

Can We Trust Their Innovation? Industrial Policy, Takeover Incentives, and Innovation Redirection in Non-Targeted Firms

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This study examines how industrial policy crowds in innovation from non-policy firms. Leveraging the “Made in China 2025” initiative as a quasi-natural experiment, I document that non-policy firms disproportionately reorient innovation toward policy-favored sectors. Mechanism analyses identify two distinct channels. First, industrial policy depresses the valuation of non-policy firms while conferring political rents (e.g., future grants) on firms that pivot their patenting, collectively rendering them attractive candidates for M&A. Consistent with this mechanism, I document that non-policy firms’ redirected innovation is followed by shareholder divestment and an increased probability of being acquired. Second, local officials steer innovation output to accumulate political capital for promotion. Using LLM technology to quantify policy prioritization, I find that innovation redirection is more prevalent in cities where higher-level authorities place greater weight on industrial targets, and that the redirected innovation from non-policy firms is linked to the career advancement of local officials. Further, the redirection concentrates among financially distressed firms and those plagued by the expropriation of minority shareholders. Finally, redirected innovations coincide with prolonged patent pendency and reduced quality, pointing to a real efficiency loss. Overall, this study highlights the unintended consequences of industrial policy by documenting an opportunistic innovation redirection.

Keywords: Industrial Policy; Innovation Redirection; Mergers and Acquisitions; Political Promotion

JEL Codes: G34; L52; O31; O38

1. Introduction

Against the backdrop of significant societal challenges, e.g., climate change, resource depletion, and inequality, an emerging strand of work on mission-oriented and transformative policy emphasizes the need for directionality in policy implementation. They contend that governments should not only promote the generation of innovation, but also select, privilege, and stabilize specific innovation trajectories over others to address grand societal challenges (Foray et al., 2012; Weber and Rohracher, 2012; Schot and Steinmueller, 2018). Industrial policy is central to operationalizing this directionality. Conventional wisdom holds that industrial policy works because it can correct market failures by

modifying relative prices, thus aligning private incentives with socially desirable innovations. Established literature documents how taxes, subsidies, and other policy instruments can steer innovation (Acemoglu et al., 2012; Aghion et al., 2016; Basilico et al., 2023), yet it remains less clear who actually generates this innovation, why they do so, and what the innovation consequences of such redirection are. This study examines distorted redirectionality that arises when industrial policy is implemented amidst market and institutional failures.

Capital markets play a vital role in forming innovation decisions. Prior studies show that market intermediaries, e.g., security analysts and social media, often bias against disruptive technologies while favoring firms that pursue incremental innovations (Benner, 2010); they also overemphasize short-term accounting performance (Dichev et al., 2013; Graham et al., 2005; He and Tian, 2013; Irani and Oesch, 2016), both of which exacerbate managerial myopia that inhibits long-run innovation.

Rather than focusing on managerial catering to short-run earnings benchmarks, this study examines how firms steer their innovation to dress up takeover market appeal. Industrial policy anchors investors' expectations to state priorities, tilting capital and attention toward policy sectors and leaving non-policy firms trading at a relative discount (e.g., Merton, 1987; Khwaja and Mian, 2005; Da et al., 2011; Pástor and Veronesi, 2013). Thus, non-policy firms' innovation towards state-favored domains yields two benefits. First, because non-policy firms are relatively undervalued vis-à-vis policy-sector counterparts, acquiring them entails lower capital outlays compared to directly absorbing established policy firms. Second, by venturing into policy-aligned technologies, non-policy firms secure a real option for future policy rents, e.g., innovation grants, thereby elevating the acquirers' expected deal gains. Given these dual effects, the main prediction of this paper is that non-policy firms direct innovation to the policy sector to dress up takeover market appeal, captured empirically by a surge in non-core vis-à-vis core patent applications after policy implementation.

To establish causality, I utilize the Made in China 2025 initiative (hereafter, MIC-2025) as a quasi-natural experiment. Descriptive analyses show that invention applications by policy firms increased from approximately 13.6 to 27.1 per firm-year before and after the MIC-2025. However, corresponding policy-related patents by non-policy firms have surged from 3.3 to 10.2 applications per firm-year (nearly tripling). Formal DID estimation indicates that, following MIC-2025, non-policy

firms increase non-core patent applications by approximately 19.70% relative to policy firms, after controlling for firm characteristics.

Evidence regarding the positive relationship between MIC-2025 and non-policy firms' innovation redirection is an implication of strategic change, but the underlying motive is rooted in the incentive to dress up appeal as acquisition targets. Thus, my second exploratory test examines whether firms innovate to exit. Results speak for this channel. I document a significant divestment by top shareholders following redirected innovation, further coupled with a heightened probability of the firm becoming a takeover target.

I extend the analysis by noting institutional failure as another driving force in redirecting innovation. Firms' operations are subject to political interference. For instance, Goldman et al. (2013) show that governments reallocate procurement after party control shifts, increasing contracts for firms connected to the winning party. Bertrand et al. (2018) find that politically connected CEOs strategically adjust employment decisions to support regional politicians' re-election. Under China's promotion tournament system, local officials' career advancement hinges on their performance in their jurisdictions (Li and Zhou, 2005; Chen et al., 2024). When top-down industrial targets become implicit political KPIs in the tournament, local officials steer innovation output to accumulate political capital for promotion.

A direct test of this mechanism is to examine whether the redirection is more prevalent in regions where superiors place greater emphasis on MIC-2025 targets. However, empirically implementing this test is challenging, as there is no established proxy for government MIC-2025 prioritization. To address this, I introduce a large language models (LLMs) methodology. As discussed later, I use a rubric-guided prompt to quantify provincial GWR narratives into standardized MIC-2025 priority scores. Evidence suggests that (i) non-policy firms located in cities whose senior officials (i.e., provincial governors) champion MIC-2025 are more likely to redirect their innovation, and (ii) their redirected innovation can statistically predict local officials' (i.e., cities') promotion.

I conduct a battery of heterogeneity analyses to further our theoretical understanding of redirection. I document that non-policy firms are more likely to redirect innovation when they face greater financial distress and exhibit more severe agency conflicts between controlling and minority shareholders. These results lend support to an opportunistic innovate-to-exit motive. I also show that

policy firms are under-granted, while non-policy firms garner higher rewards for the policy patents they obtain. This distorted incentive structure is consistent with the view that local governments steer innovation in non-policy sectors to serve their industrial upgrading narrative.

In the final part of my exploratory analyses, I examine the efficiency and the quality of redirected innovation. Results suggest that redirected firms, on average, require more time to secure patent grants and garner fewer forward citations, pointing to a real efficiency loss. My results hold across a battery of robustness tests, including matching methodology, parallel-trend, and placebo tests.

This study is motivated by and contributes to multiple streams of literature, and highlights links among industrial policy, the market for corporate control, and political promotion incentives. First, prior work shows how policy instruments can steer innovation directionality (e.g., Acemoglu et al., 2012; Aghion et al., 2016), yet we know far less about which firms ultimately generate redirected innovation, and more importantly, with what implications for innovation efficiency. Leveraging the MIC-2025 initiative, this study contributes novel causal evidence that industrial policy can unintentionally crowd in non-policy firms' patenting. I also show that both incentives from the takeover market and those of local officials drive non-policy firms to innovate towards the policy sector, and that redirected innovation results in lower innovation quality and efficiency.

Second, this study enriches the literature on corporate control by illuminating a window-dressing innovation strategy. Prior studies suggest that takeover threats can induce managerial myopia that inhibits long-run R&D, while active M&A markets promote small firms to increase R&D intensity for high-quality innovation (Stein, 1988; Phillips and Zhdanov, 2013). I demonstrate that firms can redirect innovation to capture political rents valued by the takeover market. Such redirectionality is more pronounced among financially distressed firms, suggesting an opportunistic rent-seeking innovation.

Furthermore, this study contributes to the literature on the impact of political influence on corporate behavior. Bertrand et al. (2018) find that politically connected CEOs strategically adjust employment decisions to support regional politicians' re-election. While Chen et al. (2024) show that innovation performance has become a determinant of official promotion, we lack direct empirical evidence on whether and how local officials manipulate innovation performance under political pressure. I document that innovation redirection is more prevalent in cities where superiors emphasize

policy targets (i.e., higher KPI pressure), and that redirected innovation from non-policy firms is linked to the promotion of local officials. Moreover, I provide evidence that governments reshape incentive structures to steer such redirection.

2. Related Literature

2.1 Industrial Policy, Directionality, and Firm Innovation

In light of major societal challenges, e.g., climate change, resource depletion, and inequality, scholars have urged the incorporation of directionality in innovation policy. Popp (2002) shows that increases in energy prices significantly stimulate energy-saving-related patents, indicating that price signals steer innovation toward energy-efficient technologies. Acemoglu et al. (2012) characterize how taxes and subsidies alter the relative returns to different technologies, thereby incentivizing firms to redirect R&D resources from high-polluting to clean sectors. Aghion et al. (2016) demonstrate that, when facing higher tax-inclusive fuel prices, firms reduce patenting in “dirty” internal combustion engine technologies while increasing invention in “clean” technologies. Cael et al. (2016) exploit the EU Emissions Trading System as a quasi-natural experiment and find that regulated firms increase low-carbon patenting relative to similar unregulated firms.

While the existing literature documents the stimulating effects of industrial policy on the intensity of firms’ innovation and on the directionality of technology (Civera et al., 2026), little scholarship has examined who actually undertakes this innovation and what consequences such redirection has for innovation efficiency. This study aims to address these issues.

2.2 The Market for Corporate Control and Managerial Innovation Incentives

The market for corporate control shapes managerial incentives regarding R&D investment. Stein (1988) theorizes that takeover threats can lead to managerial myopia, i.e., prioritizing short-term earnings over long-term R&D to secure corporate control. Atanassov (2013) finds that, in the absence of the threat of hostile takeovers, managers may succumb to managerial slack, prioritizing low-risk and short-term projects with diminished returns. This pursuit of a ‘quiet life’ often leads to underinvestment in R&D innovations. Phillips and Zhdanov (2013) model the R&D behavior of acquirers and targets in an active M&A market. They find that, in a more active acquisition market, small firms are more likely to increase R&D spending because they can “sell out” to larger firms. McCarthy et al. (2025) find that the structure of acquisition relationships influences the composition

of firms' subsequent patent output.

I also examine corporate innovation in the context of the corporate control market, but I focus on the redirection of innovation, i.e., the reallocation of innovative effort toward policy-endorsed domains, rather than R&D intensity. Moreover, I document an opportunistic, low-quality innovation driven by financially distressed firms and those plagued by the expropriation of minority shareholders, fundamentally distinct from the view that managers raise innovation intensity to attract acquirers through genuinely higher-quality innovation (Phillips and Zhdanov, 2013).

2.3 Political Incentives, Government Intervention, and Firm Behavior

Shleifer and Vishny (1994) frame state influence as a bargaining process where politicians seek specific political goals, e.g., jobs or stability, and persuade managers to sacrifice efficiency in exchange for support. Khwaja and Mian (2005) find that politically connected firms receive greater credit from government banks, suggesting that politically related resource allocation can sustain firm activity beyond fundamentals. Goldman et al. (2013) show that government procurement is reallocated after party control shifts, with contracts awarded preferentially to firms affiliated with the winning party. Bertrand et al. (2018) find that politically connected CEOs strategically adjust corporate employment decisions to support regional politicians' re-election efforts. They exhibit higher rates of job and plant creation and lower rates of destruction during election years.

