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How does industrial policy experimentation influence innovation performance? A case of *Made in China 2025*

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Made in China 2025 (MIC 2025), an industrial policy, aims to position China among the global leading manufacturing powers. Different from other industrial policies in China, MIC 2025 is implemented by policy experimentation of pilot cities, which gives priority to the local governments. However, whether MIC 2025 pilot cities promote firm innovation is unclear in current literature. Using MIC 2025 pilot cities as a quasi-natural experiment, this study analyzes the effect and the mechanism of MIC 2025 on firm innovation. The sample consists of 4422 firm-year observations of Chinese listed manufacturing firms in 2012–2022. The result indicates that focal firm located in MIC 2025 pilot cities facilitates its innovation. Mechanism analysis show that MIC 2025 promotes firm innovation through tax incentives, public subsidies, convenient financing, academic collaboration and talent incentives. This study extends industrial policy literature with regard to how place-based policy experimentation promote the implementation of China’s industrial policies. Local governments’ participations and their interaction with the central government are vital for a successful policy experimentation.

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Introduction

Industrial policy, defined as a policy scheme that shapes a country's industrial structure by supporting or limiting certain sectors, is widely applied in developed and developing countries (Barwick et al., 2019). Government policies that intervene business environment and change economic structure towards certain sectors or technologies can be viewed as industrial policy (Warwick, 2013; Mao et al., 2021). Evidence from East Asian industrial policies showed that sectoral industrial policies should be adequately targeted and properly governed (Aghion and Roulet, 2014; Wade, 1990).

China has implemented a highly institutionalized techno-industrial policy, namely MIC 2025 in 2015, which targets key technologies and sectors in the next ten years. The new policy is consistent with the goal of "indigenous innovation" (Liu et al., 2011; Chen and Naughton, 2016). Regarded as China's version of Industry 4.0, MIC 2025's goal is to enhance economic competitiveness by embracing emergent technologies, climbing the world's manufacturing value chain, and decreasing dependence on external technologies (Glaser, 2019). Due to government intervention, China's industrial policy is criticized with respect to whether there is a "market failure" or a "government failure" (Datta-Chaudhuri, 1990; Stiglitz et al., 2013). If there is a market failure, it needs government intervention, but government intervention may also lead to a government failure. However, because industrial policy has become very common in many countries across the world, the important question of industrial policy is not whether a policy should be practiced, but how (Barwick et al., 2019; Rodrik, 2012). Evaluation of industrial policies should focus on specific scenarios, including goals, sectors, policy contexts, rather than just in general (Warwick, 2013; Weiss, 2011).

Existing literature mainly tests whether China's industrial policies influence firm innovation using the Five-Year Plan (FYP) (Chen et al., 2017; Feng, 2019; Sun and Cao, 2021; Wu et al., 2019). First, the FYP is a comprehensive framework involving all aspects of economic and social development, although FYP has been made in various industrial fields. In comparison, MIC 2025 is a national-level industrial policy proposed by the central government to transform China into a manufacturing powerhouse. Second, FYP needs to be developed relatively independently at all levels of government, including central government and local governments. MIC 2025 is implemented by policy experiments of pilot cities, which involve the participation of local governments to interact with the central government. Third, FYPs in industrial fields mainly focus on direction, such as proposing target indicators in relevant fields, and there are relatively few specific implementation policies. Cities being selected as the MIC 2025 pilot cities have clear policy domains, goals, and policy instruments during policy implementation. Finally, moreover, MIC 2025 is the first ten-year action plan aiming at raising China's manufacturing power. It has a longer time than the FYP. Before pilot cities announcements, no local governments can forecast whether it is selected as the pilot cities of MIC 2025. Therefore, using MIC 2025 to evaluate the impact of industrial policies is cleaner than using comprehensive policies such as FYP.

Existing literature mainly regards MIC 2025 as sector-based industrial policies and tests whether MIC 2025 promotes innovation of the selected sectors¹. Scholars have focused on whether MIC 2025 promotes outward foreign direct investment (OFDI) of Chinese firms (Zhao and Lee, 2021), as well as the welfare impacts of MIC 2025 subsidies (Ju et al., 2021), and policymakers also have widely focused on MIC 2025 (Zenglein and Holzmann, 2019; Kim and VerWey 2019; Sutter, 2020). *Proponents* suggest that MIC 2025 envisions substantial incentives and requirements for leading Chinese firms to engage in high-tech industries and

acquire a better position in the global market (Petricevic and Teece, 2019). Using core business areas of MIC 2025 as identification of the treatment group in difference-in-difference (DID) analysis, scholars found that firms in areas of MIC 2025 promote research and development (R&D) input significantly after-policy implementation (Wen and Zhao, 2021). Ju et al. (2021) found that MIC 2025 subsidies actually increase U.S. welfare, and their impact on China is also positive. Zhao and Lee (2021) found that MIC 2025 has a positive effect on Chinese enterprises' OFDI.

