Industrial Policy *via* the IPO Market

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Abstract

Public equity markets can serve as a powerful industrial policy tool. Studying China's approval-based IPO system from 2002 to 2022, we find that alignment with government's Five-Year Plan priorities — rather than market fundamentals like Tobin's Q — is a primary determinant of which firms go public. Policy-aligned industries experience a 165% increase in IPO volume and raise 82 times more capital. This effect operates through firms' decisions to apply rather than regulators' approval choices, and favored firms enjoy a persistent 12% valuation premium. Our findings reveal a new channel through which the state directs economic development — by allocating risk capital, not just debt or subsidies.

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

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1 Introduction

Industrial policy-targeted government interventions aimed at altering the sectoral composition of the economy is experiencing a powerful resurgence around the world, shifting from a once-taboo topic in mainstream economics to a central pillar of development strategy in many countries (Baldwin, 1969; Krueger, 1990; Rodrik, 2004, 2008).[1] Despite this renewed interest, the existing literature has focused on traditional policy tools, such as fiscal subsidies, tax incentives, and directed credit through state-owned banks (Harrison and Rodríguez-Clare, 2010; Pack and Saggi, 2006; Lane, 2020; Juhász et al., 2023).

This paper establishes that governments can use the IPO market regulation as a powerful industrial policy instrument, a channel distinct from and potentially more consequential than traditional tools. Using comprehensive data from China's IPO market (2002–2022), we show that through the IPO regulation and approval process — typically conceived as neutral infrastructure for investor protection — has been systematically repurposed to direct equity financing toward industries aligned with national development priorities, which are stated explicitly through its Five-Year Plans (FYPs), at a scale rivaling traditional fiscal instruments.

In a frictionless capital market, the "invisible hand" allocates funds based on price signals: capital flows to sectors with the highest Tobin's Q, reflecting superior investment opportunities. However, China's financial system operates under a unique institutional logic where the state retains the ultimate prerogative to guide development. Unlike the disclosure-based registration systems of the United States or the United Kingdom, where regulators largely focus on transparency, China's IPO regime has historically been approval-based, granting the China Securities Regulatory Commission (CSRC) substantive discretion over *which* firms list and *when* (Qian et al., 2024).

[1] 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).

A simple comparison of IPO activity in the U.S. and China provides a striking illustration that motivates our study. Figure 1 plots industry-level IPO proceeds against industry Tobin's Q for both countries. In market-driven economies like the United States (Panel A), IPO activity strongly correlates with industry valuations, the canonical measure of investment opportunities (Pástor and Veronesi, 2005). This foundational relationship, however, vanishes entirely in China (Panel B). This illustrative evidence suggests that a different logic governs capital allocation in China's equity market.

[INSERT FIGURE 1 HERE]

Our paper's central thesis is that designation as a policy priority in national Five-Year Plans becomes the dominant predictor of equity market access. Our empirical analysis confirms this: industries targeted by these plans experience a 165% increase in IPOs and raise 82 times more capital compared to non-targeted industries of similar size and valuation. This divergence has strengthened dramatically over time: by 2021–2022, the policy effect represented 251% of mean IPO activity, up from 87% in 2006–2010.

The magnitude of these effects is economically large. To put this in perspective: if fiscal industrial policies amount to 4.4% of GDP in China,[2] our finding that policy-favored industries raise 82 times more capital than non-favored industries of similar fundamentals suggests that IPO regulation channels resources at a similar order of magnitude. This is not a marginal adjustment to market-based allocation — it represents a fundamental transformation of how equity capital flows across sectors. If China's IPO market operated like the United States, where Tobin's Q drives capital allocation, the industrial structure would look fundamentally different: capital-intensive traditional industries with low Q would receive less equity financing, while high-growth technology sectors with high Q would receive more, regardless of their alignment with government priorities.

[2] As an indication of the magnitude of the policy effects, recent estimates suggest China's fiscal industrial policies amount to approximately 4.4% of GDP annually (Garcia-Macia et al., 2025).

The mechanism through which policy shapes IPO outcomes is revealing. We find that policy operates primarily through firms' application decisions rather than regulators' approval choices. Firms in policy-favored industries are approximately four times more likely to apply for IPOs, while approval rates remain statistically similar across favored and non-favored industries (71.8% versus 72.3%).

This pattern suggests that market participants internalize policy priorities and adjust their strategies accordingly — a form of anticipatory governance where regulatory signals shape behavior before any formal selection occurs. This channel has important implications for state capacity: the government can guide capital allocation efficiently through credible signaling, causing firms to self-select and reducing the administrative burden of case-by-case evaluation.

Beyond the application channel, we document two additional mechanisms that reinforce policy influence. First, applications from favored industries are processed 62 days faster on average — a reduction of approximately 11% relative to the baseline processing time. This accelerated review creates a tangible benefit for firms in strategic sectors, reducing financing uncertainty and allowing them to access capital markets more quickly when conditions are favorable. Second, favored firms receive a 12% higher IPO valuation that persists for at least three years post-listing. This persistent premium indicates that policy support creates enduring market value recognized by investors, whether through implicit guarantees, expectations of future support, reduced policy risk, or coordination benefits from being in a government-prioritized sector. The fact that this premium does not reverse over three years — and appears in both domestic and Hong Kong markets for dual-listed firms — suggests the market's assessment reflects expectations of tangible benefits rather than temporary sentiment.

The explicit use of IPO regulation as an industrial policy tool is openly stated by Chinese authorities, motivating our focus on causal identification. For instance, a 2020 State Council directive on integrated circuits and software explicitly calls to "strongly support

qualified...companies to list and finance...[and] accelerate the domestic listing review process." More pointedly, the China Securities Regulatory Commission (CSRC) declared in 2014 that during IPO reviews, "issuers who do not comply with industrial policies will not be approved." These statements confirm that the patterns we observe are not accidental but the result of deliberate policy. To establish causality and rule out the alternative hypothesis that industrial policy simply reflects omitted fundamentals — for instance, that sectors like artificial intelligence attract both government support and genuine market enthusiasm — we employ three complementary identification strategies for systematic evidence, augmented by a novel firm-level measure of policy alignment.

First, we conduct placebo tests using overseas listings of Chinese firms in the United States and Hong Kong. If our results reflected fundamentals rather than policy, we should observe similar patterns abroad. We do not. Chinese industrial policy does not predict IPO activity for these firms, where industry Tobin's Q reasserts its predictive power. The coefficient on Tobin's Q in U.S. markets is statistically significant and economically meaningful, while the coefficient on Chinese industrial policy designation is small and insignificant. This cross-market comparison directly addresses the most plausible alternative hypothesis — that our results reflect omitted fundamentals correlated with both policy and investment opportunities.

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

Second, we exploit a sharp policy shock: the July 2021 "Double Reduction" policy that banned for-profit K-12 tutoring and explicitly prohibited such firms from raising capital through IPOs. This policy shock is particularly powerful because it represents an ex-

ogenous reversal: the education sector had been thriving, with Chinese education firms completing multiple IPOs annually in the U.S. and Hong Kong. Yet immediately after the policy, domestic IPO activity collapsed to zero despite the industry's strong fundamentals. This natural experiment demonstrates that policy can override market forces decisively — when the state explicitly disfavors a sector, market access disappears regardless of profitability, growth prospects, or investor demand.

Third, we leverage temporal variation across Five-Year Plans, which create discrete shifts in policy priorities every five years. Industries gain or lose policy favor as national priorities evolve, providing within-industry variation in policy treatment. For example, traditional manufacturing industries prominent in the 10th Five-Year Plan lost emphasis in later plans as the focus shifted toward strategic emerging industries, while sectors like artificial intelligence and new energy vehicles gained prominence in the 13th and 14th Five-Year Plans. This temporal variation allows us to separate policy effects from time-invariant industry characteristics, showing that IPO activity tracks policy designation rather than fixed industry attributes.

Our findings extend beyond the IPO market, revealing a comprehensive capital-market industrial policy framework. We document similar patterns in China's corporate bond market, where policy-favored industries issue significantly more bonds controlling for credit risk and financing needs. We also examine the National Equities Exchange and Quotations (NEEQ), a platform for smaller enterprises analogous to over-the-counter markets, and find that policy-favored industries have substantially more NEEQ listings. These extensions demonstrate that the mechanism we document is not specific to IPOs but represents a systematic approach to directing capital across multiple channels: public equity (IPOs), quasi-equity (NEEQ), and debt (corporate bonds). Combined with Government Guidance Funds ($912 billion of direct equity investment; Ban and Li, 2025) and subsidized bank credit, these findings reveal that state-directed capital allocation operates through multiple, potentially reinforcing channels spanning the entire capital structure.