Pressure from politicians is more pronounced in China's context because the promotion prospects of local officials are contingent upon the performance of their jurisdictions. Blanchard and Shleifer (2001) emphasize that China's combination of decentralization and political centralization can discipline local governments toward growth-oriented behavior. Li and Zhou (2005) formalize the "promotion tournament" logic by showing that provincial leaders' likelihood of promotion rises with regional economic performance. Piotroski et al. (2015) show that Chinese listed firms temporarily suppress negative information around salient political events (e.g., Party Congress meetings and promotions of high-level provincial politicians), indicating that political pressures can distort corporate operations. Wen (2020) provides evidence that the state instrumentalizes SOE employment to maintain social stability.

I examine whether industrial policy imposes political promotion pressure on local officials and, more importantly, whether redirected innovation by non-policy firms helps mitigate such pressure.

3. Hypothesis Development

Acquisition decisions reflect a trade-off between expected costs and potential synergies. Innovating into policy sectors can enhance non-policy firms' takeover market appeal by virtue of increased deal gains from implicit political rents and reduced deal costs through relative undervaluation. On the gain side, governments do not implement policy directly; instead, they identify and incentivize firms and other market participants to deliver political outputs (Piotroski et al., 2015; Cao et al., 2019; Wang and Luo, 2019; Wang et al., 2019). Exploratory innovation necessitates significant R&D expenditures and carries a high risk of failure (Manso, 2011; Tian and Wang, 2014). Thus, reallocating capital to non-core R&D serves as a costly and credible signal to the government by showing that they possess not only the willingness but also the determination to execute political targets. In a reciprocal exchange for advancing political goals, non-policy firms are entitled to a real option on political rents - such as R&D subsidies, tax relief, or priority access to credit (Faccio et al., 2006; Claessens et al., 2008; Houston et al., 2014; Colombo et al., 2016; Wang et al., 2019; Cao et al., 2024)- thereby raising the expected cash inflows for acquirers.

From a pricing perspective, as discussed in Section 4, industrial policy can create a valuation wedge by anchoring investors' expectations in state priorities, leading to a relative discount for firms outside prioritized domains. This resulting undervaluation lowers the acquisition cost of non-policy targets. Thus, when acquirers anticipate securing greater M&A synergies at lower prices (compared to direct acquiring firms in policy sectors), the transactional value of redirected non-policy firms rises accordingly.

Beyond takeover market incentives, pressure from politicians also directs firms' innovation. China adopts a political promotion tournament system in which local officials' promotion prospects are contingent upon their jurisdiction's performance. Traditional evaluation framework privileged GDP growth as the dominant metric (Li and Zhou, 2005), yet a structural change occurred in 2012 (following the 18th CPC National Congress) when the central government advanced its high-quality (innovation-driven) national development strategy. This new agenda marks a reorientation of officials' evaluation targets, from a singular focus on GDP growth, toward a broader set of high-quality development indicators, e.g., innovation. Chen et al. (2024) find that regional innovation performance, particularly the output of invention patents, has now become a determinant of officials' promotion.

Redirecting innovation by firms outside policy-prioritized sectors yields two benefits for local officials. First, it directly increases innovative outputs in policy industries, which can contribute to the innovation performance used in their promotion evaluations. Second, and more importantly, for traditional firms, which are typically located outside the policy zones, entry into policy-supported industries lays the foundation for an “industrial-upgrading” narrative that can signal greater governance capacity to superiors. Thus, when firms recognize that access to resources is contingent upon alignment with policy priorities, they reorient their innovation accordingly.

Taken together, I propose the hypothesis of this paper.

H1: The *Made in China 2025* initiative incentivizes non-policy firms to redirect innovation toward policy-designated industries.

4. Institutional Background and Validation: The “Made in China 2025” Initiative

In May 2015, the Chinese central government launched the “Made in China 2025” initiative, setting explicit targets to advance ten core technologies by 2025 (see Appendix B). This central directive not only imposes political targets on local authorities but also attracts significant attention from capital markets (Liu et al., 2022). Consequently, the MIC-2025 provides an ideal quasi-experiment to investigate how firms strategize innovation amidst the interplay of political pressure and market distortions.

To validate the empirical setting, I examine the initiative’s political and capital market consequences. Using a keyword dictionary to identify MIC-2025 terms in provincial government work reports (detailed in Appendix I),¹ I find that provincial governors placed greater emphasis on the ten strategic industries, as evidenced by the increasing prevalence of MIC-2025 vocabulary. Furthermore, Appendix C shows that firms in MIC-2025 industries receive greater investor attention—quantified as the volume of posts and comments in stock forums—and command higher market valuations (i.e., lower *BTM*).

5. Research Design

¹ Each year during January and February, executive heads across all tiers of government present their Government Work Reports to corresponding legislative bodies (People’s Congresses). The report outlines governing achievements in the past year and, more importantly, policy agendas for the next year. We focus on the provincial GWRs because provincial governments operate under the direct guidance of the central government while overseeing the performance evaluation of subordinate municipal governments.

5.1 Model Specification

To investigate the spillover impacts of MIC-2025 on innovation by non-policy firms, I estimate the following regression:

$$\begin{aligned} NoncorePat_Inv_{i,t+1} &= \beta_0 + \alpha_0 Treat_Post_{i,t} + \alpha_1 Size_{i,t} + \alpha_2 Lev_{i,t} + \alpha_3 ROA_{i,t} + \alpha_4 RD_{i,t} + \alpha_5 Cash_{i,t} + \alpha_6 BTM_{i,t} \\ &+ \alpha_7 Growth_{i,t} + \alpha_8 SOE_{i,t} + Firm\ FE + Year\ FE + \mu \quad (1) \end{aligned}$$

Where subscripts i and t index firms and years, respectively. *NoncorePat_Inv* is the proportion of invention patent applications that fall outside the firm's core industry category, i.e., policy-related patents by non-policy firms, and non-policy patents by policy firms.² A higher (lower) value of *NoncorePat_Inv*, therefore, aligned with a higher (lower) level of innovation divergence from firms' core technology set. *Treat* is an indicator variable that equals one if firm i belongs to a *non*-MIC-2025 industry and zero otherwise. *Post* is an indicator variable that equals one for years after 2015 and zero otherwise. A positive coefficient on the interaction term *Treat_Post* is consistent with H1, which predicts that non-policy firms reallocate innovation efforts towards the MIC-2025 industry.

I control for several determinants of innovation based on prior literature. To capture firm-level heterogeneity in both the willingness and capacity to innovate, I control for firm size (*Size*), leverage (*Lev*), and profitability (*ROA*) (e.g., Cohen and Klepper, 1996; Hall, 2002; Brown et al., 2009; Czarnitzki and Hottenrott, 2011; Acharya and Subramanian, 2009). I control for cash holdings (*Cash*) to capture the financial slack necessary for firms to absorb the risks of entering non-core policy domains. I include R&D intensity (*RD*) to mitigate the concern that high-RD firms are mechanically more likely to file patents and to extend into MIC-related technologies (e.g., Ahuja and Katila, 2001; Cohen and Levinthal, 1989, 1990; Griffith et al., 2004; Chan et al., 2001). I include sales growth rate (*Growth*) because firms with high growth opportunities (high *Growth*) are more inclined to pursue exploratory innovation. I further include the book-to-market ratio (*BTM*) to control for market valuation, which reflects investors' expectations and incentivizes firm innovation decisions. Finally, *SOE* status captures institutional context, and firm- and year-fixed effects are included.

5.2 Sample Selection

² The proportion is scaled by the firm's total number of patent applications in the same year.

My testing sample comprises all firms listed on the Shanghai and Shenzhen Stock Exchanges spanning the period 2009 to 2023 (as detailed in Table 1). I obtain financial data from the RESSET database and patent data from the Chinese Research Data Services Platform (CNRDS). The initial sample contains 48,861 firm-year observations. I exclude financial firms (1,604 firm-years) and firms concurrently listed on the B- or H-share market (2,488 firm-years), which are subject to distinct regulation (Chan et al., 2008). Observations with missing data for key variables are further removed (8,560 firm-years). The final sample consists of 36,209 firm-years.

6. Empirical Results

6.1 Descriptive Statistics

Table 2, Panel A, reports descriptive statistics for the full sample. The mean of *NoncorePat_Inv* is 0.156, indicating that approximately 15.6% of invention applications lie outside firms' core technology set. *Treat_Post* has a mean of 0.265, implying that 26.5% of firm-year observations fall in the post-treatment period. The average firm size (*Size*) is 22.140, leverage (*Lev*) is 0.434, and return on assets (*ROA*) is 4.50%. Furthermore, the mean R&D intensity (*RD*) is 0.039, and the average cash holding (*Cash*) is 0.179. Regarding ownership structure, 37.8% of the observations are state-owned enterprises (SOEs).

Panel B compares the mean values of key variables between treated (non-policy) and control (policy) firms in the pre- and post-policy periods. Non-policy firms are, on average, larger and more leveraged than policy firms both before and after the policy shock, and unsurprisingly, policy firms exhibit larger policy patent counts. The pronounced pre-existing differences across the two groups reinforce the need for a formal difference-in-differences analysis.

Figure 2 illustrates the time-series trends of MIC-2025 patent applications for firms in policy and non-policy industries. As shown, policy firms filed approximately 13.6 patents per year before 2015—roughly four times the volume of non-policy firms. Following the launch of MIC-2025, patenting activity in policy-supported technologies rose steadily for both groups. Between 2015 and 2023, the mean number of policy-related patents among policy firms nearly doubled, from about 13.6 to 27.1. Concurrently, the mean for non-policy firms increased from approximately 3.3 to 10.2, representing a roughly threefold increase. Together, the descriptive evidence in Table 2 and Figure 2 suggests that firms outside the designated policy industries are increasingly channeling their R&D

toward technologies favored by the industrial policy.

6.2 Baseline Effects of MIC-2025 on Innovation Redirection

H1 predicts a positive relationship between the implementation of the MIC-2025 and the extent of innovation redirection among non-policy firms. Results appear in Table 3, where t-statistics are based on robust standard errors clustered at the industry level. In Column 1 (2), where *NoncorePat_Inv_{t+1}* serves as the dependent variable controlling for firm (industry) fixed effects, the coefficient for *Treat_Post* is 0.040 (0.035) with a t-statistic of 3.07 (2.93), consistent with the theoretical prediction that non-policy-industry firms redirect their innovation efforts toward policy-targeted sectors. Beyond statistical significance, the estimated effect of the MIC-2025 on innovation redirection is also economically meaningful. Given the unconditional SD of *NoncorePat_Inv* is 0.203, the coefficient of 0.040 in Column 1 corresponds to an increase equivalent to approximately 19.70% (0.040/0.203) of a standard deviation in firms' non-core invention patenting.

For the controls, *Size* loads positively and significantly in both specifications, consistent with the view that larger firms have greater resource endowments and absorptive capacity that facilitates innovation (e.g., Cohen and Levinthal, 1990; Lee, 2009). I also observe a negative coefficient on *Lev*, suggesting that stronger creditor monitoring disciplines managers against high-risk exploratory innovation. Coefficients on *RD* are statistically positive, implying that R&D intensity provides the necessary knowledge base to explore technological opportunities across industries (e.g., Ahuja and Katila, 2001; Cohen and Levinthal, 1989, 1990; Griffith et al., 2004; Audretsch et al., 2024).

6.3 Robustness Tests

This section reports a set of robustness checks. First, to mitigate endogeneity arising from non-random treatment assignment (selection on observables), I re-estimate Equation (1) in a matched (reweighted) sample. Entropy balancing reweights control firms to exactly match pre-specified covariate moments of the treated group (Hainmueller, 2012), whereas propensity score matching pairs firms based on estimated treatment probabilities. Appendices D and E demonstrate that, despite ex-ante imbalance, both matching approaches successfully align the covariate distributions between policy and non-policy firms. Corresponding estimates in Table 4, Columns (1) and (2), confirm that the main results still hold across both matching methods.

Second, to ensure that there are no pre-treatment trends, I perform a parallel-trend test.