Opponents suggest that although the goal of MIC 2025 is correct, but it cannot eliminate short-term uncertainty and ensure long-term support from the public (Prasad, 2023). Government subsidies could lead to overabundant manufacturing capacity in MIC 2025 industries. They found that MIC 2025 does not increase firm R&D investment and patenting in the supported sectors (Branstetter and Li, 2022). The scale and range of industrial subsidies by the governments go beyond the classic conceptualization of public subsidies (Zenglein and Holzmann, 2019). Growing domestic capacity may speed up the demand for domestically innovated products in China and force the transfer of technology (Kim and VerWey, 2019).

Contradictory empirical results in innovation effect leave open an important question: Whether and how MIC 2025 influences firm innovation? It is urgent to carefully test whether and how MIC 2025 promotes firm innovation to bridge these disputes. Indeed, the previous studies ignore that MIC 2025 is implemented by place-based policy experimentation—the MIC 2025 pilot cities, which is unique compared with other industrial policies. The Ministry of Industry and Information Technology (MIIT) in China started to announce the list of MIC 2025 pilot cities in 2016. Thirty pilot cities have been announced as pilot zones for MIC 2025 in 2016 and 2017. China is implementing MIC 2025 by using various policy instruments, such as tax incentives, joint ventures, and partnerships, government subsidies, technology licensing, and talent recruitment (Sutter, 2020). Firms may not benefit from MIC 2025 even if they are in the supported sectors but without the support from the local governments.

Thus, we use MIC 2025 pilot cities to conduct a quasi-natural experiment and evaluate the innovation effects of MIC 2025, using data from Chinese listed firms located (or not) in MIC 2025 pilot cities in 2012–2022. Using the propensity score matching—difference in difference (PSM-DID) model, this study found that firms located in MIC 2025 pilot cities facilitate their innovation performance. Focal firms located in MIC 2025 pilot cities increase their invention patents and decrease non-invention patents, which improves innovation quality. The findings are further supported by multiple robustness checks, such as the placebo test and endogeneity test. Mechanism analysis showed that firms located in MIC 2025 pilot cities promote their innovation by tax incentives, public subsidies, convenient financing, academic collaboration, and talent incentives. Heterogeneity analysis showed that firms located in MIC 2025 cities are more beneficial to firm innovation of state-owned enterprises (SOEs) and firms operating in western China MIC 2025 pilot cities. Lastly, this study demonstrates that located in MIC 2025 pilot cities improve a firm's economic performance. It has a positive effect on the firm's Tobin's Q, as well as the firm's total factor productivity (TFP).

Our paper makes two contributions. First, this study improves the understanding of implementing the sector-based industrial policy by the place-based policy experimentation based on the case of MIC 2025, which integrates the sector-based development policies (such as High-Tech industry policies) and the place-based development policies (such as indigenous innovation demonstration zone policy). Studies on MIC 2025 focused on

whether government intervention leads to incentive distortions (Zenglein and Holzmann, 2019). This paper considers that MIC 2025 pilot cities differ from the top-down regulatory perspective that scholars typically adopted in industrial policy analysis (Juhász et al., 2023) and the bottom-up regional development policies such as high-tech park development policy or indigenous innovation demonstration zone. Our work shows that MIC 2025 provides central-local interactions by policy experimentations in pilot cities, which integrates sector-based and place-based policies.

Second, our paper shows how MIC 2025 pilot cities promote firm innovation using mechanism analysis. Previous empirical studies on MIC 2025 analyze the influence of MIC 2025 on firm innovation (Branstetter and Li, 2022). Our result suggests that MIC 2025 promotes firm innovation through resource incentives and competitive incentives, which provide new evidence for proponents' views. The mechanism analysis demonstrates that located in MIC 2025 pilot cities promote firm innovation by policy instruments, namely, tax incentives, public subsidies, convenient financing, academic collaboration, and talent incentives. Further analysis also shows that MIC 2025 has good economic consequences, which promotes firms' Tobin's Q and TFP.

The remaining sections of the study are as follows. Section "Theory and hypotheses" is the theory and hypotheses. It first provides a literature review and institutional background of MIC 2025 pilot cities. Then this paper proposes hypotheses on MIC 2025 pilot cities and firm innovation. Section "Methods" proposes methods, samples, and variables that can be used to assess MIC 2025's effect. Section "Results" presents the empirical results of the baseline model, mechanism analysis, and robustness tests. Section "Discussion and conclusion" is the discussion and conclusion. It discusses the contributions, policy implications, as well as research limitations, and future directions.

Theory and hypotheses

Industrial policy and MIC 2025. The term industrial policy refers to policies taken by the central and local governments that affect the competitiveness of industrial development (Robinson, 2009). There exists a contentious debate on whether industrial policies should be implemented. On one side, industrial policies have incentive effects, and the various resources allocated to competitive sectors increase firms' incentives to innovate (Aghion et al., 2015). On the other side, the government's incompetence in information sifting and crowd-out effects leads to incentive distortion, which in turn discourages firms' R&D (Mao et al., 2021; Boeing, 2016).