The welfare implications of this policy remain ambiguous and represent a crucial open question. On one hand, recent evidence documents substantial efficiency costs from industrial policy in China. Garcia-Macia et al. (2025) estimate that fiscal industrial policies reduce aggregate TFP by 1.2% through factor misallocation, and Liu et al. (2021) show that similar policies exacerbated capital misallocation. If IPO-based industrial policy operates at a comparable scale, the efficiency costs could be substantial. On the other hand, the welfare calculus is more complex than simple misallocation metrics suggest. Matray et al. (2025) demonstrate that industrial policy can improve capital allocation when targeting genuine market failures. The persistent 12% valuation premium we document suggests investors believe policy support creates genuine value. Moreover, traditional misallocation measures may not capture dynamic benefits if policy facilitates industrial coordination or finances innovation with positive spillovers that private markets undervalue (Aghion et al., 2015). Whether IPO-based industrial policy accelerates technological development or entrenches inefficiencies depends on policy design quality, sector characteristics, and governance institutions—factors that remain poorly understood and require long-horizon data on innovation and productivity outcomes.

Contributions to Related Literature

This paper contributes to three main strands of literature.

First, we make a primary contribution to the literature on industrial policy by identifying and documenting a new, powerful instrument: the regulation of public equity market access. The classic literature focused on fiscal tools like targeted credit, trade protection, and subsidies (Johnson, 1982; Amsden, 1989; Wade, 1990), and while the "new economics of industrial policy" has expanded to include tools like R&D subsidies and government venture capital (Juhász et al., 2023; Barwick et al., 2024; Aghion et al., 2015; Pan et al., 2022), no prior work has systematically documented the use of equity market access regulation as a first-order industrial policy tool. We show that this "gatekeep-

ing" mechanism multiplies state capacity by leveraging private capital, operating through market prices, and remaining less transparent than direct subsidies, allowing the state to direct private capital at a scale comparable to its entire fiscal industrial policy apparatus without commensurate fiscal outlays.

Second, we contribute to the literature on the political economy of finance and capital allocation, particularly in China. Much of this literature documents state influence in credit markets or the effects of state ownership (Song and Xiong, 2018; He and Wei, 2023; Hsieh and Klenow, 2009). We provide the first comprehensive evidence that IPO regulation is a key channel for state-directed capital allocation, systematically displacing market fundamentals. Our empirical findings—the dominance of the application channel, the accelerated processing for favored firms, and the persistent valuation premium—provide a detailed institutional account of *how* this non-market mechanism operates. Our identification strategies, including cross-market placebos and the "Double Reduction" natural experiment, causally establish the power of policy to override market forces in the equity market.

Third, our findings inform the literature on political connections versus systematic policy. A large body of work documents how firm-level political connections affect access to finance (Fan et al., 2007; Piotroski and Zhang, 2014). We show that in China's IPO market, systematic, top-down industrial policy articulated in national Five-Year Plans is a more powerful determinant of capital access than idiosyncratic firm-level connections. Our firm-level GPA index allows us to distinguish between broad industry-level policy and firm-specific alignment, demonstrating that it is a firm's congruence with national strategy, rather than specific political ties, that best predicts its access to public equity.

An important caveat is that our analysis documents the approval system era (2002–2022). China's shift toward registration, completed in 2023, may constrain this mechanism. However, existing rules continue to require compliance with "national industrial policies," suggesting regulatory discretion persists (Zhao, 2023). Whether IPO-based in-

dustrial policy operates under registration systems represents an important question for future research.

The remainder of the paper is organized as follows. Section 2 describes the institutional background. Section 3 details data and methodology. Section 4 presents main findings on IPO quantity with Section 4.2 investigating mechanisms, Section 4.3 providing identification tests and extensions. Section 5 examines IPO pricing. Section 7 concludes.

2 Institutional Background

2.1 Industrial policy in China

Industrial policy usually refers to targeted public interventions that alter the sectoral allocation of resources to accelerate structural transformation, productivity, or strategic capacity. Views on its merits differ, but industrial policy is widely used across advanced and developing economies and draws on broad toolkits (Rodrik, 2004; Harrison and Rodríguez-Clare, 2010; Stiglitz et al., 2013). China, among other emerging markets, has actively deployed industrial policy to promote structural upgrading and strategic industries (Fang et al., 2025).

Within China's hierarchical and top-down governance structure, industrial policies are organized and coordinated through Five-Year Plans (FYPs), which serve as the apex framework guiding sectoral priorities and policy implementation. By articulating strategic objectives and priority sectors over fixed five-year horizons, FYPs create time-bounded policy windows in which selected industries receive concentrated regulatory, fiscal, and administrative support (Naughton, 2021). China's system of Five-Year Plans constitutes a long-standing policy institution, beginning with the First Five-Year Plan (1953–1957) under the planned economy system. Over time, particularly since the early 2000s, their role has evolved from detailed production planning toward a more strategic and guideline-based framework, accompanied by increasingly formalized policymaking procedures. In

each planning cycle, proposals for the national Five-Year Plan are typically formulated and adopted at the Fifth Plenum of the Central Committee in the year preceding implementation, several months before the new planning period begins. These proposals are subsequently translated by the State Council and the National Development and Reform Commission into a detailed planning outline, which is formally adopted by the National People's Congress and thereby endowed with substantial political authority.

The national Five-Year Plan sets macro-level objectives and priorities but does not operate in isolation. Once adopted, it is used to orient budgetary allocations, regulatory priorities, and administrative targets across levels of government, embedding industrial policy objectives within China's broader governance apparatus. Provincial, municipal, and county-level plans are subsequently formulated in alignment with the national blueprint. In addition, sectoral and cross-cutting plans, such as the "Internet Plus" Action Plan, are issued to operationalize Five-Year Plan priorities through specific programs, standards, and regulatory arrangements. Together, these planning documents constitute a vertically integrated framework that links central directives to local implementation. During the subsequent five-year policy period, implementation is delegated to line ministries, regulators, and local governments, which translate plan priorities into concrete policies, regulatory guidance, and enforcement actions. Through this nested structure, subordinate policy instruments are aligned with the overarching objectives of the Five-Year Plan, ensuring coherence in China's industrial policy across administrative levels and sectors.

Beyond commonly studied instruments such as tax incentives and subsidies, China's industrial policy toolkit has consistently incorporated capital market facilitation. We compile industrial policy documents issued by the State Council between 2002 and 2022 and identify those containing IPO-related facilitation language, including references to encouraging firm listing, streamlining issuance review, or expanding access to direct financing.[3] Figure 2 summarizes, for each Five-Year Plan window from the Tenth to the Four-

[3]Technical details are discussed in Internet Appendix.

teenth, the share of industrial policy documents that contain such IPO-related references. On average, roughly one third of industrial policy documents issued within a given Five-Year Plan window contain IPO-related facilitation language. Importantly, the presence is persistent across all planning cycles, rather than concentrated in any single period.

[INSERT FIGURE 2 HERE]

2.2 IPO Listing Review and Government Oversight in China

China's IPO market differs from IPO markets in market-oriented economies (Qian et al., 2024). IPO listings in China are subject to extensive regulatory review and government oversight, besides a more comprehensive listing rules, which shape issuance timing, pricing, and allocation outcomes.

Under China's approval-based IPO regime, listing is not an automatic market outcome but a regulatory admission determined through a rigorous review process led by the China Securities Regulatory Commission (CSRC) and its listing committees. Established in 1992 as the unified securities regulator, the CSRC has historically exercised substantive authority over IPO applications, reviewing firms' financial performance, corporate governance, business continuity assumptions, and compliance with macroeconomic and industrial policies.

The approval process typically involves multiple rounds of document review, responses to regulatory inquiries, and formal committee deliberations, which could take months or even years to complete. A clear demonstration of the regulatory power is the multiple episodes of IPO suspensions historical data indicate repeated suspension episodes between 1994 and 2015, some lasting over a year, during which no new share offerings were approved.[4] Such policy-driven suspensions, together with the intensive substantive re-

[4]For IPO interventions including suspension episodes and their effects, see Cong and Howell (2018).

view process, contributed to alternative listing strategies, such as backdoor or reverse takeover listings, with broader asset-pricing consequences in China (Li et al., 2018; Liu et al., 2019).

Beginning in 2019, China began piloting a disclosure-oriented registration regime and completed the reform on the main boards in 2023. Under the registration system, stock exchanges conduct substantive reviews through multiple inquiry rounds and listing committee meetings, with an emphasis on information disclosure rather than administrative approval.

However, industrial policy guidance has continued to exert salient influence in the IPO process, despite the gradual effort to reduce government oversight. Specifically, article 11 of the CSRC's IPO Administrative Measures explicitly requires issuers' business operations to "comply with national industrial policies", thereby introducing a policy-based criterion into the listing review framework. This provision allows for regulatory discretion in the IPO review process, making IPO approval in China a regulatory admission decision rather than a purely disclosure-based market outcome.

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

As a demonstration, we examine how industry size and valuation relate to IPO volume and proceeds in China and the United States. We estimate Tobit models on industryyear panels, regressing log(#IPOs) and log(IPO proceeds) on industry GDP and lagged industry Q in parallel by country. Table 1 reports a clear cross-country contrast. Industry size is positively associated with IPO activity in both countries, but the elasticity is substantially larger in the U.S. than in China. In addition, industry valuation is strongly

positively related to IPO activity only in the U.S., consistent with equity issuance into high-valuation windows, whereas in China the estimated coefficients on Q are small and statistically indistinguishable from zero.