Empirically, I replace *Treat_Post* with nine event-time indicators: *Before4*, *Before3*, *Before2*, *Before1*, *Current*, *After1*, *After2*, *After3*, and *After4*, which are binary variable that indicates the period four years before, three years before, two years before, one year before, the year of policy implementation, one year after, two years after, three years and four year or more after the policy implementation (with the period five years or more prior to the policy serving as the benchmark). Evidence from Figure 3 and Table 4, Column (3), shows statistically insignificant coefficients prior to MIC-2025, followed by increasingly positive and significant estimates thereafter.

Finally, one may be concerned that confounding policies drive the observed effects; thus, I conduct a placebo test following the procedure outlined by Liu and Lu (2015). I repeatedly draw a placebo treatment group of the same size as the actual treatment group, assign each firm a random policy year, and re-estimate model (1) 1,000 times. Figure 4 shows that the distribution of placebo *Treat_Post* coefficients is centered around zero and distinct from the baseline estimation reported in Table 3. These results suggest that confounding policies or random shocks are unlikely to drive the documented effect.

6.4 Mechanism Analyses

6.4.1 Strategic Window Dressing for Capital Market Exit

Evidence regarding the positive association between the MIC-2025 initiative and innovation redirection is an implication of strategic changes, but the underlying motive is rooted in firms' dressing for exit in the capital (takeover) markets. Thus, I first examine whether redirected innovation is followed by insider selling. A surge in insider sell-downs would support an opportunistic dressing-up strategy, as incumbents monetize the valuation uplift and reduce equity exposure ahead of a potential change of control. By contrast, an opportunity strategic adaptation story predicts stable (or even increasing) insider ownership, as incumbents seek to internalize the expected cash-flow gains through value-enhancing innovation.

Panel A, Table 5, regresses *InsiderSell* (net reductions in holdings by the top three internal blockholders) on *NoncorePat_Inv*, separately for policy and non-policy firms and for one- and two-year leads. Columns (1) and (3) suggest that the coefficients on *NoncorePat_Inv* are statistically significant in the T+1 and T+2 periods. This result indicates that major shareholders initiate a gradual divestment following their cross-boundary patent filings. In comparison, the coefficients on

NoncorePat_Inv are all insignificant from zero for the policy firms.

Table 5 (Panel B) presents the results using *AcqTarget* as the dependent variable. *AcqTarget* is an indicator variable that equals one if firm *i* becomes the target of an acquisition in year *t*, and zero otherwise. I restrict the sample to the post-policy period because the takeover channel is conceptually operative only after MIC-2025.³ Corroborating established evidence, the coefficient on *NoncorePat_Inv* is significantly positive for non-policy firms in T+2 (Column 3). This result suggests that there is an increased probability of being the target of acquisition in the two years following their redirected patent applications.⁴ Collectively, these findings support the view that the MIC-2025 incentivizes firms to pursue an opportunistic rather than a value-enhancing innovation.

6.4.2 Promotion Tournament and Innovation Redirection

Beyond takeover market incentives, local officials may seek to steer innovation output that facilitates their promotion. One direct test of this mechanism is to examine whether firms located in regions whose senior governors prioritize MIC-2025 industries are more likely to undertake innovation redirection.⁵ However, no established literature provides an accurate measure that directly quantifies such policy priorities. To address this, I construct a novel index via advanced LLMs.

Since late 2022, rapid advances in large language models (LLMs) have broadened the tools available for text analysis. Existing literature shows that LLMs can generate more concise and informative MD&A summaries and extract risk indices from annual reports that predict future stock return volatility (Kim et al., 2023a, 2023b). They can also produce auditing judgments comparable to those of experienced professionals (Wei et al., 2023) and can pass the CPA, CMA, CIA, and EA examinations (Eulerich et al., 2024).

Building on these advances, I construct a novel LLM-based index to measure the extent of the

³ Nonetheless, untabulated results show that non-policy firms' redirected innovation does not significantly predict acquisition targeting in the pre-policy period.

⁴ The insignificance of the coefficient on *NoncorePat_Inv* in T+1 likely reflects the natural gestation period of M&A transactions, which accounts for the time required for suitors to identify the signal, conduct due diligence, and finalize the deal.

⁵ This is because when senior government place a higher priority on specific industrial targets, they are more likely to incorporate the development of these industries into the performance evaluation system of subordinate officials. Consequently, driven by promotion incentives, subordinate governments have stronger motivations to intervene in local firms' resource allocation to align with these priorities.

senior (provincial) government’s support for the MIC-2025 sectors. Each January, governments across tiers present Government Work Reports (GWRs) to their respective people’s congresses, summarizing

last year’s performance and outlining goals for the coming year (illustrated in Appendix F).⁶ I hand-collect all provincial GWRs from 2007 to 2023 and prompt each report to an AI model to obtain a score for each government’s forward-looking emphasis on the MIC-2025 industries.⁷

The scoring prompt is presented in Appendix G. I first cast the model as a professional industrial policy analyst, anchoring its expertise in policy analysis. The prompt lays out detailed guidelines that link observable policy signals to a scaled support score. I distinguish four levels, i.e., minimal, limited, intermediate, and strong support, each defined by target industries, specific policy measures, and resource commitments. It also imposes explicit constraints to mitigate central tendency bias.⁸

I conduct a validation test on my LLM-based scoring methodology to confirm the effectiveness of the AI measure (*MIC25_Priority*). Specifically, I manually construct a set of benchmark passages that differ clearly in the extent to which local governments support MIC2025 industries and feed them to the model for scoring. Evidence in Appendix H suggests that the resulting scores vary systematically across the three test cases. The first passage makes only a vague reference to manufacturing upgrading and therefore receives a low score of 2. Evaluation Corpus 2 clearly outlines several supporting policy instruments and receives a mid-range score of 5. In the third passage, the government explicitly designates MIC2025 industries as the city’s core development priority and sets quantitative targets. The model assigns the highest score of 9. This result suggests that the LLM-based measure can effectively capture the strength of provincial governments’ emphasis on MIC2025

⁶ I focus on provincial instead of city’s Government Work Reports because provincial leaders are the key ‘senior’ decision-makers in China’s promotion tournament, and their annual reports provide a standardized and comprehensive statement of policy priorities across regions and over time.

⁷ Specifically, I implement the scoring with Grok-4.1 Fast, a frontier multimodal large language model developed by xAI and optimized for high-performance long-context reasoning and structured outputs. It offers a 2-million-token context window and achieves state-of-the-art performance on agentic benchmarks (e.g., 100% on τ^2 -bench Telecom and 72% accuracy on the Berkeley Function Calling v4 benchmark) (see <https://x.ai/news/grok-4-1-fast> for more details).

⁸ Central tendency bias refers to the tendency of the model to systematically prefer “safe” middle-range scores (typically 5~7) rather than using the full scoring scale (e.g., Marcinek et al., 2025). If I do not impose explicit negative constraints to correct for central tendency bias, the variance of the AI scores is too limited to distinguish between higher and lower levels of priority.

industries.

I also examine the convergent validity of the AI measure vis-à-vis the classical word frequency analysis (the keyword dictionary for identifying MIC-2025 terms is documented in Appendix I). The rationale is that if the AI measure indeed captures the government's priority for MIC-2025, regions whose reports frequently mention these industries (as reflected in higher keyword density) should also receive higher AI scores. Untabulated results indicate a 0.317 correlation between the AI measure and MIC-2025 keyword density. Table 6, Panel A (Columns 1 and 2), indicates that the MIC-2025 effect is more pronounced in regions where provincial governors prioritize the agenda.

Moreover, firms with political connections are often leveraged by the government to pursue political objectives (Faccio et al., 2006; Fan et al., 2007; Khwaja and Mian, 2005; Sapienza, 2004; Shleifer, 1998; Tihanyi et al., 2019). Results in Columns 3 and 4 show that politically connected firms are more likely to engage in redirected innovation.

To examine a political promotion channel, I test whether non-policy firms' redirected invention is linked to local officials' promotion prospects. I employ web scraping techniques to collect the profiles of all mayors and define a promotion as an appointment to a position of higher bureaucratic rank or a powerful department. I construct a city-level redirection measure, *CityNoncorePat_Inv*, defined as the mean of redirected inventions among *non-policy* firms. Empirical evidence in Panel B of Table 6 shows *CityNoncorePat_Inv* is positively associated with local mayor's promotion, and the effect is stronger for cities in provinces with a higher MIC25_Priority score.⁹ Together, the above results lend support to the promotion-tournament story.

6.5 Additional Analyses

6.5.1 Heterogeneity

First, I examine whether firms redirect innovation to compensate for unfavorable financial conditions. Redirected innovation may reflect a strategic adaptation to industrial policy, as there is a greater opportunity in the policy industry. Given that exploratory innovation requires significant R&D expenditures, we expect firms in better financial condition to be more likely to redirect innovation if it is opportunity-driven. By contrast, an opportunistic redirection would predict that

⁹ I also conduct a parallel test using redirected innovation among target firms. Untabulated results indicate that policy firms' redirected innovation can not predict the promotion probability of local mayors.

financially distressed firms dress up their appeal in the takeover market. I partition the sample by Altman Z-score (Altman, 1968), where a lower score indicates deteriorated operating conditions and, hence, a higher probability of bankruptcy. Table 7, Panel A reveals that the effect of the MIC-2025 is stronger for financially distressed firms with low Z-scores.

The final heterogeneity links innovation redirection to firms' agency conflicts. Insiders, e.g., controlling shareholders and management, wield substantial control over corporate resource allocation by virtue of their influence on the board and dominance over decision-making. However, due to limited legal enforcement, they face disproportionately low costs for misconduct. Thus, the Classical Agency Conflicts hold that insiders are structurally incentivized to pursue self-serving activities at the expense of the firm's own value maximization. If redirected innovation is a manifestation of insiders' rent-seeking, I anticipate that firms with severe agency conflicts are more likely to redirect innovation. Consistent with expectations, Panel B indicates that the redirection effects concentrate among firms plagued by the expropriation of minority shareholders.¹⁰

6.5.2 Asymmetric Incentives for Strategic Patenting

Traditional firms venturing into the policy industry can serve as an industrial-upgrading narrative to demonstrate local mayor's governing competence. Although direct verification of this hypothesis is challenging, because the promotion evaluation process is unobservable to the public, I examine whether governmental grants are asymmetrically distributed across policy and non-policy firms. If redirected innovation is the byproduct of distorted political incentives, non-policy firms should receive disproportionately higher subsidies per policy patents relative to policy firms.

Government grants on patents received by firm i in year $t+1$ (*Grant*) is employed as the outcome variable. I collect the number of policy patents granted by firm i in year t (*StrategyPatent*) as the explanatory variable and add its interaction term with *Treat* (*StrategyPatent_Treat*) to capture whether the government asymmetrically incentivizes non-policy firms.

Table 8 presents the results. The coefficient on *StrategyPatent* is significantly positive across the specifications, suggesting that firms granted more policy inventions are indeed rewarded with greater

¹⁰ Two tunneling proxies (i.e., *Separation* and *Tunnel*) are used following prior literature (Claessens et al., 2000; Claessens et al., 2002; Masulis et al., 2009; Jiang et al., 2010). A higher value of *Separation* and *Tunnel* indicates more severe Type II agency conflicts.

government subsidies. Two intriguing findings come out when I examine the interaction term *StrategyPatent_Treat* and compare the results across the pre- and post-policy periods. First, the coefficient on *StrategyPatent_Treat* is statistically positive, only in the post-policy sample. This result suggests that non-policy firms are more rewarded by the government for their redirection to the policy sector. Second, the coefficient on *StrategyPatent* is 0.414 in the pre-period (Column 1), while it drops to 0.149 in the post-period (Column 2). The deterioration in the coefficient on *StrategyPatent* between the pre- and post-policy periods suggests that, for firms in targeted industries, the marginal subsidy benefit from each additional policy patent has diminished following MIC-2025. Together, these findings suggest that the government reallocates subsidies to steer non-policy firms' innovation toward priority sectors.