Innovation frequently has high costs (Phelps, 2010) and high uncertainties (Ahuja and Lampert, 2001). During China's shift towards a market-oriented economy, the market itself is not perfect. Firms face high information asymmetry and insufficient incentives and do not make enough private R&D investments. MIC 2025 pilot city, as indigenous policy-making of "proceeding from point to surface" in China, is implemented by the local governments with the backing of policymakers from higher levels (Heilmann, 2008). It provides embedded autonomy for the local government (Evans, 1995; Victor and Sabel, 2022) to negotiate and renegotiation of goals and policies. When firms' strategies or major businesses are consistent with the MIC 2025 plan, they can receive guidance in promising technological areas supported by the local governments (Gao et al., 2021). The support of local governments can alleviate the problem of information asymmetry to some extent.

MIC 2025 pilot cities promote iterative public-private interactions, which clears the conditions regarding which type of business meets the requirements for the incentives. For example, as the first MIC 2025 pilot city, Ningbo had released a policy,

namely-*Opinions on Promoting the MIC 2025 Pilot City of Ningbo*, on March 9th, 2017. The private sector responded with enthusiasm to ask for the conditions and criteria for the policy incentives. In response, the local government of Ningbo released detailed implementation rules, on August 16th, 2017. The new policy text sets clear criteria for firms to get subsidies, supporting high-level industrial technology research institutes with a maximum subsidy of 30 million RMB and providing annual funding of 200 million RMB to implement the city's MIC 2025 Major Science and Technology Special Project.

MIC 2025 pilot cities also promote central-local government interactions. Selecting a group of cities to carry out pilot demonstrations is conducive to providing strong support for the systematic improvement of manufacturing ability in the country (Taeihagh and Li, 2021). Place-based policy experiments help to explore the paths for advancing the transformation and improvement of the manufacturing industries in various regions (Kline and Moretti, 2014). It will form a batch of typical experiences to provide demonstration and implications for national policy implementation across the country. Conducting a pilot demonstration is conducive to protecting the local government's enthusiasm, mobilizing resources, and appealing advantageous elements to cluster into the pilot cities. With the policy support from the local government, the industrial policy promotes firm innovation through resource incentives and competitive incentives (Aghion et al., 2015).

On the perspective of the resource-based view (RBV) (Barney, 1991; Wernerfelt, 1984), unique resource is the origin of firm innovation. Resource incentives in terms of industrial policy mean that the government can bring resource advantages to firms' innovation by policy instruments, such as tax incentives, public subsidies, and convenient financing. It is possible that resource incentives can alleviate the resource constraints typically faced by firms in innovation, reduce the marginal cost of innovation activities, and disperse innovation risks (Boeing, 2016). More resource goes to high-quality and innovation-driven firms, which could improve resource input structure (Chen, 2022) and the efficiency of resource allocation across firms in MIC 2025 pilot cities.

Competitive incentives related to industrial policy mean that the government encourages firms to gain competitive advantages by collaborating with academics and talent policies. Certainly, industrial policy incentives may produce incentive effects or incentive distortions. MIC 2025 pilot cities provide a better innovation ecosystem, which provides circulation of academic, and talent resources, altogether resulting in stimulating firms' competitive incentives to gain comparative advantages.

Institutional background of MIC 2025 pilot cities. As a multi-faceted blueprint, MIC 2025 aims to comprehensively upgrade the entire manufacturing process (Wang et al., 2020). However, there exist great differences in the industrial foundations among the western, central, and eastern regions of China. The improvement of the manufacturing industry has obvious regional characteristics. Thus, China's MIIT started to announce the list of MIC 2025 pilot cities in 2016 (Li, 2018). Thirty pilot cities have been announced as pilot zones for MIC 2025 after applications. The list of pilot cities, along with their respective dates of approval, are reported in Table A1.

There are several institutional principles in MIC 2025 pilot cities. First, it gives priority to the local governments and provides guidance from the central government. Pilot cities should be the main implementers, and their initiative and creativity should be fully utilized. The MIIT, together with other relevant central departments, will strengthen the policy guidance and form a synergistic effect through the joint efforts of the ministries,

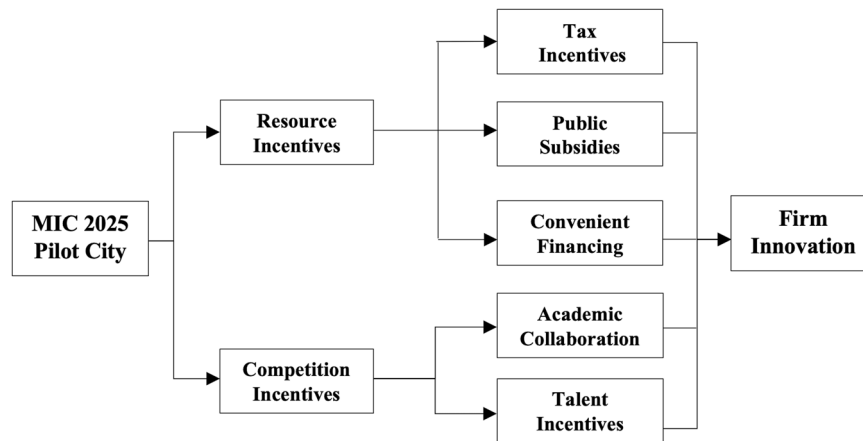


Fig. 1 Theoretical mechanism.