[INSERT TABLE 1 HERE]

3 Data and Empirical Measurement

3.1 Industry-level Policy Designation

To capture the government's industrial policy orientation at the industry level, we construct a measure of policy emphasis based on China's Five-Year Plans language. These plans articulate the government's medium-term strategic priorities across economic, technological, and social domains. While the official documents do not provide explicit industry-level indicators or tabulated policy targets, they contain extensive narrative descriptions of targeted sectors and strategic objectives such as the development of strategic emerging industries and modernization of core manufacturing and service sectors.

To render these qualitative indications into a tractable empirical proxy, we leverage a structured policy text database from CNRDS, whose approach echoes those used in previous studies (e.g. Chen et al., 2017; Cen et al., 2022) that systematically identify industry mentions and associated policy language from the official plan documents and maps them to a standardized CSRC 2001 industry classification.

Building on this information, we construct the measure #Emphasize, which quantifies the intensity of policy emphasis placed on an industry in the Five-Year Plans. The measure counts the number of supportive keywords, such as "vigorously develop," "key support," "pillar industry," "priority development," that appear in the policy text. Each occurrence of these keywords adds one to the industry's #Emphasize score, allowing multi-

ple mentions within the same plan to reflect cumulative emphasis.[5] A higher #Emphasize score indicates stronger or more frequent policy support, capturing the priority given to an industry in national planning and signaling favorable conditions for its growth and investment.

In addition to the continuous measure, we construct an indicator variable, #Emphasize>0, which equals one if an industry is designated as a policy-favored industry in a given Five-Year Plan and zero otherwise. This indicator forms the basis for the favored versus non-favored industry classifications used throughout the empirical analysis. We provide the complete list of identified favored industries, and more descriptive results and technical details are provided in the Internet Appendix.

3.2 Measuring Firm-Level Policy Alignment

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

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

The construction of *GPA* proceeds in two steps. First, we quantify the semantic prox-

[5] We manually verify and, where necessary, revise industry assignments to ensure consistency and accuracy.

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

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

3.3 Data and Summary Statistics

Our empirical analysis is mainly based on a sample of China's A-share IPO market over the period from 2002 to 2022, which falls across five Five-Year Plan periods (from the 10th to the 14th). IPO-related information is obtained from the Wind database. Industry-level information is obtained from the National Bureau of Statistics. Firm-level financial and accounting variables are obtained from THS iFinD.

Panel A of Table 2 reports summary statistics for the industry-year panel. From the indicator variable #Emphasize>0, we can see that approximately 26% of industry-year observations are classified as policy-favored. Turning to the continuous measure #Emphasize, we observe substantial dispersion across industry-year observations, indicating meaningful variation in the intensity of policy emphasis beyond the binary designation and capturing differences along the intensive margin. Our IPO pricing analysis is conducted in the IPO sample, which covers 3,483 IPO events over the sample period. As

shown in Panel B of Table 2, approximately 61% of IPOs are from policy-favored industries. This share is substantially higher than the corresponding fraction at the industry-year level, suggesting that IPOs are not evenly distributed across policy-favored and non-favored industries.

[INSERT TABLE 2 HERE]

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

[INSERT TABLE 3 HERE]

For the U.S. analysis, IPO data are obtained from SDC Platinum, and industry-level GDP contributions are derived from the U.S. Bureau of Economic Analysis. Additional details are provided in the Internet Appendix.

4 Empirical Results: Industrial Policy and IPOs

This section presents the main test results of our hypothesis: industrial policy directs capital allocations through IPO markets. We first examine the empirical relationship between industrial policy and IPO activity. We then investigate the mechanisms through which

policy influences the IPO process, such as IPO approval process. Finally, we provide identification tests to address endogeneity concerns.

4.1 Industrial Policy and IPO Activity

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

[INSERT FIGURE 3 HERE]

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

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

where $y^*_{i,t}$ is the latent variable and the observed dependent variable, $y_{i,t} = \log(\text{IPO Activity})_{i,t}$, equals $y^*_{i,t}$ when positive and is censored at zero otherwise. The "IPO Activity" variable is either the number of IPOs or total IPO proceeds for industry i in year t. The main independent variable, $\text{PolicyFavor}_{i,t}$, is our measure of industry-level policy support, proxied by either a dummy variable (`#Emphasize>0`) or a continuous measure (`#Emphasize`). Control variables include the logarithm of industry GDP and lagged industry Tobin's Q. We include year fixed effects, γ_t, to absorb macroeconomic shocks common to all industries.

Table 4 reports the estimation results. Industries prioritized by industrial policy have significantly more IPO activity. In columns (1) and (2), where the dependent variable is

log(#IPOs), the coefficient on the policy favor dummy (`#Emphasize>0`) is 0.973 and statistically significant at the 1% level. The continuous measure in column (2) yields a similar conclusion. Columns (3) and (4) show that this effect extends to the scale of capital raised: the coefficient on the policy favor dummy is 4.407, indicating that favored industries raise significantly more capital via IPOs.

[INSERT TABLE 4 HERE]

The economic magnitude of our estimates is large. To interpret our findings, we compare the Tobit coefficients to the summary statistics reported in Table 2. The coefficient of 0.973 on policy favor represents 120% of the mean log(#IPOs) of 0.81, or approximately 1.07 standard deviations of the distribution. Converting to levels, this implies that *favored industries have roughly 2.6 times more IPOs than non-favored industries* ($e^{0.973} \approx 2.65$).

For IPO proceeds, the coefficient of 4.407 implies that favored industries raise approximately 82 times more capital than non-favored industries ($e^{4.407} \approx 82$). The large standard deviation of log(proceeds) (6.13) and the fact that the median (10.73) exceeds the mean (7.03) reflect the highly skewed distribution: many industry-years have zero or minimal IPO activity, while active industries raise substantially more. This skewness underscores the concentration of capital in policy-favored sectors.[6]

In stark contrast to the predictive power of industrial policy in China, the coefficient on lagged industry Tobin's Q is statistically insignificant across all specifications in Table 4. This finding is noteworthy, as industry Q is a standard proxy for investment opportunities and a strong predictor of IPO activity in market-driven economies (Hayashi, 1982; Blundell et al., 1992). To highlight this difference, we replicate the analysis using data from the U.S. IPO market and report the results in Table 5. In the U.S., Industry Q is a strong and significant predictor of both the number of IPOs and proceeds raised, with

[6]For robustness, we also estimate linear OLS regressions on the uncensored sample and report the results in the Internet Appendix. The OLS coefficients are qualitatively similar.

Tobit coefficients of 0.589 and 1.686, respectively. A one-unit increase in Industry Q is associated with an increase in latent log(#IPOs) of 0.589 — a substantial effect given that the standard deviation of Industry Q is typically around 0.5 - 1.0. In contrast, the coefficient on Industry Q in China is statistically insignificant. This comparison underscores the unique, policy-driven nature of capital allocation in China's IPO market, where government priorities appear to dominate market-based fundamentals.

[INSERT TABLE 5 HERE]

Finally, we investigate whether the relationship between industrial policy and IPO activity varies over time. We re-estimate our baseline specification for each Five-Year Plan (FYP) period from the 10th to the 14th. The results, reported in Table 6, reveal a clear temporal pattern. While the relationship is consistently positive and significant from the 11th FYP onward, the magnitude increases monotonically — from 0.702 in the 11th FYP (2006–2010) to 2.030 in the 14th FYP (2021–2022). Relative to the unconditional mean of log(#IPOs) of 0.81, the coefficient in the 11th FYP represents 87% of the mean, while the coefficient in the 14th FYP represents 251% of the mean — a nearly threefold increase in the relative effect of policy favor over 15 years. This trend is consistent with recent literature documenting the expanding scope and intensity of China's industrial policy (Naughton, 2021; Heilmann and Shih, 2012). Our finding provides novel, market-based evidence of this intensification, showing that the government's guiding hand in the IPO market has grown substantially heavier over time.

[INSERT TABLE 6 HERE]

4.2 The Mechanism: The IPO Application and Approval Process

Having established that industrial policy is strongly associated with IPO activity — industries favored by industrial policies have significantly more IPOs and raise more capital — we now investigate the mechanisms through which this influence operates.

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

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

We first examine the approval channel. A natural hypothesis is that firms from favored industries enjoy a higher approval rate. However, the data do not support this hypothesis. We find no statistically significant difference in the overall approval rate between the two groups (71.8% for favored vs. 72.3% for non-favored) as Table 7 shows. In fact, from 2014 to 2021, we find no single calendar year when the firms in favored industries have on average statistically higher approval rates than those in non-favored industries.