6.5.3 Joint vs. Sole Patenting

I further examine how non-policy firms redirect their innovation. Joint patents necessitate collaboration and may lead to property conflicts, whereas sole patents allow for lower coordination costs and faster production (Gulati and Singh, 1998; Belderbos et al., 2014; Chan et al., 2021). Thus, if non-policy firms redirect innovation for window-dressing or political signaling purposes, I anticipate a more quickly sole patent application. Consistent with this expectation, results in Table 9 suggest that the coefficient on *Treat_Post* is 0.013 ($t = 1.54$) for joint patents, while 0.060 ($t = 3.29$) for sole patents.

6.5.4 Patent Grant Efficiency and Innovation Quality

Finally, I assess the efficiency and quality of redirected innovation. Cross-boundary patenting integrates technologically distant knowledge and often entails more iterations with examiners (Harhoff and Wagner, 2009; Gruber et al., 2013; Zhu et al., 2022). Thus, I would expect redirected applications to exhibit longer time-to-grant. Moreover, if such redirection is incentive- rather than capability-driven, non-policy firms lack the absorptive capacity to generate influential inventions. Table 10 shows that redirected innovators experience significantly longer grant lags (Column 1) and receive fewer forward citations (Column 2). These results reinforce an opportunistic redirection story.

7. Concluding Remarks

This study examines how industrial policy reshapes the direction of corporate innovation through takeover-market incentives and political pressure. Exploiting the Made in China 2025 initiative as a

quasi-natural experiment, I find that firms outside the targeted industries redirect patenting toward policy-prioritized technologies. This response increases their takeover appeal and helps local officials satisfy politically salient innovation objectives. However, the redirection is concentrated among financially distressed firms and is associated with longer patent pendency and lower patent quality. These findings show that the effects of industrial policy depend not only on which technologies are encouraged, but also on which firms respond and why.

The results have implications for both the takeover and political-economy literatures. Prior research emphasizes how takeover pressure affects the level of R&D and innovation. I show that firms also alter the direction of innovation, using policy-oriented patents as a form of strategic window dressing. Although this strategy improves target attractiveness, its concentration among underperforming firms and its adverse quality consequences suggest that acquirers should evaluate the technological relevance and quality of a target's innovation rather than relying primarily on patent counts or R&D intensity.

The evidence also reveals a political channel through which industrial policy affects firm behavior. Firms located in cities where superior governments place greater emphasis on policy objectives are more likely to redirect innovation toward targeted technologies. Such redirection is associated with local officials' subsequent promotion and receives disproportionately greater government funding. These results suggest that career incentives can induce local governments to mobilize firms outside the policy sectors, generating innovation that is politically valuable but potentially economically inefficient.

Several questions remain for future research. Opportunistic patenting by non-target firms may congest patent examination, increase uncertainty, and crowd out innovation by firms with genuine technological capabilities. Future work could quantify these spillovers and their welfare consequences. Research could also examine the demand side of the takeover market by identifying which acquirers purchase innovation-redirecting firms and whether such acquisitions create value or merely transfer the costs of policy-induced distortion. Finally, although China's promotion system provides a particularly visible setting, political incentives to redirect corporate innovation may arise more broadly wherever firms can use innovation to accommodate government objectives.

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Figure 1 Time-Series Trend of MIC 2025 Terms in Provincial Government Work Reports

This figure plots the time-series trend of the frequency of MIC2025-related keywords (see Appendix I) relative to the total word count in provincial Government Work Reports. The marked post-2015 rise in MIC2025-related terms suggests that provincial governments placed growing emphasis on MIC2025 industries in their policy agendas.

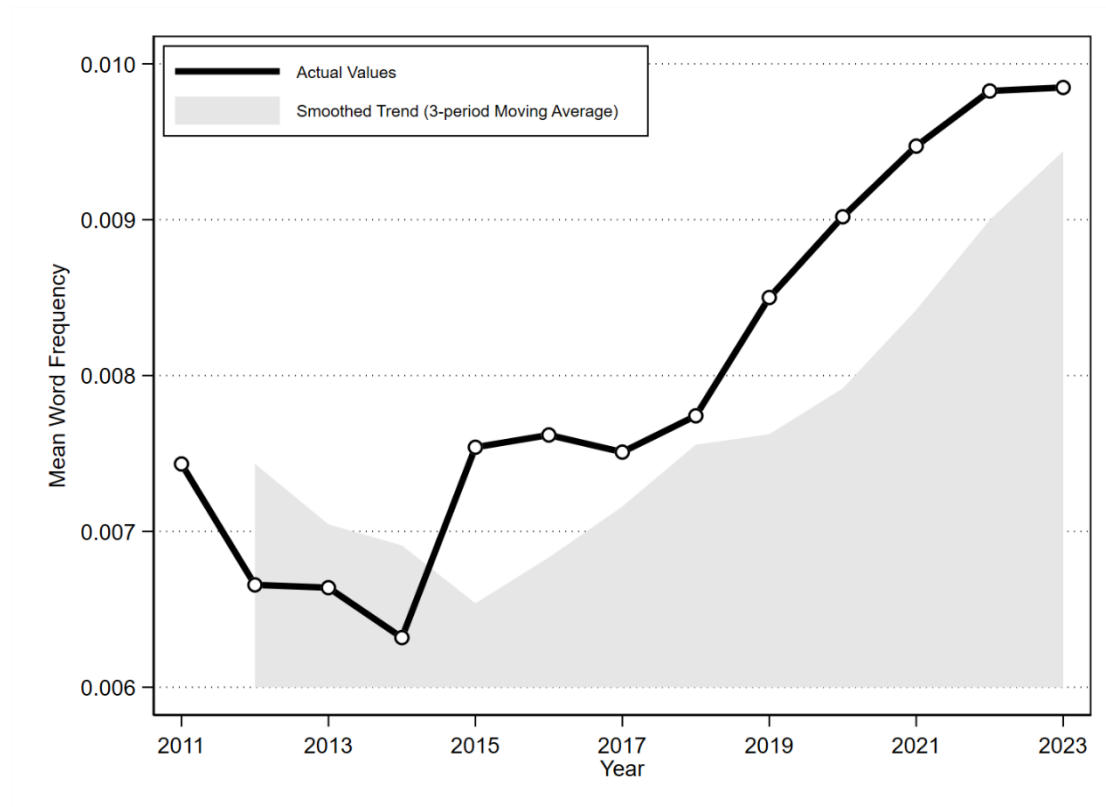


Figure 2 Time-Series Trend of Policy-related Patent Applications Around the 2015 Policy

This figure plots the time-series trend of MIC-2025-related invention patent applications. The x-axis reports calendar years, and the y-axis reports the average number of policy-related patent applications per firm-year.

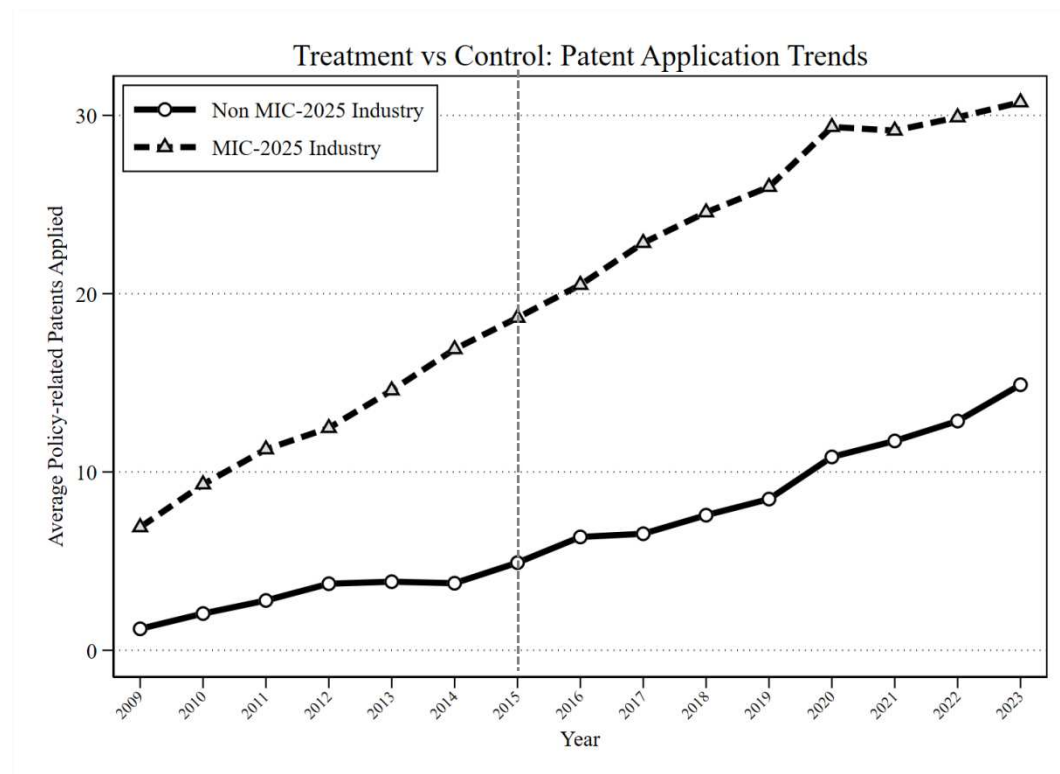


Figure 3 Parallel Trends in Innovation Redirection

This figure plots the coefficients and 95% confidence intervals from an event-study specification examining the evolution of redirected innovation around the introduction of the MIC-2025 policy.

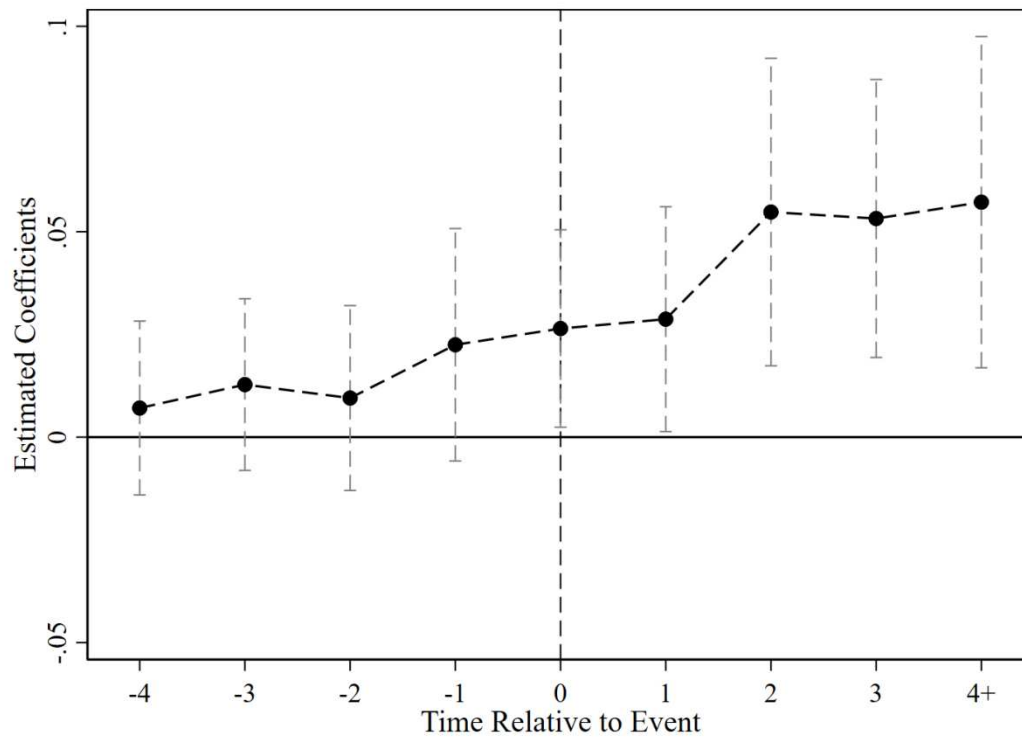


Figure 4 Distribution of Placebo Treatment Effects for the Policy Shock

This figure plots the kernel density distribution of the coefficients from 1,000 placebo regressions. In each regression, the policy year is randomly assigned to a placebo treatment group. The distribution of these placebo coefficients is centered around zero, indicating that our main finding is unlikely to be driven by other contemporaneous policy interventions.