provinces, and cities. The experimentation is not a top-down nor bottom-up governance but both in turn, as lower levels of institutions correct high ones and vice versa (Victor and Sabel, 2022). Second, adhering to the principle of “one city, one case”, pilot cities should highlight local advantages based on different characteristics, such as development stage, factor endowment, and industrial foundation. Each pilot city selects the pilot direction accurately and formulates implementation plans. Pilot cities designed a comprehensive pilot scheme, covering industrial growth and upgrading, technology innovation, policy support system, and talent incentives. MIC 2025 pilot cities have relaxed various kinds of resource constraints and created new competitive advantages.

To sum up, MIC 2025 pilot cities are unique compared with other China’s industrial policies. It merges the policy objectives of the central government with extensive local governments’ implementation (Heilmann et al., 2013). It gives priority to local governments to provide a relatively flexible policy support system. The pilot cities consist of a wide range of cities with different features in manufacturing. Thus, each city participates in providing policy support and interacts with the central government. Moreover, the implementation process of pilot city experiments is dynamic. The MIIT announced the plan of pilot cities and then local governments applied for it. Only when the condition or policy support system is well prepared shall the MIIT announce the city into the list of MIC 2025 pilot cities. Thus, the announcement date spans from August 2016, the first pilot city of Ningbo, to August 2017, the 30th pilot city of Guangzhou. It is possible to evaluate the policy effects on innovation by comparison between firms being located in pilot cities of MIC 2025 and those that are not.

Located in MIC 2025 pilot cities and firm innovation. Being located in MIC 2025 pilot cities gain more resource incentives, which promotes firm innovation. According to the policy text of MIC 2025, the policy highlights the improvements in the tax/subsidy system and financing supports. First, the MIC 2025 policy promotes value-added tax reform, which reduces a firm’s tax burden. Local governments of MIC 2025 pilot cities have released tax credits and tax relief in high-tech sectors. Tax incentives can be used as an external control to alleviate the risks of low innovation investment. It can secure the innovation supply of the firms in high-tech sectors (Hoppmann, 2021). Second, MIC 2025 subsidizes the manufacturing operation process and the use of major technical equipment, reducing the resource constraints of conducting R&D and value-added services. Public subsidies solve the problems of coordination failure and improve technology spillovers by reducing externality (Hausman and Rodrik, 2003). Third, the MIC 2025 policy actively leverages the

advantages of policy finance, increasing support for key domains, such as next-generation information technologies, high-end equipment, and new materials. Financing constraints severely restrict the development of technological firms because of their engagement in frontier research and riskier investments (Mina et al., 2021). With both sector-based industrial funds and venture capital guidance funds, firms in MIC 2025 pilot cities receive more convenient financing. To sum up, MIC 2025 pilot cities have relatively flexible policy support systems, which can relax the resource constraints related to firm innovation through tax incentives, public subsidies, and convenient financing.

Being located in MIC 2025 pilot cities gain more competition incentives, which promotes firm innovation. Firms located in MIC 2025 pilot cities can gain a new competitive advantage from their external environment (Salancik and Pfeffer, 1978). First, certain priorities have been implemented in MIC 2025 pilot cities to improve academic collaboration. The policy supported key firms and universities to co-found the Industrial Technology Research Institute for high-level advanced manufacturing. These co-founded institutes, which have been awarded the designation of State Key Laboratory or National Engineering Technology Research Center, will get an award from the pilot cities’ governments. In addition, MIC 2025 pilot cities have implemented the *Major Science and Technology Project of MIC 2025*, to encourage collaboration on basic research. This encourages firms to adopt novel knowledge and accelerate the transformation of their science and technology achievements. Second, MIC 2025 issued the *Talent Development Plan for Manufacturing Industry* guideline, to establish a multi-level talent training system designed for talents with high technology and manufacturing skills. MIC 2025 pilot cities encourage high-quality talents to gather in manufacturing firms. High-quality or high-tech talents have positive externalities, which in turn promote the knowledge spillover between talents and improve firm innovation. The MIC 2025 pilot cities have relatively flexible policy support systems, which can improve competition incentives related to firm innovation through academic collaboration and talent incentives. Figure 1 illustrates the theoretical model and mechanisms.

Thus, considering the relaxation of resource constraints and improving competitive advantages in MIC 2025 pilot cities, we argue that:

Hypothesis 1 (H1): Located in MIC 2025 pilot cities facilitates firm innovation.

Methods

Samples and data source. This study selects Chinese manufacturing listed firms in Shanghai and Shenzhen A-share stock

markets, targeted by ten priority sectors in MIC 2025 as the preliminary samples. Excluding firms with missing data, the samples include 8151 firm-year observations from 2012 to 2022. The PSM method is used to find the control firms located in non-pilot cities with characteristics like the treatment firms in pilot cities. The treatment group and the control group both consist of 201 firms. The final samples are a balanced panel with 4422 firm-year observations (201 firms \times 2 \times 11 years). Since most of the pilot cities were selected from 2016 to 2017, we selected data from 2012 to 2022, and an approximately four-year time window before and after MIC 2025 pilot cities were selected to conduct PSM-DID tests.