[INSERT TABLE 7 HERE]

This leads us to investigate the application channel, which implies that significantly more firms in favored industries file for IPOs compared to non-favored industries. De-

scriptively, favored industries receive an average of 9.9 IPO applications per year, compared to 2.5 for non-favored industries — a fourfold difference. The difference in log applications between the two groups is approximately 1.39 (log(9.9) − log(2.5)). We test this channel formally by re-estimating our baseline specification with the logarithm of the number of IPO applications as the dependent variable. The results, presented in Table 8, strongly support the application channel. The coefficient on the policy favor dummy (`#Emphasize>0`) is 1.156 and statistically significant at the 1% level — close to the raw difference of 1.39 after controlling for industry size and investment opportunities. This substantial effect indicates that a large portion of the observed increase in IPOs from favored industries is driven by a larger pool of applicants entering the approval process.

[INSERT TABLE 8 HERE]

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

First, we find that the time between application and approval is significantly shorter for firms in favored industries. We find that favored industries experience an average of 488 days from application to approval, compared to 550 days for non-favored industries — a difference of 62 days (significant at the 1% level). The median difference is 50 days (454 vs. 504 days). This pattern is particularly pronounced in recent years: from 2018 to 2021, favored industries consistently enjoyed significantly shorter waiting times.[7] We formalize this finding by regressing the logarithm of waiting days on our policy favor measures, controlling for firm characteristics (SOE status, ROA, leverage, and firm size) and year fixed effects. Table 9 reports the results. The coefficient on `#Emphasize>0` is −0.088 and statistically significant at the 1% level, implying that firms in favored indus-

[7] More detailed summary statistics of the approval waiting times is provided in Online Appendix.

tries experience approximately 8.4% shorter waiting times ($1 - e^{-0.088} \approx 0.084$). Applied to the non-favored baseline of 550 days, this translates to roughly 46 fewer days — consistent with the 62-day raw difference after accounting for firm-level controls.

[INSERT TABLE 9 HERE]

Besides, we also find evidence that firms in favored industries receive substantially more government subsidies after their IPOs. We regress the average subsidy-to-revenue ratio on our policy favor measures, controlling for firm characteristics (SOE status, firm size, ROA, and leverage) and year fixed effects. As reported in the Internet Appendix, the coefficient on `#Emphasize>0` is 0.288 (significant at 1%) for subsidies received within 3 years post-IPO, and 0.294 for subsidies within 5 years. These results suggest that policy favor translates into direct financial support, which may further incentivize firms in favored industries to pursue IPOs.[8]

Taken together, the evidence points to a clear mechanism: industrial policy primarily operates through the **application channel**. More firms in favored industries file for IPOs, and this larger pool of applicants drives the observed increase in IPO activity. Importantly, the rules governing IPO eligibility remain binding even for firms in favored industries — approval rates are similar across the two groups. We also find suggestive evidence that the government facilitates this process through faster approval times and post-IPO subsidies. These findings demonstrate that the government plays an active role in facilitating capital market access for firms aligned with national strategic priorities, not by relaxing approval standards, but by encouraging applications and supporting firms through the process.

[8] We do not observe the data on subsidies before IPOs.

4.3 Identification: Isolating the Effects of Industrial Policy

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

First, as detailed in the institutional background, government and regulatory bodies explicitly state their intention to guide capital allocation through the IPO process. Central government policies call for "priority support" for IPOs in designated sectors — for example, the 2020 State Council notice on integrated circuits and software called for "vigorously supporting" qualified firms to list and "accelerating the domestic listing review process." The CSRC has been equally direct: a 2014 press release stated that IPO applicants in overcapacity industries that "do not comply with industrial policy will not be approved." These are active commands, not passive reflections of market trends.

Second, we conduct a placebo test exploiting the fact that many Chinese firms list in the United States and Hong Kong, markets less directly impacted by mainland regulatory policy. If our results were driven by intrinsic firm quality, we should observe similar patterns overseas. Table 10 presents results for Chinese firms listing in the United States. The coefficient on the policy favor dummy (`#Emphasize>0`) is 0.227 for the number of IPOs and 1.194 for proceeds — neither statistically significant. In contrast, industry Tobin's Q is a significant predictor (0.589*** and 1.686**), indicating that market fundamentals, rather than policy alignment, drive U.S. listings by Chinese firms.

[INSERT TABLE 10 HERE]

Table 11 presents results for Chinese firms listing in Hong Kong. The coefficients on policy favor are statistically insignificant (0.169 and 0.947). Even when restricting to IPOs by mainland Chinese firms, the coefficients (0.302 and 1.892) remain far smaller

than the mainland China estimates (0.973*** and 4.407***). Relative to the unconditional mean of log(#IPOs) of 0.81, the Hong Kong coefficient of 0.302 represents only 37% of the mean, compared to 120% for mainland China. The stark contrast demonstrates that the IPO advantage enjoyed by favored industries is specific to mainland China's regulatory environment.

[INSERT TABLE 11 HERE]

Third, we examine the for-profit education industry as a natural experiment. In July 2021, the "Double Reduction" policy banned for-profit K-12 tutoring and explicitly prohibited such firms from raising capital through IPOs. Figure 4 plots education sector IPO activity by mainland Chinese firms in Hong Kong and the U.S. from 2017 to 2024. Prior to the policy, the sector was highly active: Hong Kong saw 10 education IPOs in 2019 raising nearly 10 billion HKD; the U.S. saw 5–6 IPOs annually in 2017–2018. After mid-2021, activity collapsed to near zero. This sharp discontinuity cannot be explained by gradual deterioration in firm quality.

[INSERT FIGURE 4 HERE]

Taken together, this evidence strongly rejects the alternative hypothesis that our results merely reflect better firms in favored industries. The overseas listings analysis shows that the IPO advantage enjoyed by favored industries is specific to mainland China and disappears in the U.S. and Hong Kong. The education case study demonstrates that policy disfavor abruptly shuts off capital market access. Combined with the baseline results and mechanism evidence, we conclude that industrial policy, operating through the IPO approval process, is a first-order determinant of which firms access China's equity markets.

5 Industrial Policy and IPO Pricing

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

We measure IPO valuation using Tobin's Q on the first trading day, calculated as the market value of equity plus book value of debt divided by book value of assets. Because IPO prices in China are subject to regulatory caps and often hit daily price limits on the first trading day, we use the first "non-hit day" price — the first day when the stock does not hit its price limit — to compute market value. Q is winsorized at the 1st and 99th percentiles within each calendar year.

5.1 Industry-Level Policy Favor and IPO Valuation

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

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

where $Q_{i,t}$ is firm i's first-day Tobin's Q, $\text{PolicyFavor}_{j,t}$ is our industry-level measure (either the dummy `#Emphasize>0` or the continuous count), $X_{i,t}$ includes firm-level controls (SOE status, ROA, leverage, and log assets), and δ_t represents year fixed effects. Standard errors are clustered at the year and industry level.

Table 12 reports the results. The coefficient on the policy favor dummy (`#Emphasize>0`) is 0.348 and statistically significant at the 1% level. Given that the mean first-day Q in our sample is 2.98 (Table 2), this coefficient implies that firms in policy-favored industries receive valuations that are 11.7% higher (0.348/2.98) than firms in non-favored industries.

Using the continuous measure, each additional policy mention is associated with a 0.218 increase in Q (significant at 5%), representing a 7.3% valuation premium per mention.

Columns (3) and (4) introduce interactions with firm size. The baseline effect of policy favor increases to 0.406–0.438, but the interactions with small and medium firms are negative and significant, indicating that the valuation premium from policy favor is concentrated among large firms. This pattern is consistent with large firms being better positioned to benefit from policy support and more visible to investors seeking policy-aligned investments.

[INSERT TABLE 12 HERE]

5.2 Firm-Level Policy Alignment and IPO Valuation

We next examine whether, within the same industry, firms with closer alignment to government industrial policy receive higher valuations. We use our firm-level GPA measure, constructed from pre-IPO prospectus text, which captures how closely a firm's business description matches the language of industrial policy documents. GPA is scaled by 1000 and winsorized at the 1st and 99th percentiles.

We estimate the following regression:

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

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

Table 13 presents results, progressively adding controls and fixed effects. The coefficient on GPA is 0.073 in the univariate specification (Column 1) and remains highly significant at 0.051–0.053 after adding firm controls and industry fixed effects (Columns 2–4). To interpret the economic magnitude: the standard deviation of GPA (scaled by 1000) is 5.81, so a one-standard-deviation increase in GPA is associated with a 0.30 increase in Q (0.051×5.81), or approximately 10% of the mean Q (0.30/2.98). In other words, moving from the 25th to the 75th percentile of GPA within an industry corresponds to roughly a 7% valuation premium.

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

[INSERT TABLE 13 HERE]

5.3 Long-Run Effects

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

Table 14 reports the results. Across all specifications, using the industry-level policy favor dummy, the continuous `#Emphasize` measure, and the firm-level GPA, we find no evidence of return reversal. The coefficients on policy favor and GPA are statistically insignificant across all horizons. This null result is economically meaningful: it indicates that the valuation premium observed at IPO does not subsequently reverse, suggesting

that the market's initial pricing of policy alignment reflects persistent expectations rather than temporary mispricing.