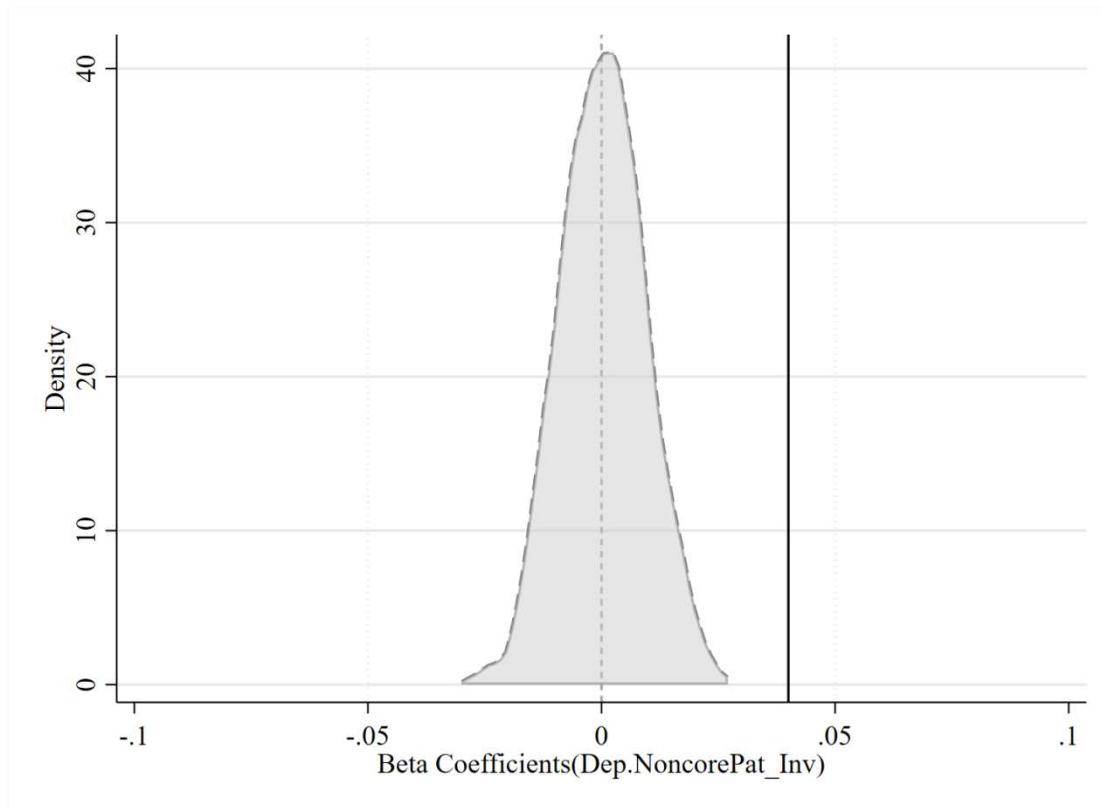


Table 1 Sample Construction

This table details the step-by-step sample selection process.

Sample selection	Excluded	Remaining
Initial sample of A-shares firms spanning the period 2009 to 2023		48,861
Less: Financial firms	(1,604)	47,257
Less: Firms listed in B-share or H-share	(2,488)	44,769
Less: Observations with missing data for key variables	(8,560)	36,209
Final sample		36,209

Table 2 Summary Statistics

This table summarizes the sample characteristics and provides a preliminary comparison between treated and control firms around the MIC-2025 policy shock. Panel A presents the descriptive statistics of the main testing variables, and Panel B compares the mean values of firm characteristics between treated and control firms before and after MIC-2025.

Policy Patents (Level/Log) denotes the annual count (and natural logarithm) of invention patent applications related to the MIC-2025 policy. *NoncorePat_Inv* is the proportion of new invention patent applications in year t that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). Detailed definitions of variables are reported in Appendix A.

Panel A: Descriptive Statistics of Key Variables

	N	Mean	SD	P25	P50	P75
<i>NoncorePat_Inv_{t+1}</i>	36,209	0.156	0.203	0.000	0.091	0.223
<i>Treat_Post</i>	36,209	0.265	0.441	0.000	0.000	1.000
<i>Size</i>	36,209	22.140	1.215	21.280	22.000	22.870
<i>Lev</i>	36,209	0.434	0.208	0.269	0.425	0.585
<i>ROA</i>	36,209	0.045	0.075	0.015	0.044	0.081
<i>RD</i>	36,209	0.039	0.046	0.004	0.031	0.051
<i>Cash</i>	36,209	0.179	0.125	0.091	0.146	0.233
<i>Growth</i>	36,209	0.159	0.419	-0.040	0.096	0.255
<i>BTM</i>	36,209	0.609	0.249	0.419	0.603	0.792
<i>SOE</i>	36,209	0.378	0.485	0.000	0.000	1.000

Panel B: Group Mean Comparison

Variables	Pre			Post		
	Policy Firms	Non-policy Firms	T-stat (mean diff.)	Policy Firms	Non-policy Firms	T-stat (mean diff.)
<i>Size</i> (Log)	21.694	22.062	-17.632	22.118	22.545	-27.055
<i>Lev</i>	0.409	0.492	-21.019	0.398	0.473	-29.085
<i>ROA</i>	0.053	0.052	1.056	0.043	0.039	4.711
Policy Patents (Level)	13.625	3.322	20.447	27.080	10.222	28.232
Policy Patents (Log)	1.595	0.619	44.617	2.269	1.244	55.121
<i>NoncorePat_Inv</i> (Ratio)	0.140	0.125	4.043	0.140	0.162	-9.295

Table 3 Baseline MIC-2025 Effects on Non-policy Firms Innovation Redirection

This table presents regression results examining the impact of the MIC-2025 on non-policy firms' innovation redirection. *NoncorePat_Inv_{t+1}* is defined as the proportion of new invention patent applications in year $t+1$ that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). *Treat_Post* equals one for non-MIC-2025 firms in the post-2015 period and zero otherwise. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	<i>NoncorePat_Inv_{t+1}</i>	
	(1)	(2)
<i>Treat_Post</i>	0.040***	0.035***
	(3.07)	(2.93)
<i>Size</i>	0.019***	0.024***
	(4.17)	(5.76)
<i>Lev</i>	-0.023*	-0.036***
	(-1.84)	(-3.12)
<i>ROA</i>	-0.025	-0.023
	(-1.30)	(-0.83)
<i>RD</i>	0.109*	0.281***
	(1.98)	(2.83)
<i>Cash</i>	-0.013	-0.017
	(-0.76)	(-1.06)
<i>Growth</i>	-0.003	-0.004
	(-1.12)	(-1.46)
<i>BTM</i>	0.014	-0.023*
	(1.28)	(-1.74)
<i>SOE</i>	0.041	-0.001
	(1.50)	(-0.13)
Constant	-0.281***	-0.360***
	(-2.90)	(-4.11)
Fixed Effects	Firm, Year	Ind, Year
Observations	36,209	36,209
Adjusted R^2	0.347	0.122

Table 4 Robustness Tests

This table reports a series of robustness checks. Columns (1) and (2) report estimates using entropy balancing (E-Balance) and propensity score matching (PSM), respectively. Column (3) implements a parallel trend test around the MIC-2025. *Before4*, *Before3*, *Before2*, *Before1*, *Current*, *After1*, *After2*, *After3*, and *After4* are binary variables that indicate the periods four years before, three years before, two years before, one year before, the year of MIC-2025 implementation, one year after, two years after, three years, and four years or more after the MIC-2025 implementation. *NoncorePat_Inv_{t+1}* is the proportion of new invention patent applications in year $t+1$ that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). *Treat_Post* equals one for non-MIC-2025 firms in the post-2015 period and zero otherwise. Detailed definitions of other variables are reported in 7A. T-statistics based on standard errors clustered at the industry level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	<i>NoncorePat_Inv_{t+1}</i>		
	E-Balance (1)	PSM (2)	Parallel Test (3)
<i>Treat_Post</i>	0.045*** (3.48)	0.043*** (2.94)	
<i>Before4</i>			0.007 (0.67)
<i>Before3</i>			0.013 (1.22)
<i>Before2</i>			0.010 (0.84)
<i>Before1</i>			0.022 (1.58)
<i>Current</i>			0.026** (2.19)
<i>After1</i>			0.029** (2.09)
<i>After2</i>			0.055*** (2.92)
<i>After3</i>			0.053*** (3.13)
<i>After4</i>			0.057*** (2.83)
Controls	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Observations	36,209	21,588	36,209
Adjusted R ²	0.342	0.320	0.347

Table 5 Strategic Exit Incentives: Insider Selling and Corporate Control Markets

This table examines whether non-policy firms' innovation redirection is associated with subsequent insider selling (Panel A) and an increased likelihood of being acquired (Panel B). The testing sample is restricted to the post-policy period.

InsiderSell is the net shareholdings reduction by the top three shareholders in year t , scaled by the number of total outstanding shares at the beginning of the year. *AcqTarget* is an indicator variable that equals one if the firm becomes the target of an acquisition in year t , and zero otherwise. *NoncorePat_Inv* is the proportion of new invention patent applications in year t that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation Redirection and Subsequent Insider Selling

Sample	<i>InsiderSell</i>			
	T+1		T+2	
	Non-Policy Firms (1)	Policy Firms (2)	Non-Policy Firms (3)	Policy Firms (4)
<i>NoncorePat_Inv</i>	0.003** (2.37)	-0.002 (-1.60)	0.003* (1.69)	-0.000 (-0.09)
<i>Size</i>	0.000 (0.14)	0.001 (1.72)	0.002** (2.06)	0.005*** (3.51)
<i>Lev</i>	-0.001 (-0.15)	-0.004 (-1.21)	0.003 (1.05)	-0.006* (-1.92)
<i>ROA</i>	-0.013* (-1.92)	-0.017** (-2.85)	-0.004 (-0.73)	-0.028*** (-7.14)
<i>RD</i>	0.027 (1.06)	0.019*** (2.92)	0.089*** (3.38)	-0.006 (-0.37)
<i>Cash</i>	-0.002 (-0.64)	-0.005 (-1.43)	0.002 (0.42)	-0.002 (-0.52)
<i>Growth</i>	-0.001 (-1.37)	-0.001 (-1.45)	0.000 (0.03)	0.001 (1.01)
<i>BTM</i>	-0.007** (-2.23)	0.001 (0.73)	0.005** (2.31)	0.003 (1.28)
<i>SOE</i>	-0.002 (-0.60)	-0.013* (-2.05)	-0.004 (-0.77)	-0.005 (-1.19)
Constant	0.013 (0.56)	-0.014 (-0.81)	-0.043* (-1.87)	-0.091*** (-3.06)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	9,599	14,438	8,224	12,346
Adjusted R^2	0.144	0.104	0.161	0.119

Panel B: Innovation Redirection and Probability of Acquisition

Sample	<i>AcqTarget</i>			
	T+1		T+2	
	Non-Policy Firms (1)	Policy Firms (2)	Non-Policy Firms (3)	Policy Firms (4)
<i>NoncorePat_Inv</i>	0.018 (0.83)	-0.005 (-0.20)	0.059** (2.17)	0.016 (0.44)
<i>Size</i>	0.029* (2.00)	0.018* (1.76)	0.017 (0.93)	-0.018* (-1.75)
<i>Lev</i>	0.106* (1.82)	0.129** (2.58)	0.017 (0.26)	0.112* (1.86)
<i>ROA</i>	-0.359*** (-4.92)	-0.228*** (-4.10)	-0.192* (-1.94)	-0.158** (-2.24)
<i>RD</i>	0.523 (1.02)	0.103 (0.73)	0.888 (1.64)	0.082 (0.43)
<i>Cash</i>	-0.052 (-0.73)	-0.100** (-2.20)	0.006 (0.07)	-0.133*** (-3.60)
<i>Growth</i>	-0.018* (-1.92)	0.012 (1.26)	0.008 (0.77)	0.005 (0.48)
<i>BTM</i>	-0.197*** (-4.83)	-0.119*** (-3.63)	0.019 (0.41)	0.096** (2.42)
<i>SOE</i>	0.109* (1.70)	0.016 (0.09)	-0.079 (-0.64)	-0.241** (-2.20)
Constant	-0.228 (-0.71)	0.062 (0.30)	0.013 (0.03)	0.865*** (3.93)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	9,601	14,445	8,226	12,352
Adjusted R^2	0.348	0.352	0.319	0.309

Table 6 Political implication of Redirected Innovation

This table examines how government political incentives motivate non-policy firms' innovation redirection. Panel A investigates the moderating effects of provincial priority on MIC-2025. A priority value implies that MIC-2025 targets are more likely to be incorporated into city officials' promotion evaluation criteria. Panel B tests whether city-level innovation redirection among non-policy firms is linked to the their local mayor's subsequent promotion.