Firms' patent data is from the Chinese Research Data Services (CNRDS). This study uses three different types of patents, namely, invention patents, utility model patents, and design patents. Firms' financing and governance data comes from the China Stock Market & Accounting Research Database (CSMAR), which provides detailed financing information on Chinese listed firms in the Shanghai and Shenzhen stock markets. Both CNRDS and CSMAR provide a list of stock names and code numbers (Hsu et al., 2021). In this study, a one-to-one matching method was used to merge the variables in the two datasets. Also, the Winsor command in Stata: Software for Statistics and Data Science was used for all the non-discrete variables at 1 and 99% levels and eliminated potential effects caused by extreme values.

Measurements

Dependent variables. Dependent variables are the focal firm's innovation performance, specifically the innovation output based on patent data. Since the technical difficulty of China's utility model patents and design patents is relatively low (in comparison with invention patents), innovation output is divided into the number of invention patents (*Invention*) and the sum up of utility model and design patents, as the number of non-invention patents (*Non-Invention*) (Pang and Wang, 2020). It normally takes from around two to four years to get from patent application to patent granting in China (Tong et al., 2018; Liegsalz and Wagner, 2013, He et al., 2018). This study uses the patent application numbers to dynamically capture changes in firm innovation (Li and Zheng, 2016). The number of invention patents is represented by logarithm applications of invention patents. The number of non-invention patents is defined by the logarithm application of non-invention patents. The data source of the dependent variable is from the CNRDS.

Independent variables. This paper uses binary variables to define manufacturing firms located in the pilot cities from those in non-pilot cities; *Treat* represents whether a firm is located in MIC 2025 pilot cities, also regarded as the treatment group. Firms in the treatment group are defined by *Treat* = 1; otherwise, defined by *Treat* = 0. Variable *Post* represents whether the period is before or after being selected as MIC 2025 pilot cities. The period before MIC 2025 is defined as *Post* = 0; otherwise, defined as *Post* = 1. In time-varying DID model, we use *Treat* \times *Post* as the main independent variable.

Control variables. Our model controls both firm-specific and industry-specific features in our baseline model, mechanism analysis, and robustness tests. The firm-specific variables include the control variables detailed below (Ellis et al., 2020; Fang et al., 2014; Chemmanur et al., 2014). The control variable data were sourced from CSMAR.

Firm size (*Size*) is defined by the logarithm of firm's total assets. Firm age (*Age*) is represented by the logarithm of years after a focal firm was founded, plus one. Firm fixed assets (*Pee*)

are defined by a focal firm's net worth, equipment, and plant, divided by its total assets. Ownership type (*SOE*) is defined as *SOE* = 1 if the firm's ownership is state-owned; otherwise, if the firm is not state-owned, *SOE* = 0. Institutional ownership (*Inst*) is represented by the ratio of shares held by institutional investors to the total number of shares.

A firm's return on assets (*ROA*) is represented by the ratio of the firm's net profit to its assets. The ratio of liabilities (*Lev*) is represented by the ratio of the firm's total debt to its total assets; R&D input (*RD*) is represented by the ratio of the firm's R&D investment to its total assets. Free cash flow (*CFC*) is represented by a focal firm's net free cash flow, divided by its total assets. Capital expenditure (*Capex*) is represented by a focal firm's capital expenditure, divided by its total assets. Operating capability (*NWC*) is represented by a focal firm's operating expenditure, divided by its total assets. The KZ index (*KZ*), defined by Kaplan and Zingales (1997), measures a firm's relative dependence on external financing.

The proposed model also controls for a focal firm's industry concentration and competition, represented by the Herfindahl-Hirschman index (*HHI*); $HHI = \sum (xi/x)^2$. Here, *xi* represents the sale of a particular *i* firm in a sector, *x* is the total sales of the sector, and (*xi/x*) is the percent of total sales in a sector generated by a particular *i* firm.

The firm fixed effect and year fixed effect are included in the model.

Other variables. In order to test the mediator effect of industrial policy instruments, tax incentives (*Tax*), public subsidies (*Subsidy*), convenient financing (*Financing*), academic collaboration (*Collaboration*), and talent incentives (*Talent*) are included.

Tax incentives (*Tax*) are defined as the rate of income tax, which is the ratio of income tax expense to the firm's profit before tax (Porcano, 1986). If the income tax rate is lower, the firm receives higher tax incentives. The data source of *Tax* is taken from CSMAR.

Public subsidies (*Subsidy*) are defined as a government subsidy divided by the focal firm's revenue (Fang et al., 2018). The data source of the variable *Subsidy* is taken from CSMAR.

Convenient financing (*Financing*) is defined as using a bank loan ratio, which is represented by the percentage of a focal firm's total bank loans divided by its total assets (Yeh et al., 2013). The data source of the variable *Financing* is taken from CSMAR.