[INSERT TABLE 14 HERE]

We further examine the A-H premium for firms dual-listed in mainland China and Hong Kong. If the valuation premium for policy-aligned firms reflects China-specific factors — such as expectations of government support or preferential treatment — we would expect this premium to be larger in the A-share market than in Hong Kong. However, Table 15 shows that the coefficients on policy favor and GPA are not statistically significant, suggesting that both domestic and foreign investors recognize and price in the long-term benefits of policy alignment similarly across markets.

[INSERT TABLE 15 HERE]

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

6 Evidence from Broader Chinese Capital Markets

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

6.1 The NEEQ Market

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

We re-estimate our baseline specification from Equation (1), with the dependent variable being the logarithm of the number of NEEQ listings. The results, presented in Table 16, confirm this prediction. The coefficient on the policy favor dummy (`#Emphasize>0`) is 1.233 and statistically significant at the 1% level. As these are Tobit coefficients, they represent the marginal effect on the latent variable and are not directly interpretable as percentage changes. However, the magnitude of the coefficient is substantially larger than the corresponding Tobit coefficient of 0.973 for main board IPOs, suggesting a stronger effect in the NEEQ market. This finding underscores the pervasive role of industrial pol-

icy in guiding capital flows, particularly in markets explicitly designed to serve national strategic objectives.

[INSERT TABLE 16 HERE]

6.2 The Corporate Bond Market

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

We estimate our baseline specification with the logarithm of the number of bond issuances and the logarithm of total bond proceeds as dependent variables. The results, presented in Table 17, show that the effect of industrial policy extends to the bond market. For the number of bond issuances, the coefficient on the policy favor dummy is 0.758 and statistically significant at the 1% level. For bond proceeds, the coefficient is 1.145 and also significant at the 1% level. As these are Tobit coefficients, they are not directly interpretable as percentage changes. However, the magnitudes are comparable to those observed in the IPO market, suggesting that the influence of industrial policy is similarly powerful in the much larger debt market. Interestingly, we find that Industry Q has a significant *negative* relationship with bond issuance in China. This contrasts with the positive relationship typically observed in developed markets and further highlights the unique, policy-driven dynamics of China's capital markets.

[INSERT TABLE 17 HERE]

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

7 Conclusion

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

Our evidence demonstrates that this policy works through a powerful signaling channel, where firms in favored industries are overwhelmingly more likely to apply for IPOs, are processed faster, and receive a persistent valuation premium. These findings, robust to a suite of identification strategies, reveal a comprehensive capital-market industrial policy that extends beyond IPOs to corporate bonds and other financing platforms. While the long-term welfare implications of prioritizing policy over market signals remain an open and critical question, our research makes one thing clear: the regulatory architecture of capital markets is not neutral infrastructure. It can be, and is, a core arena for industrial

policy, with profound implications for corporate finance, economic development, and the global balance of economic power. As nations worldwide reconsider the role of the state in shaping economic outcomes, understanding this powerful, non-fiscal channel is more critical than ever.

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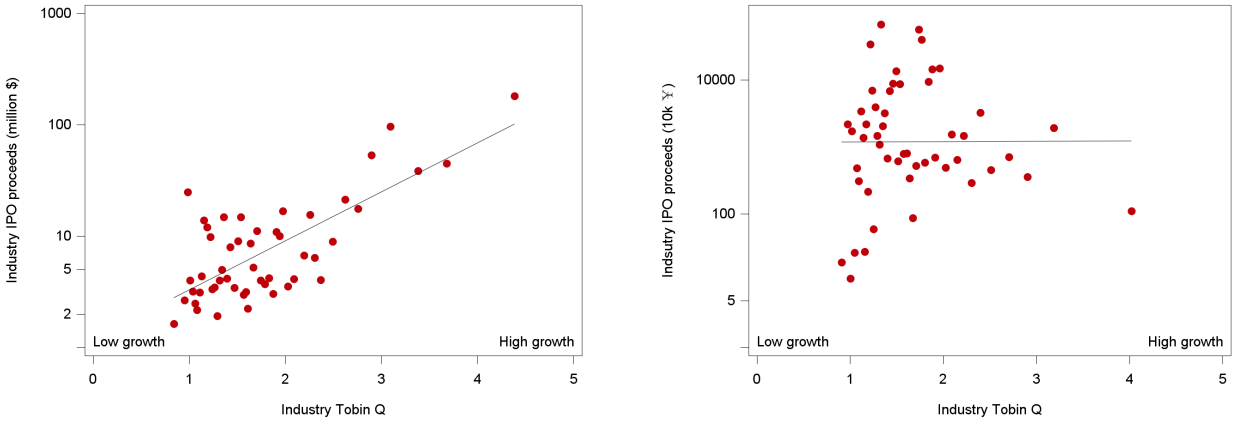
Figures and Tables

Figure 1: Industry IPO Proceeds vs. Industry Tobin's Q: U.S. vs. China (2006–2020)



(a) United States

(b) China

Notes: This figure plots binned scatter plots of industry-level IPO proceeds (log scale) against industry Tobin's Q for the United States (Panel A) and China (Panel B) from 2006 to 2020. In the U.S., proceeds are strongly positively correlated with Tobin's Q. In China, this relationship is absent, as indicated by the lines in the graphs.

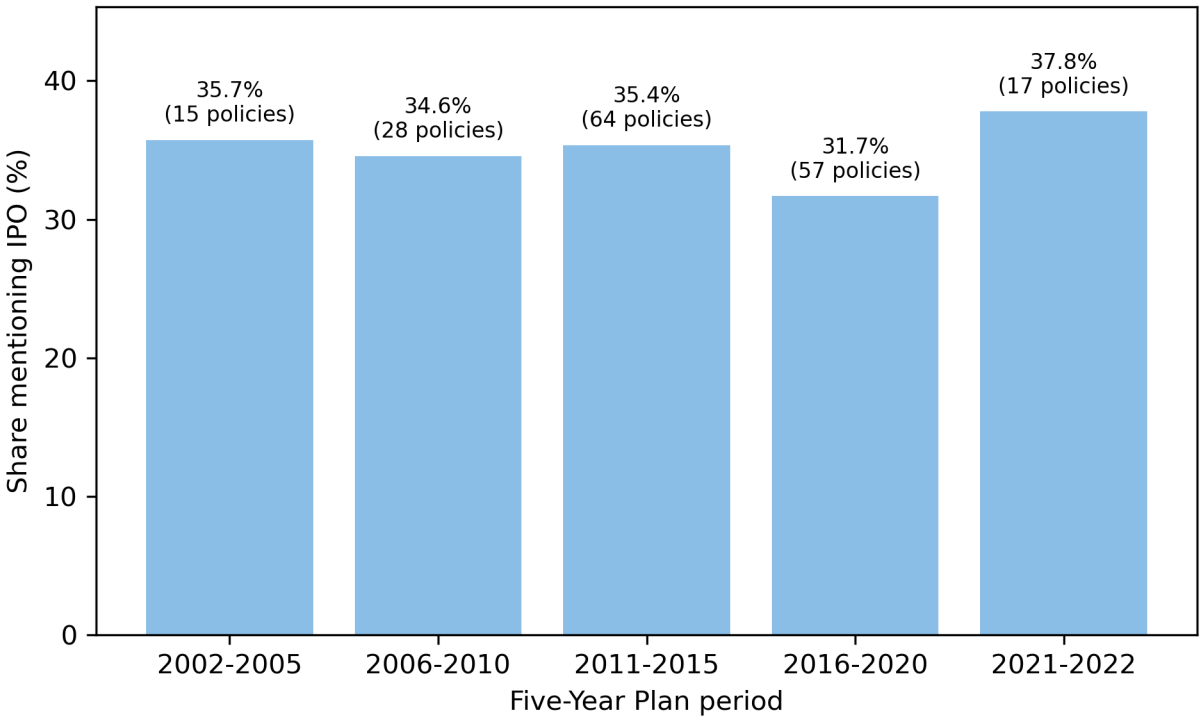


Figure 2: Share of industrial policies mentioning IPO support

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 IPO indicator is constructed using the LLM-based text classification approach described in the Internet Appendix. Numbers in parentheses indicate the number of industrial policy documents that mention IPO support in each period.