MIC25_Priority is an AI-based measure of provincial priority for MIC-2025 industries. Firms in regions with *MIC25_Priority* scores exceeding seven (see Appendix G for the detailed scoring criteria) are classified as high MIC-2025 priority. I define a firm as politically connected when its CEO or any director has previously served in a government department.

NoncorePat_Inv_{t+1} is the proportion of new invention patent applications in year $t+1$ that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). *Promotion* is an indicator variable that equals one if the mayor of the city in which the firms are located receives a political promotion within the subsequent three years, and zero otherwise. *CityNoncorePat_Inv* is a city-year measure of innovation redirection among non-policy firms, defined as the city-level average of *NoncorePat_Inv* by non-policy firms in year t . *Treat_Post* equals one for non-MIC-2025 firms in the post-2015 period and zero otherwise. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry (city) level (in Panel B) are reported in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Regional MIC-2025 Priority, Political Connection and Policy Effects on Innovation

Sample	<i>NoncorePat_Inv_{t+1}</i>			
	High <i>MIC25_Priority</i>	Low <i>MIC25_Priority</i>	Firms with <i>PC</i>	Firms without <i>PC</i>
	(1)	(2)	(3)	(4)
<i>Treat_Post</i>	0.055***	0.029**	0.060***	0.030**
	(2.96)	(2.25)	(4.44)	(2.28)
p-value (Coeff. Diff.)	<0.010***		<0.010***	
Controls	YES	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	13,629	21,974	10,457	25,705
Adjusted R^2	0.389	0.343	0.362	0.368

Panel B: Innovation Redirection and Local Officials' Promotion Prospects

Sample	<i>Promotion_{it}</i>		
	Full (1)	High <i>MIC25_Priority</i> Scores (2)	Low <i>MIC25_Priority</i> Scores (3)
<i>CityNoncorePat_Inv</i>	0.227*** (2.67)	0.334* (1.70)	0.149 (1.60)
<i>GDPPerCapita</i>	0.108 (1.05)	0.561*** (2.85)	0.052 (0.40)
<i>TertShare</i>	0.393 (0.42)	0.695 (0.40)	0.192 (0.16)
<i>GDP</i>	-0.106 (-0.76)	-0.471** (-2.00)	-0.108 (-0.60)
<i>SecGDPShare</i>	-0.562 (-0.67)	-0.313 (-0.19)	-0.697 (-0.66)
<i>BudgetExp</i>	0.096 (0.96)	0.030 (0.18)	0.198 (1.61)
Constant	-0.245 (-0.26)	-2.256 (-1.27)	-0.031 (-0.03)
p-value (Coeff. Diff.)	<0.010***		
Fixed Effects	City, Year	City, Year	City, Year
Observations	2,221	651	1,570
Adjusted <i>R</i> ²	0.417	0.522	0.395

Table 7 Heterogeneity Analyses

This table reports the results of heterogeneity tests. Panel A investigates the moderating role of financial stability by partitioning the sample based on bankruptcy risk. Panel B examines whether the MIC-2025 effect is driven by Type II agency conflicts and opportunistic behavior by controlling shareholders.

Z-scores proxy for bankruptcy risk and financial distress and are calculated following Altman (1968); lower Z-scores indicate weaker financial condition and a higher likelihood of financial distress.

Separation measures the separation of control rights and cash flow rights of the ultimate controller and *Tunnel* is the ratio of other receivables to total assets, serving as the second proxy for tunneling activities; a higher value of *Separation* and *Tunnel* indicates more severe Type II agency conflicts.

For all heterogeneity analyses, the sample is divided into High and Low groups based on sample median. *NoncorePat_Inv_{t+1}* is the proportion of new invention patent applications in year $t+1$ that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). *Treat_Post* equals one for non-MIC-2025 firms in the post-2015 period and zero otherwise. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The Moderating Role of Financial Health (Bankruptcy Risk)

Sample	<i>NoncorePat_Inv_{t+1}</i>	
	Low <i>Zscore</i> (High operation risk)	High <i>Zscore</i> (Low operation risk)
	(1)	(2)
<i>Treat_Post</i>	0.046***	0.030**
	(3.45)	(2.00)
p-value (Coeff. Diff.)	<0.010***	
Controls	YES	YES
Fixed Effects	Firm, Year	Firm, Year
Observations	18,081	18,128
Adjusted R^2	0.354	0.369

Panel B: The Moderating Role of Agency Conflicts (Type II Conflicts)

Sample	<i>NoncorePat_Inv_{t+1}</i>			
	High <i>Separation</i>	Low <i>Separation</i>	High <i>Tunnel</i>	Low <i>Tunnel</i>
	(High Type II Conflicts)	(Low Type II Conflicts)	(High Type II Conflicts)	(Low Type II Conflicts)
	(1)	(2)	(3)	(4)
<i>Treat_Post</i>	0.053***	0.029**	0.044***	0.035**
	(3.60)	(2.58)	(2.87)	(2.51)
p-value (Coeff. Diff.)	<0.010***		<0.050**	
Controls	YES	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	18,104	18,105	17,004	19,205
Adjusted R^2	0.327	0.388	0.352	0.368

Table 8 Asymmetric Incentives for Strategic Patenting

This table investigates whether government incentives for strategic patenting are asymmetrically distributed between policy and non-policy industries. $Grant_{t+1}$ is the natural logarithm of one plus patent-specific government subsidies received by the firm in year $t+1$. $StrategyPatent$ is the natural logarithm of one plus the number of MIC-2025 related inventions obtained by firm i in year t . Columns (1) and (2) report the results utilizing the sample before and after the MIC-2025, respectively. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample	$Grant_{t+1}$	
	Before MIC-2025	After MIC-2025
	(1)	(2)
<i>StrategyPatent_Treat</i>	0.042	0.296**
	(0.25)	(2.61)
<i>StrategyPatent</i>	0.414***	0.149**
	(4.39)	(2.33)
<i>Size</i>	0.250*	-0.379***
	(1.73)	(-3.54)
<i>Lev</i>	-0.247	-0.150
	(-0.61)	(-0.41)
<i>ROA</i>	-0.847	-0.626
	(-1.07)	(-1.07)
<i>RD</i>	1.073	1.230
	(0.28)	(0.76)
<i>Cash</i>	-1.203***	-0.882***
	(-3.12)	(-2.82)
<i>Growth</i>	0.083	0.127**
	(1.25)	(2.16)
<i>BTM</i>	-0.247	-0.156
	(-0.69)	(-0.49)
<i>SOE</i>	0.220	0.689
	(0.20)	(0.59)
Constant	-2.392	10.844***
	(-0.68)	(4.61)
p-value (Coeff. Diff.)	<0.010***	
Fixed Effects	Firm, Year	Firm, Year
Observations	12,158	24,012
Adjusted R^2	0.519	0.338

Table 9 Joint vs. Sole Patenting

This table explores how non-policy firms redirect their innovation. $NoncorePat_JointInv_{t+1}$ is the proportion of joint invention patent applications in year $t+1$ that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). $NoncorePat_SoleInv_{t+1}$ is the proportion of new sole invention patent applications in year $t+1$ that fall outside the firm's core industry category (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms). $Treat_Post$ equals one for non-MIC-2025 firms in the post-2015 period and zero otherwise. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	<i>NoncorePat_JointInv_{t+1}</i>	<i>NoncorePat_SoleInv_{t+1}</i>
	(1)	(2)
<i>Treat_Post</i>	0.013	0.060***
	(1.54)	(3.29)
<i>Size</i>	0.012***	0.030***
	(3.45)	(4.41)
<i>Lev</i>	0.003	-0.048**
	(0.34)	(-2.24)
<i>ROA</i>	0.059***	0.023
	(2.94)	(0.67)
<i>RD</i>	0.056	0.320***
	(1.12)	(3.28)
<i>Cash</i>	0.002	-0.024
	(0.18)	(-0.95)
<i>Growth</i>	0.000	0.006
	(0.14)	(1.21)
<i>BTM</i>	-0.002	0.013
	(-0.24)	(0.77)
<i>SOE</i>	-0.011	-0.017
	(-0.65)	(-0.62)
Constant	-0.200***	-0.276*
	(-2.74)	(-1.82)
Fixed Effects	Firm, Year	Firm, Year
Observations	36,209	36,209
Adjusted R^2	0.330	0.427

Table 10 Patent Grant Efficiency and Innovation Quality

This table examines the MIC-2025 effects on patenting efficiency and quality. $GainTime_{t+1}$ is the average of the natural logarithm of one plus duration from application to grant for patents filed by firm i in year $t+1$. $Citation_{t+1}$ is the average of the natural logarithm of one plus forward citations for patents filed by firm i in year $t+1$. $Treat_Post$ equals one for non-MIC-2025 firms in the post-2015 period and zero otherwise. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$GainTime_{t+1}$	$Citation_{t+1}$
	(1)	(2)
<i>Treat_Post</i>	0.075***	-0.191***
	(3.54)	(-3.07)
<i>Size</i>	0.088***	0.311***
	(9.41)	(7.36)
<i>Lev</i>	-0.069**	-0.080
	(-2.32)	(-1.26)
<i>ROA</i>	-0.167***	0.430***
	(-3.59)	(3.83)
<i>RD</i>	0.975***	2.083***
	(5.34)	(5.73)
<i>Cash</i>	-0.099**	-0.107
	(-2.43)	(-1.32)
<i>Growth</i>	-0.006	0.030***
	(-0.99)	(2.97)
<i>BTM</i>	-0.068***	-0.251***
	(-3.06)	(-3.99)
<i>SOE</i>	-0.010	-0.006
	(-0.16)	(-0.06)
Constant	-1.054***	-5.934***
	(-5.21)	(-6.37)
Fixed Effects	Firm, Year	Firm, Year
Observations	36,209	36,209
Adjusted R^2	0.486	0.579

