \tilde{e}_j \sum_{i \in I_j} \tilde{e}_{ij}, \quad Y_j = \tilde{e}_j \sum_{i \in I_j} m_{ij},$$

so that, writing $M_j = Y_j/E_j$ for average proceeds per IPO, the industry-level accounting identity $Y_j = E_j \times M_j$ of Equation (3) follows immediately from these firm-level definitions. Because M_j averages $\hat{m}_{ij}$ over the firms that actually list, and both which firms list and how much each raises depend on fundamentals, $M_j = M_j(F, G)$ as in Equation (5).

When the extensive margin depends on G alone. Taking expectations, and using that the gate is independent of the firm-level terms,

$$\mathbb{E}[E_j] = e(G_j) \times N_j \times \bar{E}_j, \quad \bar{E}_j \equiv \mathbb{E}[\tilde{e}_{ij} | j],$$

where $\bar{E}_j$ is the listing rate among the firms of industry j . Since F_{ij} enters $\tilde{e}_{ij}$, the extensive margin is governed by G alone exactly when $\bar{E}_j$ does not vary with the industry's

fundamental F_j . Two readings deliver this, and they are the same idea:

1. *A quota.* The gate fixes the number of slots, $\sum_{i \in I_j} \tilde{e}_{ij} = \kappa(G_j)$, and fundamentals determine only *which* firms occupy them. Then $E_j = \tilde{e}_j \kappa(G_j)$ depends on G by construction, while F_{ij} fully determines the identity of the listing firms.
2. *Relative selection.* More generally, if $\tilde{e}_{ij}$ depends on firm i 's *rank* in the within-industry distribution of F rather than on the level of F_{ij} , then $\bar{E}_j$ is invariant to that distribution, and E_j again depends only on G .

Either way, the firm-level sorting documented in Section 4.4 is not evidence against $E_j = E_j(G)$. Fundamentals allocate a given number of listing slots across the firms of an industry; policy sets how many slots the industry receives. The decomposition of Section 4.2 is therefore unaffected: F enters through the intensive components—which firms list, and how much each raises—and leaves the industry-level count to G .