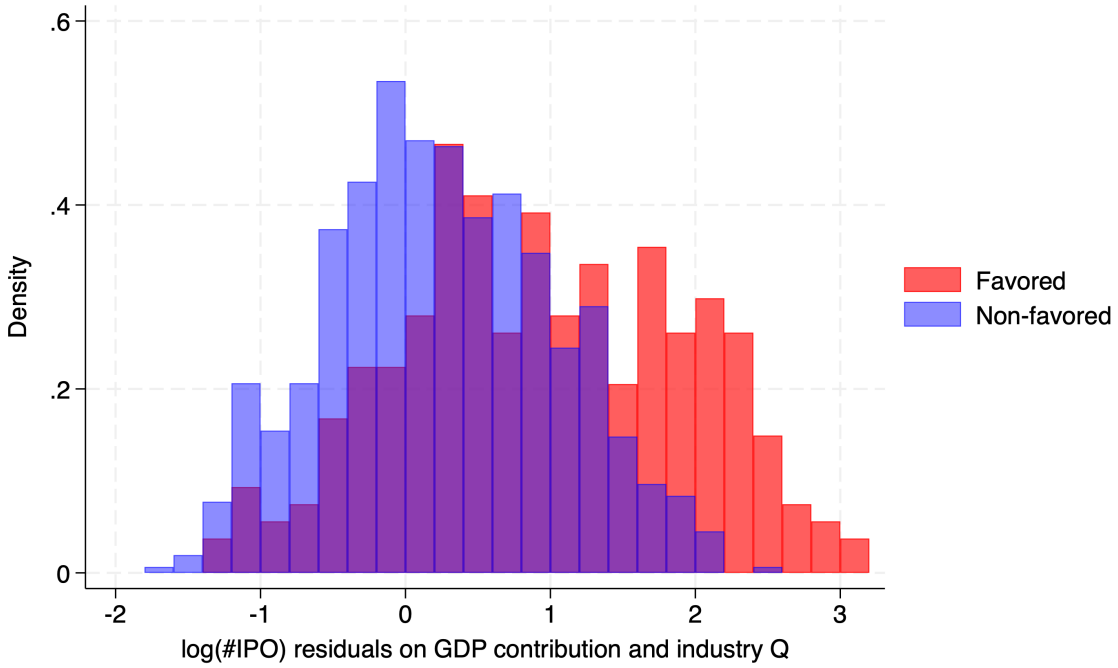
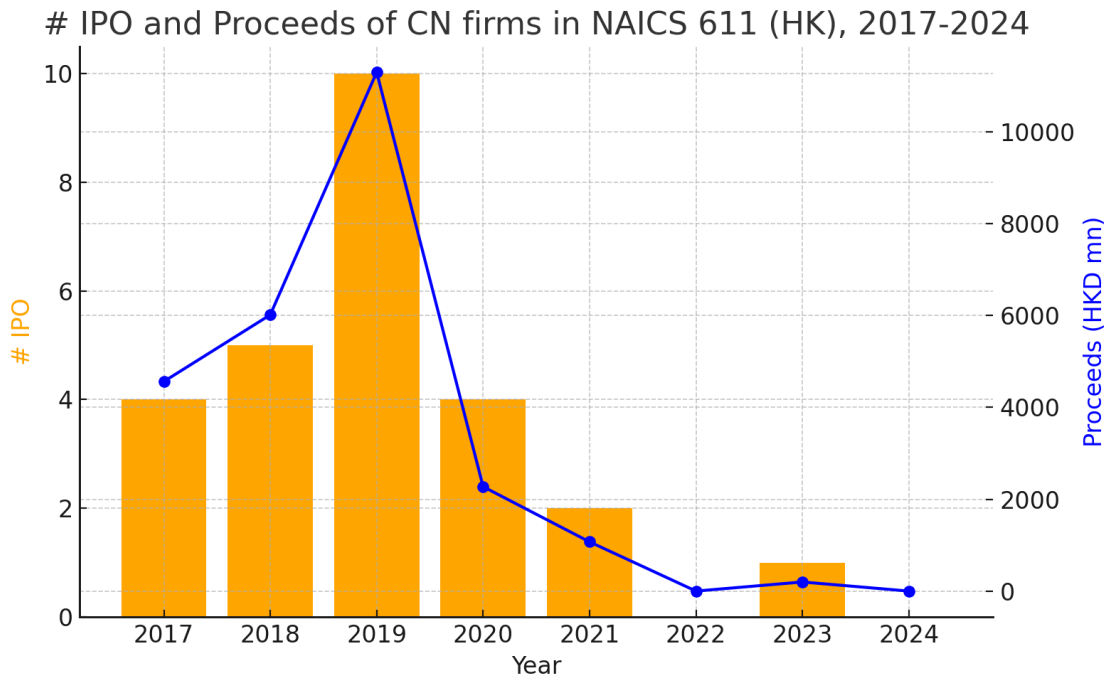
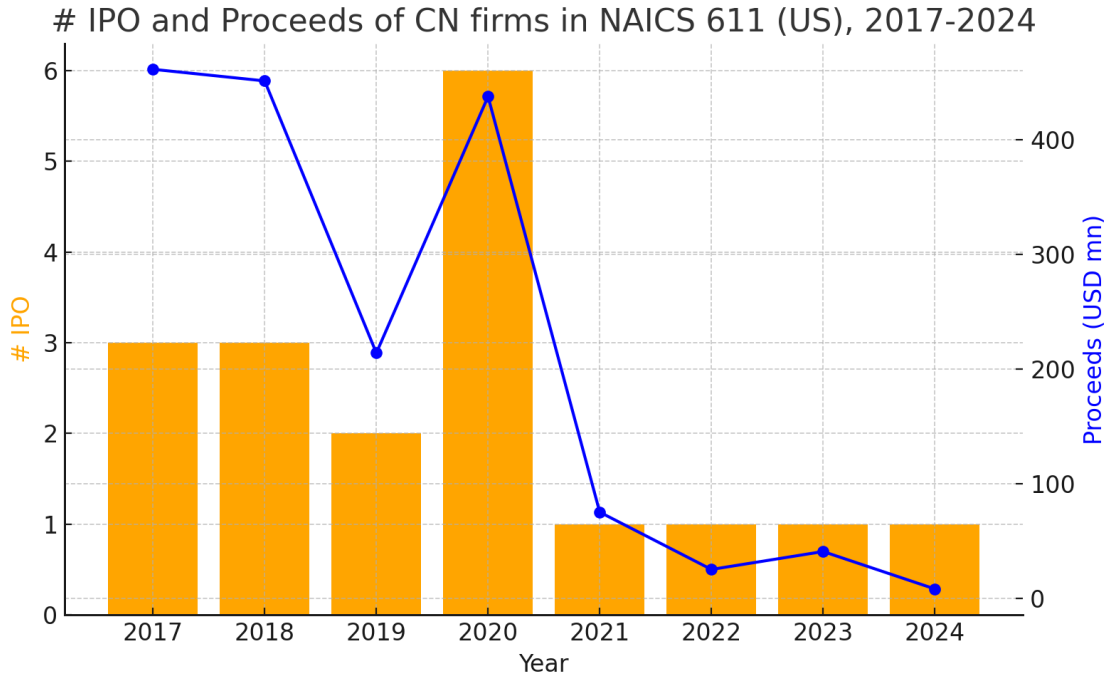


Figure 3: Distribution of residual IPO activity

Notes: This figure plots the histogram of residuals from a Tobit regression model in Column (1) in Table 1. The residuals are based on the log number of IPOs after controlling for GDP contribution and industry Q, and are shown separately for favored and non-favored industries. An industry is classified as favored if #Emphasize>0.



(a) Hong Kong market



(b) U.S. market

Figure 4: China's ban on private tutoring shakes education sector

Notes: This figure plots IPO activity of mainland Chinese firms in NAICS 611 (Educational Services) in Hong Kong (left panel) and the United States (right panel) over 20172024. Bars show the annual number of IPOs, while lines plot total IPO proceeds in each market (HKD million for Hong Kong; USD million for the U.S.).

Table 1: IPO activity across industries

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

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

Table 2: Summary Statistics

Panel A: Variables at the industry-year level

	N	Mean	Median	St. Dev.	Min	Max
log(#IPOs)	1044	0.81	0.69	0.91	0.00	4.32
log(IPO proceeds)	1044	7.03	10.73	6.13	0.00	16.45
log(Industry GDP)	1044	8.46	8.47	1.12	5.17	11.25
Industry Q	1044	1.66	1.41	0.78	0.91	5.53
#Emphasize>0	1044	0.26	0.00	0.44	0.00	1.00
#Emphasize	1044	0.31	0.00	0.56	0.00	2.13

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

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
#Emphasize	3,484	0.614	0.487	0	1	1
#Emphasize>0	3,484	0.865	0.840	0	1	1

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Q (winsorized)	3,504	2.975	2.142	1.588	2.296	3.575
GPAx1000	3,504	33.391	5.805	28.774	33.483	37.567
SOE	3,504	0.205	0.403	0	0	0
Log(Total Assets)	3,504	20.665	1.334	19.873	20.409	21.072
ROA	3,504	16.832	11.421	10.738	15.277	20.961
Leverage	3,504	1.126	1.705	0.423	0.758	1.289

Notes: The continuous measure #Emphasize may take non-integer values due to the aggregation of policy emphasis across multiple industry classifications when mapping policy texts to industries. Firms GPA scores ("GPAx1000") are winsorized at 1% and 99% and multiplied by 1000. Size terciles are determined for an IPO firm at its IPO date when compared among all stocks listed then based on their market capitalization of equity.