Academic collaboration (*Collaboration*) is defined as whether a focal firm announced a proposal to collaborate with universities or research institutes after the MIC 2025 pilot cities were selected. If the focal firm engages in academic collaboration, then *Collaboration* = 1; otherwise, *Collaboration* = 0 (Song et al., 2009). The data source of the variable *Collaboration* is from the Cninfo-a stock marketing online website page, and web scraping with Python was used to analyze the announcements of listed firms.

Talent incentives (*Talent*) are defined by the proportion of R&D personnel to all personnel in the firm (Liu et al., 2018). Firms attracting more human resources have larger chances of rapid growth. The data source of the variable *Talent* is taken from CSMAR.

We also include some city-specific variables in the robustness checks. City GDP (*GDP per capita*) is represented by a logarithm of the city's GDP per capita. City GDP growth (*GDP growth rate*) is represented by the increasing rate of a city's GDP. City science and technology expenditure (*Science and Technology*) is represented by the ratio of science and technology expenditure to GDP. City population (*LnPopulation*) is represented by the logarithm of a city's population in 10,000 units. City R&D

Table 1 Variable in detail.

| Type | Variable | Notation | Definition | Data source |
|---|--------------------------|---|---|---|
| Dependent variables | Invention patents | <i>Invention</i> | Ln (applications of invention patents +1) | CNRDS |
| | Non-Invention patents | <i>Non-Invention</i> | Ln (applications of utility model patents and design patents +1) | CNRDS |
| Independent variables | Influenced by the policy | <i>Treat × Post</i> | after being selected into MIC 2025 pilot cities equals 1, otherwise, equals 0 | Website of MIIT |
| Control variables | Firm size | <i>Size</i> | Ln (total assets) | CSMAR |
| | Firm age | <i>Age</i> | Ln (age+1) | CSMAR |
| | Return on assets | <i>ROA</i> | net profit/total assets | CSMAR |
| | Ratio of liabilities | <i>Lev</i> | total debt/total assets | CSMAR |
| | R&D input | <i>RD</i> | R&D investment/total assets | CSMAR |
| | Fixed assets | <i>Pee</i> | firm's net worth, plant and equipment divided by total assets | CSMAR |
| | Institutional ownership | <i>Inst</i> | shares held by institutional investors/total number of shares | CSMAR |
| | Industry concentration | <i>HHI</i> | Herfindahl-Hirschman index | CSMAR |
| | KZ index | <i>KZ</i> | According to Kaplan and Zingales (1997) | CSMAR |
| | Free cash flow | <i>CFC</i> | net free cash flow/total assets | CSMAR |
| | Capital expenditure | <i>Capex</i> | capital expenditure/total assets | CSMAR |
| | Operating capability | <i>NWC</i> | operating expenditure/total assets | CSMAR |
| | Other variables | Ownership type | <i>SOE</i> | state owned, $SOE = 1$; otherwise, $SOE = 0$. |
| Tax incentives | | <i>Tax</i> | income tax rate of the focal firm | CSMAR |
| Public subsidies | | <i>Subsidy</i> | government subsidy divided by the focal firm's revenue | CSMAR |
| Convenient financing | | <i>Financing</i> | percentage of a focal firm's total bank loans to its total assets | CSMAR |
| Academic collaboration | | <i>Collaboration</i> | firm with academic collaboration equal 1; otherwise, equals 0 | Web scraping |
| Talent incentives | | <i>Talent</i> | proportion of R&D personnel in the focal firm | CSMAR |
| City GDP | | <i>GDP per capita</i> | logarithm of a city's GDP per capita in RMB yuan | CNRDS |
| City GDP growth | | <i>GDP growth rate</i> | growth rate of a city's GDP | CNRDS |
| City science and technology expenditure | | <i>Science and Technology</i> | city's science and technology expenditure/city's GDP | CNRDS |
| City population | | <i>LnPopulation</i> | the logarithm of a city's population in 10,000 unit | CNRDS |
| City R&D personnel | | <i>Research_Employment</i> | the ratio of R&D personnel on population | CNRDS |
| City infrastructure expenditure | | <i>Infra_Spending</i> | the ratio of city's infrastructure investment on city's GDP | CSMAR |
| City patent applications | | <i>Apply_Patent</i> | logarithm of a city's patent applications | CNRDS |
| City patent grants | <i>Obtain_Patent</i> | logarithm of a city's patent grants | CNRDS | |
| Tobin's Q | <i>TQ</i> | the ratio of market value on total assets | CSMAR | |
| Total factor productivity | <i>TFP_LP</i> | according to Levinsohn and Petrin (2003) | CSMAR | |

personnel (*Research_Employment*) is defined by the ratio of R&D personnel to population. City infrastructure expenditure (*Infra_Spending*) is defined by the ratio of infrastructure investment to GDP. City patent applications (*Apply_Patent*) are represented by the logarithm of a city's patent applications. City patent grants (*Obtain_Patent*) are represented by the logarithm of a city's patent grants. The data source of *Infra_Spending* is taken from CSMAR. The data source of other city-specific variables is CNRDS.