Appendix A Variable Definitions

Variables	Variable Definitions
Dependents	
<i>NoncorePat_Inv</i>	Proportion of invention patent applications in year t that fall outside the firm's core industry category, scaled by the firm's total number of patent applications in the same year (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms).
<i>NoncorePat_JointInv</i>	Proportion of joint invention patent applications in year t that fall outside the firm's core industry category, scaled by the firm's total number of patent applications in the same year (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms).
<i>NoncorePat_SoleInv</i>	Proportion of sole invention patent applications in year t that fall outside the firm's core industry category, scaled by the firm's total number of patent applications in the same year (i.e., MIC-2025-related patents by non-MIC-2025 firms and non-MIC-2025 patents by MIC-2025 firms).
<i>InsiderSell</i>	The net shareholdings reduction by the top three shareholders in year t , scaled by the total number of outstanding shares at the beginning of the year.
<i>AcqTarget</i>	An indicator variable that equals one if the firm becomes the target of an acquisition in year t , and zero otherwise.
<i>Comment</i>	The natural logarithm of one plus the total number of comments on the firm's stock forum in year t .
<i>Message</i>	The natural logarithm of one plus the total number of posts regarding the firm on the stock forum in year t .
<i>PosMessage</i>	The natural logarithm of one plus the total number of positive posts regarding the firm on the stock forum in year t .
<i>Read</i>	The natural logarithm of one plus the total number of reads of the posts on the firm's stock forum in year t .
<i>GainTime</i>	The average of the natural logarithm of one plus duration from application to grant for patents filed by firm i in year t .
<i>Citation</i>	The average of the natural logarithm of one plus forward citations for patents filed by firm i in year t .
<i>Grant</i>	The natural logarithm of one plus the patent-specific government subsidies received by firm i in year t .
<i>Promotion</i>	An indicator variable that equals one if the mayor of the city in which the firms are located receives a political promotion within the subsequent three years, and zero otherwise. A promotion is recorded if the mayor is appointed to a position of higher bureaucratic rank or a powerful department.
Independents	
<i>Treat</i>	An indicator variable that equals one if firm i belongs to a non-MIC-2025 industry and zero otherwise.
<i>Policy</i>	An indicator variable that equals one if firm i belongs to a MIC-2025 industry and zero otherwise.
<i>Post</i>	An indicator variable that equals one for years after 2015 and zero otherwise.

<i>StrategyPatent</i>	The natural logarithm of one plus the number of MIC-2025 related inventions obtained by firm <i>i</i> in year <i>t</i> .
<i>MIC25_Priority</i>	AI-based index measuring provincial governors' priority for MIC-2025. The detailed scoring prompt is in Appendix G.
<i>CityNoncorePat_Inv</i>	The city-year measure of innovation redirection among non-MIC-2025 firms, defined as the city-level average of <i>NoncorePat_Inv</i> by non-MIC-2025 firms in year <i>t</i> .

Controls

<i>Size</i>	The natural logarithm of firm <i>i</i> 's total assets in year <i>t</i> .
<i>Lev</i>	Financial leverage, measured as total liabilities divided by total assets in year <i>t</i> .
<i>ROA</i>	Return on assets, calculated as net income divided by total assets in year <i>t</i> .
<i>BTM</i>	Book-to-market ratio, equals the ratio of the book value of equity to the market value of equity at the end of year <i>t</i> .
<i>RD</i>	R&D intensity, defined as firm <i>i</i> 's R&D expenditures scaled by operating revenue in year <i>t</i> .
<i>SOE</i>	An indicator variable equals one if the ultimate controller of the firm is the state and zero, otherwise.
<i>Cash</i>	Cash holdings, defined as cash and cash equivalents scaled by total assets at the end of year <i>t</i> .
<i>Growth</i>	Sales growth rate, measured as the year-over-year percentage change in sales (operating revenue).
<i>GDP</i>	The natural logarithm of the Gross Domestic Product (GDP) of the city where the firm is located in year <i>t</i> .
<i>GDPPerCapita</i>	The natural logarithm of the per capita Gross Domestic Product (GDP) of the city where the firm is located in year <i>t</i> .
<i>SecGDPSHare</i>	The share of the secondary industry's value added in the city's GDP in year <i>t</i> .
<i>TertShare</i>	The share of the tertiary industry's value added in the city's GDP in year <i>t</i> .
<i>BudgetExp</i>	The natural logarithm of the local government's public budget expenditure in year <i>t</i> .

Moderating Variables

<i>PC</i>	Political connection, an indicator equals one if a firm's CEO or director has previously served in a government department.
<i>Zscore</i>	Bankruptcy risk and financial distress scores calculated following Altman (1968); lower scores indicate weaker financial condition.
<i>Separation</i>	The separation of control rights and cash flow rights of the ultimate controller; higher values indicate more severe Type II agency conflicts (i.e., a greater degree of expropriation of minority shareholders by controlling shareholders).
<i>Tunnel</i>	The ratio of other receivables to total assets, serving as a proxy for tunneling activities; higher values indicate more severe Type II agency conflicts (i.e., a greater degree of expropriation of minority shareholders by controlling shareholders).

Appendix B MIC 2025 Industries

The Made in China 2025 (MIC-2025) initiative designates ten strategic industries as core engines for upgrading China's manufacturing sector.

- a) New Generation Information Technology, e.g., 5G Communication, Ultra-high-speed Optical Fiber Transmission, integrated circuits, and industrial software;
- b) High-end Numerical Control (NC) Machine Tools and Robots, e.g., high-precision machine tools, additive manufacturing (3D printing), and industrial/service robots;
- c) Aerospace and Aviation Equipment, e.g., large passenger aircraft, advanced engines, drones, and new-generation launch vehicles;
- d) Marine Engineering Equipment and target Ships, e.g., deep-sea exploration systems, large cruise ships, and LNG carriers;
- e) Advanced Rail Transit Equipment, e.g., new generation high-speed trains and urban rail transit systems;
- f) Energy-saving and New Energy Vehicles, e.g., pure electric vehicles, plug-in hybrids, fuel cell vehicles, and key components like power batteries;
- g) Power Equipment, e.g., advanced efficient power generation units (like nuclear and ultra-supercritical coal), large-scale wind turbines, and intelligent grid equipment;
- h) Agricultural Machinery Equipment, e.g., high-horsepower tractors, combine harvesters, and intelligent farming systems;
- i) New Materials, e.g., high-performance structural materials, advanced composites, graphene, and superconducting materials;
- j) Biopharmaceuticals and High-performance Medical Devices, e.g., new drugs for major diseases, antibody drugs, high-end medical imaging equipment, and medical robots.

Appendix C Capital-Market Recognition of Redirected Innovation in MIC-2025 Industries

This appendix examines whether firms in MIC2025 industries receive greater investor attention and command higher market valuations. $Comment_t$ is the natural logarithm of one plus the total number of comments on the firm's stock forum in year t . $Message_t$ is the natural logarithm of one plus the total number of posts regarding the firm on the stock forum in year t . $PosMessage_t$ is the natural logarithm of one plus the total number of positive posts regarding the firm on the stock forum in year t . $Read_t$ is the natural logarithm of one plus the total number of reads (or views) of the posts related to the firm in year t . BTM is the ratio of the book value of equity to the market value of equity at the end of year t . A lower BTM indicates a higher market valuation. $Policy$ equals one for firms operating in MIC2025 industries and zero otherwise, and $Post$ equals one for years after 2015 and zero otherwise. Detailed definitions of other variables are reported in Appendix A. T-statistics based on standard errors clustered at the industry level are reported in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$Comment_{t+1}$	$Message_{t+1}$	$PosMessage_{t+1}$	$Read_{t+1}$	BTM_{t+1}
	(1)	(2)	(3)	(4)	(5)
<i>Policy_Post</i>	0.235***	0.189***	0.164***	0.205***	-0.021***
	(4.90)	(4.83)	(4.31)	(5.40)	(-3.15)
<i>Size</i>	0.310***	0.321***	0.303***	0.325***	0.054***
	(15.27)	(19.37)	(20.90)	(18.55)	(16.26)
<i>Lev</i>	0.102*	-0.006	-0.003	0.029	-0.073***
	(1.71)	(-0.11)	(-0.07)	(0.56)	(-7.81)
<i>ROA</i>	-0.713***	-0.529***	-0.418***	-0.553***	0.017
	(-7.16)	(-6.12)	(-4.98)	(-6.32)	(0.99)
<i>RD</i>	0.286	0.302	0.235	0.269	-0.175***
	(0.68)	(1.04)	(0.72)	(0.89)	(-4.27)
<i>Cash</i>	-0.308***	-0.297***	-0.280***	-0.304***	-0.014
	(-5.15)	(-6.40)	(-6.50)	(-6.49)	(-1.39)
<i>Growth</i>	-0.043***	-0.040***	-0.036***	-0.031***	-0.003
	(-3.42)	(-3.84)	(-3.53)	(-2.98)	(-1.07)
<i>BTM</i>	-0.585***	-0.608***	-0.569***	-0.699***	0.510***
	(-10.10)	(-11.91)	(-12.82)	(-14.31)	(47.16)
<i>SOE</i>	0.222**	0.188**	0.181**	0.161*	0.014
	(2.21)	(2.33)	(2.45)	(1.97)	(0.86)
Constant	2.543***	1.960***	1.080***	8.508***	-0.844***
	(5.91)	(5.58)	(3.50)	(22.98)	(-11.89)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	32,078	32,078	32,078	32,078	32,078
Adjusted R^2	0.566	0.555	0.555	0.738	0.814

Appendix D Entropy Balancing Diagnostics

This appendix validates the entropy balancing procedure used to construct a comparable control group. Panel A shows significant distributional differences (mean, variance, and skewness) between the treatment and control groups before balancing. Panel B demonstrates that after entropy balancing, the first three moments (mean, variance, and skewness) of the control group covariates perfectly match those of the treatment group, ensuring the sample distributions are identical.

Panel A: Covariate Balance Before Entropy Balancing

	Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness
<i>Size</i>	22.370	1.661	0.420	21.980	1.281	0.598
<i>Lev</i>	0.480	0.045	0.058	0.401	0.040	0.340
<i>ROA</i>	0.043	0.005	-0.644	0.047	0.006	-0.737
<i>RD</i>	0.016	0.001	3.274	0.056	0.003	2.010
<i>Cash</i>	0.168	0.014	1.415	0.187	0.016	1.327
<i>Growth</i>	0.156	0.209	3.017	0.160	0.151	3.042
<i>BTM</i>	0.670	0.067	-0.084	0.567	0.054	0.204
<i>SOE</i>	0.491	0.250	0.038	0.298	0.209	0.882

Panel B: Covariate Balance After Entropy Balancing

	Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness
<i>Size</i>	22.370	1.661	0.420	22.370	1.661	0.420
<i>Lev</i>	0.480	0.045	0.058	0.480	0.045	0.058
<i>ROA</i>	0.043	0.005	-0.644	0.043	0.005	-0.644
<i>RD</i>	0.016	0.001	3.274	0.016	0.001	3.283
<i>Cash</i>	0.168	0.014	1.415	0.168	0.014	1.415
<i>Growth</i>	0.156	0.209	3.017	0.156	0.209	3.017
<i>BTM</i>	0.670	0.067	-0.084	0.670	0.067	-0.084
<i>SOE</i>	0.491	0.250	0.038	0.491	0.250	0.038

Appendix E Propensity Score Matching Diagnostics

This appendix evaluates the effectiveness of Propensity Score Matching (PSM). The table compares the standardized bias before (Unmatched) and after (Matched) the procedure. The results show a substantial reduction in bias (Bias M is significantly lower than Bias U) across all covariates (e.g., *Size*, *Lev*, *ROA*), confirming that PSM effectively eliminated observable differences between the treated and control firms.

Var	T(U)	C(U)	Bias(U)	T(M)	C(M)	Bias(M)
<i>Size</i>	22.371	21.983	32.000	22.370	22.388	-1.500
<i>Lev</i>	0.480	0.401	38.400	0.480	0.484	-1.700
<i>ROA</i>	0.043	0.047	-4.200	0.043	0.037	8.400
<i>RD</i>	0.016	0.056	-100.300	0.016	0.016	-1.200
<i>Cash</i>	0.168	0.187	-15.600	0.168	0.168	-0.200
<i>Growth</i>	0.156	0.160	-0.800	0.157	0.132	5.700
<i>BTM</i>	0.670	0.566	42.100	0.670	0.690	-8.300
<i>SOE</i>	0.491	0.298	40.100	0.491	0.501	-2.100

Appendix F Illustrative Provincial Government Work Report: Shanghai Case

Deputies,

Now, on behalf of the Shanghai Municipal People's Government, I present this report for your deliberation.