Table 3: IPO activity and GDP contribution by policy favor

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

Notes: This table summarizes annual IPO activity, proceeds, and GDP contributions across policy-favored and non-favored industries in China, where a favored industry is defined as one prioritized in China's Five-Year Plans, indicated by #Emphasize > 0. Columns include the IPO year, total IPO count and proceeds, the number and proportion of IPOs and proceeds from favored industries, and the ratio of GDP contribution from favored industries to the total.

Table 4: IPO activity in favored industries

VARIABLES	(1) log(#IPOs)	(2) log(#IPOs)	(3) log(IPO proceeds)	(4) log(IPO proceeds)
#Emphasize>0	0.973***		4.407***	
	(0.263)		(1.327)	
#Emphasize		0.784***		3.442***
		(0.202)		(0.987)
log(Industry GDP)	0.211**	0.202**	1.019**	0.987**
	(0.083)	(0.082)	(0.499)	(0.500)
Industry Q	-0.058	-0.048	-0.635	-0.589
	(0.114)	(0.114)	(0.824)	(0.829)
Constant	-2.043***	-1.912***	-6.291	-5.783
	(0.729)	(0.708)	(4.402)	(4.389)
Observations	1,044	1,044	1,044	1,044
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0955	0.0998	0.0304	0.0306

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics for the sample period from 2002 to 2022. The year 2013 is excluded due to the suspension of IPOs. The dependent variables are the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. #Emphasize>0 is a dummy variable indicating whether an industry is policy-favored. #Emphasize represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: IPO activity in favored industries US

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

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics for the sample period from 2002 to 2022. The dependent variables are the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. policy_favor is an indicator of industrial policy in the U.S., technical details can be found in Online Appendix. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: log(#IPO) in favored industries: by subperiod

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2002-2005		2006-2010		2011-2015		2016-2020		2021-2022	
#Emphasize>0	0.033		0.702**		0.941***		1.183***		2.030***	
	(0.296)		(0.275)		(0.338)		(0.368)		(0.306)	
#Emphasize		0.017		0.433*		0.683**		1.154***		1.450***
		(0.269)		(0.240)		(0.263)		(0.218)		(0.282)
log(Industry GDP)	0.562***	0.564***	0.293***	0.304***	0.201*	0.177*	0.140	0.098	0.033	0.073
	(0.177)	(0.178)	(0.089)	(0.094)	(0.113)	(0.106)	(0.113)	(0.105)	(0.130)	(0.134)
Industry Q	-0.743	-0.742	-0.230	-0.179	-0.261**	-0.228*	-0.034	-0.041	0.268**	0.268**
	(0.811)	(0.810)	(0.170)	(0.177)	(0.127)	(0.124)	(0.172)	(0.161)	(0.115)	(0.117)
Constant	-3.417	-3.429	-2.216***	-2.324***	-0.551	-0.402	-0.894	-0.545	-0.172	-0.468
	(2.161)	(2.165)	(0.717)	(0.755)	(0.951)	(0.901)	(1.144)	(1.032)	(1.185)	(1.234)
Observations	130	130	268	268	228	228	298	298	120	120
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.148	0.148	0.0916	0.0828	0.0717	0.0747	0.0760	0.106	0.169	0.139

Notes: This table presents Tobit regression results analyzing the relationship between IPO activity and industry characteristics over different subperiods, corresponding to China's Five-Year Plans, from 2002 to 2021 (excluding 2013 due to the suspension of IPOs). The dependent variable is the natural logarithm of the number of IPOs (log(#IPOs)). #Emphasize>0 is a dummy variable indicating whether an industry is policy-favored (#Emphasize > 0.5), and #Emphasize is the cumulative policy emphasis score based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) represents the GDP contribution of each industry, and Industry Q is lagged industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: IPO Approval Rate in Favored vs. Non-Favored Industries

	Favored		Non-favored		Difference
Year	#App	Mean approval rate	#App	Mean approval rate	
2014	54	0.778	44	0.75	-0.028
2015	149	0.852	97	0.897	0.045
2016	166	0.783	133	0.722	-0.061
2017	342	0.763	218	0.798	0.035
2018	148	0.446	104	0.375	-0.071
2019	187	0.749	98	0.622	-0.126**
2020	325	0.778	166	0.831	0.053
2021	533	0.653	193	0.689	0.036
2014-2021	1904	0.718	1053	0.723	0.005

Notes: This table presents a comparison of IPO approval rates for firms in policy-favored versus non-favored industries from 2014 to 2021. Panel A shows the comparison by year. Panel B shows the comparison by exchange board. Mean approval rate is the fraction of IPO applications that are successfully approved. The difference in means is reported, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively, from a t-test of equal means.

Table 8: IPO Applications in favored industries

VARIABLES	(1) log(#IPO applications)	(2) log(#IPO applications)
#Emphasize>0	1.156***	
	(0.128)	
#Emphasize		1.027***
		(0.095)
log(Industry GDP)	0.184***	0.159***
	(0.054)	(0.052)
Industry Q	-0.042	-0.039
	(0.069)	(0.066)
Constant	-1.074**	-0.907*
	(0.523)	(0.501)
Observations	476	476
Year FE	Yes	Yes
Pseudo R-squared	0.0777	0.0972

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO application activity and industry characteristics during 2014 to 2021. The dependent variable is the natural logarithm of the number of IPO applications (log(#IPO applications)) in the given year and industry. Independent variables include #Emphasize>0, a dummy variable indicating whether an industry is policy-favored (where #Emphasize is greater than 0.5), and #Emphasize, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: IPO Applications time used in favored industries

VARIABLES	(1) log(#Days to IPO)	(2) log(#Days to IPO)	(3) log(#Days to IPO)
#Emphasize>0	-0.088***		
	(0.028)		
#Emphasize		-0.040**	
		(0.017)	
GPA			-0.018***
			(0.002)
SOE	-0.027	-0.026	-0.042
	(0.036)	(0.037)	(0.040)
ROA	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)
leverage	0.013	0.015	-0.021
	(0.010)	(0.010)	(0.017)
Log(Assets)	0.026	0.027	0.005
	(0.018)	(0.017)	(0.020)
Constant	4.881***	4.835***	5.802***
	(0.367)	(0.349)	(0.420)
Observations	2,108	2,108	2,108
R-squared	0.337	0.335	0.390
year FE	Yes	Yes	Yes
Industry FE	No	No	yes

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO application activity and industry characteristics during 2014 to 2021. The dependent variable is the natural log of the number of calendar days between a firm's IPO application date and its listing. Independent variables include #Emphasize>0, a dummy variable indicating whether an industry is policy-favored, and #Emphasize, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Chinese IPOs in the U.S. market

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	log(#IPOs)		log(IPO proceeds)		IPO Occurrence	
#Emphasize>0	0.227		1.194		0.257	
	(0.201)		(0.968)		(0.208)	
#Emphasize		0.230		1.124		0.243*
		(0.145)		(0.684)		(0.146)
Industry Q	0.386**	0.389**	1.857**	1.876**	0.359*	0.363**
	(0.182)	(0.177)	(0.877)	(0.857)	(0.186)	(0.182)
Constant	-8.128***	-8.094***	-39.902***	-39.773***	-8.452***	-8.426***
	(0.437)	(0.435)	(1.934)	(1.873)	(0.436)	(0.432)
Observations	1,311	1,311	1,311	1,311	1,311	1,311
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0890	0.0923	0.0595	0.0614	0.0809	0.0836

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics during 2002 to 2024 for Chinese firms in the U.S. market. The dependent variables are the natural logarithm of IPO proceeds (log(IPO proceeds)) and the natural logarithm of the number of IPOs (log(#IPOs)) in the given year and industry. IPO Indicator is equal to one if at least one IPO occurs, and zero otherwise. Independent variables include #Emphasize>0, a dummy variable indicating whether an industry is policy-favored, and #Emphasize, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Chinese IPO in the Hong Kong market

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(#IPOs)				log(IPO proceeds)			
	All IPOs		IPOs from mainland		All IPOs		IPOs from mainland	
#Emphasize>0	0.169		0.302		0.947		1.892	
	(0.179)		(0.197)		(0.924)		(1.224)	
#Emphasize		0.162		0.262**		0.904		1.663**
		(0.121)		(0.124)		(0.595)		(0.747)
Industry Q	-0.065	-0.068	-0.005	-0.009	-0.254	-0.266	0.109	0.086
	(0.120)	(0.121)	(0.125)	(0.125)	(0.633)	(0.636)	(0.785)	(0.787)
Constant	0.422*	0.427*	-0.984***	-0.966***	1.385	1.414	-6.789***	-6.679***
	(0.235)	(0.238)	(0.279)	(0.288)	(1.206)	(1.225)	(1.978)	(2.035)
Observations	1,322	1,322	1,322	1,322	1,322	1,322	1,322	1,322
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0250	0.0265	0.0233	0.0263	0.00941	0.0103	0.0123	0.0139