This paper uses Tobin's Q and TFP to test the economic performances of the firms located in MIC 2025 pilot cities. Tobin's Q (*TQ*) is represented by market value divided by its total assets (La Porta et al., 2002); TFP (*TFP_LP*) is defined by Levinsohn and Petrin (2003).

Details of the main variables are provided in Table 1.

Propensity score matching. Considering the observable heterogeneity between firms that located in the MIC 2025 pilot cities and other firms, the PSM method was used to find manufacturing firms in non-pilot cities with characteristics like those of manufacturing firms in pilot cities. The matched manufacturing firms from the non-pilot cities are the control group. The Logit regression was applied to estimate the possibility of firms located

in the sample city becoming a MIC 2025 pilot city in the next year. The matching method is year-by-year matching using lagged covariates to estimate the treatment of becoming MIC 2025 pilot city in the next year. After obtaining the treatment and the control group, data from all their firm-year observations were retained. The one-to-one matching method was used, and the Logit regression model was run as follows:

$$\begin{aligned}
 \text{Treat}_{it} = & \beta_0 + \beta_1 \text{Size}_{it} + \beta_2 \text{Age}_{it} + \beta_3 \text{ROA}_{it} \\
 & + \beta_4 \text{Lev}_{it} + \beta_5 \text{RD}_{it} + \beta_6 \text{Pee}_{it} + \beta_7 \text{Inst}_{it} \\
 & + \beta_8 \text{HHI}_{it} + \beta_9 \text{KZ}_{it} + \beta_{10} \text{CFC}_{it} + \beta_{11} \text{Capex}_{it} \\
 & + \beta_{12} \text{NWC}_{it} + \beta_{13} \text{SOE}_{it} + \text{error}_{it}
 \end{aligned} \tag{1}$$

Here, *Treat* represents whether the firm is from the MIC 2025 pilot cities. Firms in pilot cities are defined by *Treat* = 1; otherwise, *Treat* = 0 in Eq. (1). It includes all the control variables in Eq. (1).

Figure 2 provides the distribution of propensity scores before and after the matching in both the treatment group and the control group. In the 'before matching' panel, the control groups are the firms not located in MIC 2025 pilot cities. Before matching, the propensity scores of the treatment and the control groups are different. In the 'after matching' panel, control groups

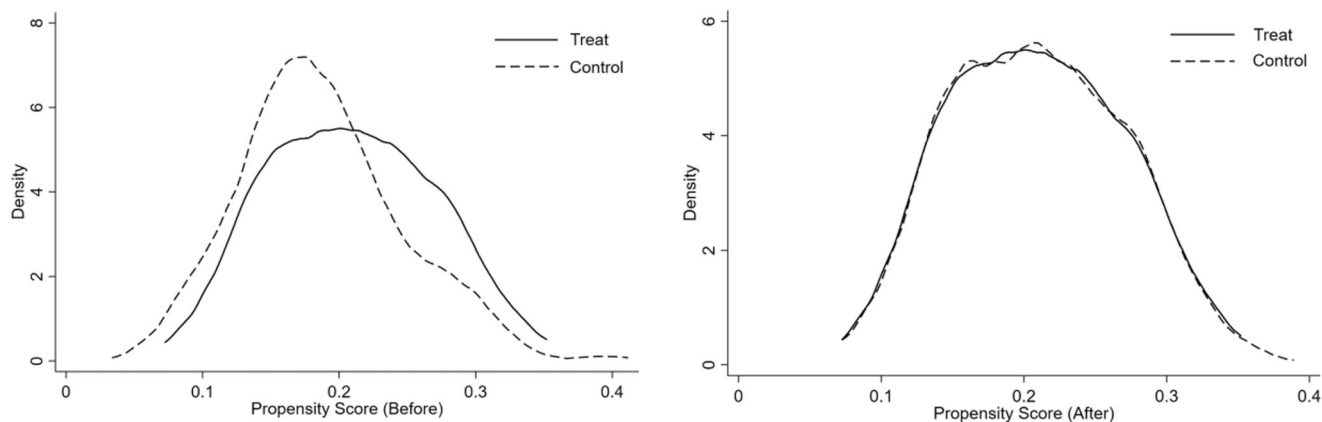


Fig. 2 Propensity scores density before and after matching.

are those successfully matched. After matching, the propensity scores of the two groups are much similar, indicating that the treatment and control groups have the same probabilities of receiving treatment. The observable characteristics of the treatment and the control groups do not differ systematically, and the matching process is effective.