I. Review of Work in 2016

In the past year, we adhered to the general principle of seeking progress while maintaining stability...

The city's economic and social development remained generally stable. The city's GDP grew by 6.8%, the tertiary industry accounted for 70.5% of GDP, the construction of the China (Shanghai) Pilot Free Trade Zone (FTZ) essentially met its three-year development targets, the development of the Science and Technology Innovation Center began to bear fruit, and people's livelihoods continued to improve.

Over the past year, we have mainly carried out the following work:

...

II. Major Tasks for 2017

...

This year, we must focus on eight areas:

(I) Better leveraging the demonstrative and leading role of the FTZ...

(II) Comprehensively promoting the construction of the Science and Technology Innovation Center... *Establish R&D and transformation platforms for smart manufacturing, biomedicine, and Integrated Circuits (ICs).*

(III) Deepening supply-side structural reform... Accelerate the "Four New" Economy. *Develop smart manufacturing; promote leading projects in intelligent connected vehicles and the industrial internet. Eliminate 1,000 items of backward production capacity.*

(IV) More forcefully guaranteeing and improving public livelihood...

(V) Innovating social governance and urban management...

(VI) Deeply promote urban-rural integrated development... *Deepen agricultural supply-side structural reform.*

Promote the integration of primary, secondary, and tertiary industries in rural areas.

(VII) Prosperously developing advanced socialist culture... Enhance the competitiveness of cultural industries (e.g., film/TV, publishing).

(VIII) Strengthening ecological construction and environmental governance...

...

i. Comprehensively Strengthening the Governmental Capability Development

In the past year, we implemented the outline for building a law-based government and vigorously advanced government reform and innovation...

In the new year, we must... further advance the reform of "streamlining administration, delegating power, strengthening regulation, and improving services"...

Appendix G Prompt for AI-Based Measurement of Provincial Priority on MIC-2025 Industries

You are a professional industrial policy and macroeconomic analyst. Your task is to review the local Government Work Report below and assess the strength of the local government's substantive support in the coming year for the following industry clusters:

- Advanced Equipment Manufacturing
- Next-generation Information Technology
- Energy-saving and New-energy Vehicles
- Advanced Rail Transit Equipment
- Aerospace Equipment
- Power Equipment
- Agricultural Machinery
- New Materials
- Biomedicine and Advanced Medical Devices

Base your assessment only on support for the industries listed above and ignore support for other sectors.

Assign an integer score from 1 to 10 according to the following rules:

1–3 (slogan-level support only)

- The industries are only mentioned in passing or in a long list, using vague verbs such as “encourage”, “promote”, or “accelerate”.
- There are no specific projects, budgets, quantitative targets, or concrete factor support.
- The industries are mentioned but are not clear near-term priorities.

4–6 (important but qualitatively defined priorities)

- The report identifies some of these industries as key or priority sectors and describes plans such as building parks, platforms, or bases.
- However, it lacks clear quantitative targets (for example, explicit output or investment goals) and dedicated fiscal, tax, or financing policies.
- Support appears meaningful but is not yet backed by detailed and measurable commitments.

7–8 (core drivers with substantive input commitments)

- The report positions some of these industries as core growth engines or pillar industries for the region.
- It specifies quantitative goals such as target output, investment, or project counts and or names concrete major projects or programs.
- It promises tangible resource tilts, such as special funds, dedicated land quotas, or tailored talent and factor policies.

9–10 (flagship strategic focus with overwhelming support)

- The report labels these industries as top strategic priorities, such as a “No 1 project” or equivalent flagship status.
- It announces highly preferential policies, large scale or multi year funding programs, or major national or provincial initiatives being implemented locally.
- The level of support is clearly stronger and more exclusive than that given to ordinary industries, with priority access to key resources.

Negative constraints on scoring:

- If the report relies only on broad slogans such as “vigorously promote” or “comprehensively deepen” and provides no numbers, named projects, or funding amounts for these industries, the score must not exceed 5.

- A score of 7 or above is allowed only if the text mentions at least one of the following for these industries: specific funding or subsidies, dedicated land or other factor allocation, clearly named major projects or platforms, or explicit quantitative targets.

Avoid compromise scores that blur these categories. Choose the score that best matches the strongest level of support evidenced in the text.

Return your assessment strictly in the following JSON format:

```
{  
  score: <an integer from 1 to 10>,  
  reason: <a concise justification for the score, no more than 100 words>  
}
```

Appendix H Placebo Corpus Test for the AI-Based MIC-2025 Priority Index

Evaluation Corpus 1

Throughout the reporting period, we systematically advanced the coordinated development of industry and services. We continuously improved the business environment, supported enterprises in technological upgrading, and encouraged greater R&D investment. We prioritized the development of modern manufacturing and services, fostered deep integration with the internet, and nurtured a group of competitive enterprises and industrial clusters. In addition, we improved the supporting facilities of industrial and development parks to strengthen their capacity for enterprise agglomeration and thereby promote the high-quality development of the real economy.

AI Score: 2

AI Reason: None of the nine specified industry clusters are explicitly mentioned. The report only uses vague, high-level slogans such as “prioritized the development of modern manufacturing”, “fostered industrial clusters”, and “improved supporting facilities of parks” with no named sectors, no projects, no quantitative targets, no funding, and no concrete policies for the listed industries.

Evaluation Corpus 2

Our city has identified advanced manufacturing as a key driver of industrial upgrading, with a particular focus on next-generation information technology, energy-efficient vehicles, and new energy vehicles. We are supporting traditional pillar industries, such as electronic information and auto components, in moving up to the mid-to-high end of the value chain.

Under the “Advanced Manufacturing Enhancement Action” initiative, we provide targeted equipment subsidies and loan-interest support for the technological and intelligent upgrading of key enterprises. We also support industry leaders in establishing specialized production lines and R&D platforms in development zones. At the same time, we encourage financial institutions to expand medium- and long-term credit to eligible manufacturing firms and guide private capital to participate in industrial investment funds.

These measures aim to deliver steady growth in the output value of advanced manufacturing industries by 2025 and to foster several industrial clusters with significant regional influence.

AI Score: 5

AI Reason: Next-generation IT and new-energy vehicles are explicitly mentioned as focus areas within advanced manufacturing. The report announces a named initiative (“Advanced Manufacturing Enhancement Action”) with concrete tools (equipment subsidies, loan-interest support, specialized production lines, R&D platforms, and guided industrial funds). However, it lacks quantitative targets, named major projects, dedicated budgets, or exclusive resource tilts limited to the listed clusters, and support remains broadly phrased for “advanced manufacturing” rather than sharply prioritized for the specific industries, capping the score at 5.

Evaluation Corpus 3

The municipal government is vigorously implementing the Made in China 2025 initiative and is firmly committed to building a strong manufacturing city. We identify equipment manufacturing, next-generation information technology, and energy-saving and new-energy vehicles as the city’s “Number One Project” industries. The city has established a Leading Group for Building a Strong Manufacturing City, headed by the

principal leaders of the Municipal Party Committee to coordinate specialized planning, project construction, and key reforms. The government has also created a special fund of RMB 10 billion to integrate and deploy policy instruments that support the development of target industries. By 2025, the city aims to increase the total industrial output value of Made in China 2025–related industries to more than RMB 300 billion, introduce or cultivate over 300 industrial enterprises above the designated size threshold, establish more than 50 innovation platforms at or above the municipal level, secure more than 5,000 new inventions, and develop several advanced manufacturing clusters of nationwide influence.

AI Score: 9

AI Reason: Equipment manufacturing (including advanced equipment, rail transit, aerospace, power, agricultural machinery), next-generation IT, and new-energy vehicles are explicitly designated as the city’s “Number One Project” industries with top-level political leadership. A dedicated RMB 10 billion special fund is created for target industries, backed by ambitious 2025 quantitative targets (RMB 300+ billion output, 300+ large enterprises, 50+ innovation platforms, 5,000+ inventions) and a push for nationally influential clusters. This represents flagship strategic focus with large-scale funding and clear priority status.

Appendix I Keyword Dictionary for Identifying MIC-2025 Terms

This appendix summarizes representative keywords used to identify MIC2025-related content in provincial Government Work Reports. I first conduct a random sampling of text from provincial Government Work Reports and corporate annual reports to identify candidate terminology used in practice. I then manually screened and selected keywords that explicitly map to the ten strategic MIC-2025 industries.

Category	Representative keywords
Made in China 2025 and manufacturing strategy	Made in China 2025, manufacturing powerhouse, industrial powerhouse, strategic emerging industries, advanced manufacturing, high-end manufacturing
Next-generation information technology	next-generation information technology, electronic information industry, communications equipment, integrated circuits, semiconductor chips, cloud computing, big data, Internet of Things, artificial intelligence, blockchain, quantum computing, virtual reality
High-end CNC machine tools and robotics / equipment manufacturing	high-end equipment manufacturing, intelligent manufacturing equipment, CNC machine tools, high-end CNC machine tools, industrial robots, collaborative robots, automated production lines, additive manufacturing, 3D printing, industrial automation
Aviation and aerospace equipment	aerospace industry, large commercial aircraft, aero engines, unmanned aerial vehicles, satellites, BeiDou navigation system, launch vehicles, space station, deep-space exploration
Marine engineering equipment and target ships	marine engineering equipment, target ships, offshore engineering vessels, offshore platforms, LNG carriers, large cruise ships, offshore wind power equipment
Advanced rail transit equipment	advanced rail transit equipment, high-speed rail, intercity railways, urban rail transit, metro systems, intelligent trains, smart rail transit
Energy-saving and new energy vehicles	energy-saving and new energy vehicles, new energy vehicles, battery electric vehicles, plug-in hybrid electric vehicles, hydrogen fuel cell vehicles, intelligent connected vehicles, autonomous driving, automotive electronics, power batteries, charging and swapping infrastructure
Power equipment and new energy	power equipment, smart grids, ultra-high-voltage transmission, renewable energy, wind power, offshore wind power, solar photovoltaics, PV modules, energy storage, hydrogen energy, fuel cells
New materials	new materials, advanced materials, high-performance materials, composite materials, nanomaterials, rare-earth functional materials, graphene, carbon fiber, superalloys, semiconductor materials, lightweight materials
Biopharmaceuticals and high-end medical devices	biopharmaceuticals, biotechnology, innovative drugs, modernization of traditional Chinese medicine, vaccines, gene therapy, precision medicine, high-end medical devices, in vitro diagnostics, medical imaging equipment, telemedicine

Agricultural machinery and smart agriculture	agricultural machinery and equipment, intelligent agricultural machinery, agricultural robots, smart agriculture, digital agriculture, modern agriculture, facility agriculture, smart villages
Green manufacturing and environmental protection	green manufacturing, green factories, green supply chains, energy conservation and environmental protection, low-carbon development, environmental governance, wastewater treatment, waste-to-energy power generation, circular economy, cleaner production
Urban and infrastructure digitalization	smart cities, smart transportation, smart energy systems, smart industrial parks, smart ports, smart mines, digital infrastructure, new-type infrastructure, BeiDou applications, spatiotemporal information services
Science, technology, and core technology breakthroughs	science and technology innovation, technological innovation, indigenous innovation, original innovation, critical core technologies, breakthroughs in core technologies, core components, high-end components, industrial design, engineering technology research centers
Other target industry expressions	high value-added industries, innovation-oriented industrial clusters, strategic emerging industry clusters, future industries, leading industries