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO activity and industry characteristics during 2002 to 2024 for Chinese firms in the Hong Kong market. log(#IPOs) is ln(1 + number of IPOs) at the NAICS 3digit industryyear level; All IPOs includes all HKEX listings, while IPOs from mainland restricts to mainland Chinese issuers. log(IPO proceeds) is ln(1 + total IPO proceeds) in that industryyear, measured in HKD million. Independent variables include #Emphasize>0, a dummy variable indicating whether an industry is policy-favored (where #Emphasize is greater than 0.5), and #Emphasize, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Government's Favored Industry and Firms' Q During IPO

	Dependent variable: Q First Day			
	(1)	(2)	(3)	(4)
#Emphasize >0	0.348***			
	(0.094)			
#Emphasize		0.218**	0.406***	0.438***
		(0.078)	(0.111)	(0.143)
SOE	0.058	0.064	0.024	0.117*
	(0.053)	(0.052)	(0.115)	(0.057)
ROA	0.014**	0.014**	−0.008***	−0.008**
	(0.006)	(0.006)	(0.003)	(0.003)
Leverage	−0.038	−0.040	0.124**	0.124**
	(0.057)	(0.056)	(0.044)	(0.043)
Log(Assets)	−0.307***	−0.308***	−1.076***	−1.079***
	(0.067)	(0.067)	(0.220)	(0.219)
Small			−3.151***	−3.134***
			(0.437)	(0.453)
Medium			−2.167***	−2.151***
			(0.296)	(0.311)
#Emphasize >0 × Small			−0.404***	−0.422***
			(0.089)	(0.107)
#Emphasize >0 × Medium			−0.291***	−0.305***
			(0.054)	(0.060)
#Emphasize >0 × SOE				−0.125
				(0.117)
Year FE	Yes	Yes	Yes	Yes
Observations	3,484	3,484	3,484	3,484
Adjusted R^2	0.301	0.302	0.505	0.505

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

Table 13: Firms' GPA Scores and Q During IPO

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

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

Table 14: Industrial Policy and Long-Term Abnormal Returns Post IPO

	Dependent variable: BHAR		
	12-month	24-month	36-month
	(1)	(2)	(3)
Panel A: Favored Industry (#Emphasize > 0)			
#Emphasize > 0	-3.101	-0.055	6.417
	(2.345)	(3.033)	(5.891)
Panel B: Favored Industry (#Emphasize)			
#Emphasize	-0.868	1.203	5.588*
	(1.067)	(1.544)	(3.171)
Panel C: Firm-Level GPA			
GPA	0.090	0.541	0.506
	(0.248)	(0.396)	(0.408)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,005	3,005	3,003

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

Table 15: AH Premium and Favored Industry and GPA

	AH_premium		
	(1)	(2)	(3)
#Emphasize>0	−8.036		
	(9.644)		
#Emphasize		−2.846	
		(7.052)	
GPA			0.097
			(1.079)
SOE	11.259	11.535	14.360
	(12.344)	(12.557)	(12.431)
ROA	−4.839***	−4.899***	−3.889***
	(0.989)	(1.006)	(0.995)
B/M	−66.898***	−65.965***	−63.895***
	(17.882)	(17.933)	(18.089)
Log(ME)	−39.087***	−38.582***	−45.347***
	(4.820)	(4.958)	(5.202)
Date FE	Yes	Yes	Yes
Ind FE	Yes	No	No
Observations	14,127	14,127	14,127
R^2	0.462	0.461	0.493
Adjusted R^2	0.453	0.452	0.483
Residual Std. Error	77.073 (df = 13882)	77.133 (df = 13882)	74.886 (df = 13871)
Note:			*p<0.1; **p<0.05; ***p<0.01

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

Table 16: NEEQ in favored industries

VARIABLES	(1) log(#NEEQ)	(2) log(#NEEQ)
#Emphasize>0	1.233***	
	(0.113)	
#Emphasize		1.008***
		(0.086)
log(Industry GDP)	0.371***	0.354***
	(0.048)	(0.047)
Industry Q	0.077	0.081
	(0.060)	(0.059)
Constant	-1.756***	-1.630***
	(0.465)	(0.457)
Observations	536	536
Year FE	Yes	Yes
Pseudo R-squared	0.235	0.243

Notes: This table presents the results of Tobit regressions analyzing the relationship between NEEQ listing and industry characteristics during 2014 to 2022. The dependent variable is the natural logarithm of the number of listing in the NEEQ market. Independent variables include #Emphasize>0, a dummy variable indicating whether an industry is policy-favored, and #Emphasize, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 17: Bond Issuance in favored industries

VARIABLES	(1) log(Bond proceeds)	(2) log(Bond proceeds)	(3) log(#Bond Issues)	(4) log(#Bond Issues)
#Emphasize>0	1.145***		0.758***	
	(0.420)		(0.289)	
#Emphasize		0.900***		0.579**
		(0.311)		(0.225)
log(Industry GDP)	0.729***	0.712***	0.541***	0.530***
	(0.196)	(0.196)	(0.142)	(0.143)
Industry Q	-1.315***	-1.304***	-0.859***	-0.852***
	(0.298)	(0.297)	(0.196)	(0.196)
Constant	-2.758	-2.630	-2.785**	-2.697**
	(1.763)	(1.752)	(1.216)	(1.213)
Observations	903	903	903	903
year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.112	0.113	0.162	0.161

Notes: This table presents the results of Tobit regressions analyzing the relationship between IPO application activity and industry characteristics during 2014 to 2021. The dependent variable log(Bond proceeds) and log(#Bond Issues) are defined as ln(1 + total corporate bond proceeds in RMB) and ln(1 + the number of corporate bond issues), respectively. Independent variables include #Emphasize>0, a dummy variable indicating whether an industry is policy-favored (where #Emphasize is greater than 0.5), and #Emphasize, which represents the cumulative policy emphasis score for an industry based on the frequency of priority terms in China's Five-Year Plans. log(Industry GDP) measures the GDP contribution of each industry, and Industry Q represents the industry Tobin's Q, which is the asset-weighted average of firms' Tobin's Q ratios within an industry. Year fixed effects are included, and standard errors are clustered by industry and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table .1.T: Definitions of Variables

Variable	Definition
#Emphasize	Cumulative policy emphasis score mapped from Five-Year Plan texts to industries (industry-year); higher values indicate greater policy emphasis.
#Emphasize>0	Indicator for policy-favored industry in a given year (industry-year); 1 if emphasized (threshold per mapping), else 0.
policy_favor	U.S. sample policy-favored industry indicator used in cross-country regressions; 1/0.
log(#IPOs)	Natural log of 1 plus the annual number of IPOs in an industry: $\ln(1 + \#\text{IPOs})$.
log(IPO proceeds)	Natural log of 1 plus total annual IPO proceeds in an industry: $\ln(1 + \text{proceeds})$; currency by market (RMB for China, USD for U.S., HKD for Hong Kong).
log(Industry GDP)	Natural log of industry GDP in the year: ln(industry GDP); units per source (state statistical yearbooks).
Industry Q	Asset-weighted industry Tobins Q, lagged one year ($t-1$).
IPO Indicator	Indicator for whether at least one IPO occurs in the industry-year; 1/0.
log(#NEEQ)	Natural log of 1 plus NEEQ listings in the industry-year: $\ln(1 + \#\text{NEEQ})$.
log(Bond proceeds)	Natural log of 1 plus corporate bond proceeds by industry: $\ln(1 + \text{RMB proceeds})$.
log(#Bond Issues)	Natural log of 1 plus the number of corporate bond issues by industry: $\ln(1 + \#\text{issues})$.
log(#IPO applications)	Natural log of 1 plus annual IPO applications in an industry: $\ln(1 + \#\text{applications})$.
log(#Days to IPO)	Natural log of 1 plus calendar days from application acceptance to listing: $\ln(1 + \text{days})$.
GPA	Firm-level policy alignment measure from pre-IPO prospectus text; level.
Q (winsorized)	Tobins Q at the IPO event used in summary stats; winsorized at 1%/99% within calendar year.
Q First Day	Tobins Q using the first non-limit-up day IPO price; winsorized at 1%/99% within calendar year.
SOE	State-owned enterprise indicator; 1 if SOE, else 0.
ROA	Return on assets; percent unless otherwise noted.
Leverage	Total liabilities / shareholders' equity; ratio.
Log(Assets)	Natural log of total assets: ln(assets).
Small	Indicator for bottom tercile of market capitalization at IPO among then-listed firms; 1/0.
Medium	Indicator for middle tercile of market capitalization at IPO among then-listed firms; 1/0.
BHAR	Buy-and-hold abnormal return from the first non-limit-up day over 12/24/36 months, minus matched benchmark returns; percent.
AH_premium	Monthly A/H market cap premium $(\text{A/H} - 1) \times 100$; winsorized at 1%/99% by calendar year.
B/M	Book-to-market ratio; unitless.
Log(ME)	Natural log of total market capitalization (A + H): ln(market cap).