Model design. The PSM-DID method should first pass a statistical test for parallel trend assumption. A dynamic regression model is constructed, as follows:

$$\begin{aligned}
 \text{Innovation}_{it} = & \chi_0 + \chi_1 \text{Treat}_{it} \times \text{Year}_{i,t-4} \\
 & + \chi_2 \text{Treat}_{it} \times \text{Year}_{i,t-3} + \chi_3 \text{Treat}_{it} \times \text{Year}_{i,t-2} \\
 & + \chi_4 \text{Treat}_{it} \times \text{Year}_{i,t-1} + \chi_5 \text{Treat}_{it} \times \text{Year}_{it} \\
 & + \chi_6 \text{Treat}_{it} \times \text{Year}_{i,t+1} + \chi_7 \text{Treat}_{it} \times \text{Year}_{i,t+2} \\
 & + \chi_8 \text{Treat}_{it} \times \text{Year}_{i,t+3} + \chi_9 \text{Control}_{it} + \text{Year}_t + \text{Firm}_i + \text{error}_{it}
 \end{aligned} \tag{2}$$

Control variables in Eq. (2) are the same as given in Eq. (1). Equation (2) adds a new variable, *Year*, representing the periods before or after the implementation of MIC 2025 pilot cities. Subscripts $t - 1, t, t + 1$ represent the year before, the present year, and the year after the pilot cities were selected, respectively. If the increase in the number of inventions and the decrease in non-inventions are caused by MIC 2025, the coefficient of *Treat* × *Year* in year T should be significantly positive, while that in years $t - 1$ to $t - 4$ should be statistically insignificant.

To test our hypotheses, it uses the following time-varying DID model to evaluate pilot cities' influence on firm innovation:

$$\begin{aligned}
 \text{Innovation}_{it} = & \alpha_0 + \alpha_1 \text{Treat}_{it} \times \text{Post}_{it} + \alpha_2 \text{Size}_{it} + \alpha_3 \text{Age}_{it} \\
 & + \alpha_4 \text{ROA}_{it} + \alpha_5 \text{Lev}_{it} + \alpha_6 \text{RD}_{it} + \alpha_7 \text{Pee}_{it} \\
 & + \alpha_8 \text{Inst}_{it} + \alpha_9 \text{HHI}_{it} + \alpha_{10} \text{KZ}_{it} + \alpha_{11} \text{CFC}_{it} + \alpha_{12} \text{Capex}_{it} \\
 & + \alpha_{13} \text{NWC}_{it} + \alpha_{14} \text{SOE}_{it} + \text{Year}_t + \text{Firm}_i + \text{error}_{it}
 \end{aligned} \tag{3}$$

Where *Innovation* represents the focal firm's innovation performance, including *Invention* and *Non-Invention*; *Treat* × *Post* represents whether the firm was located in the pilot cities or not before or after-policy implementation. Since the firm and year fixed effect have both been included, we only involve the interaction of *Treat* × *Post*. This study mainly focuses on the coefficient α_1 , which represents the DID effect, and controls the year effect and firm effect using dummy variables. Control variables are similar as given in Eq. (1).

Results

Descriptive statistics. Table 2 provides the descriptive statistics in the treatment group, control group, and PSM samples, including the number of observations, mean, standard deviation, and quantiles (P25, P50, P75) across the entire period. Table 3 provides the correlation matrix. The main variables are not highly correlated with each other.

Figure 3 plots the trends of *Invention* and *Non-invention* of the treatment and control groups before and after the policy. The year when policy implements is time 0. In before-policy periods, the differences between the groups are smaller. In after-policy periods, *Invention* of the treatment group starts to be much higher than the control group, while *Non-Invention* of the treatment group starts to be much lower than the control group.

Results of the baseline model. Table 4 shows the results of Model (2). The coefficients of *Treat* × *Post* are 0.395 and -0.325 . The impact of firms being located in MIC 2025 pilot cities on *Invention* is statistically positive ($p < 0.01$). The impact of being located in MIC 2025 pilot cities on *Non-Invention* is statistically negative ($p < 0.01$). Thus, there is an increase in *Invention* and a decrease in *Non-Invention*, which improves firm innovation quality in MIC 2025 pilot cities. In line with existing research (Shefer and Frenkel, 2005; Acharya and Xu, 2017), our results suggest that firms having greater size, R&D input, and capital expenditure result in more innovation output. These results suggest that firms located in MIC 2025 pilot cities facilitate its innovation, a finding that supports H1.

For parallel trend assumption, Table 5 reports the coefficients of the dynamic model. In both specifications where we employ *Invention* and *Non-Invention* to be the dependent variables, the coefficients in the before-policy periods ($\text{Treat} \times \text{Before}^{-4}$, $\text{Treat} \times \text{Before}^{-3}$, $\text{Treat} \times \text{Before}^{-2}$) are consistently insignificant. Further, the coefficients of the variables indicating the post-policy periods ($\text{Treat} \times \text{Current}$, and $\text{Treat} \times \text{After}^1$, $\text{Treat} \times \text{After}^2$, $\text{Treat} \times \text{After}^3$) are statistically significant. These coefficient estimates combine to show a significant and persistent influence of MIC 2025 on treatment firms' innovation.

Figure 4 shows the estimated coefficients and 95% confidence intervals of the parallel trend tests. First, before-policy implementation, the innovation effect of the treatment and the control groups move in parallel. Such a pattern mitigates the concern that treated firms have responded to the policy before its implementation. Second, compared with control firms, the treated firms experience a rapid and significant increase in the number of invention patents after the policy implementation, and a decrease

Table 2 Descriptive statistics.

Variables **Samples after PSM (N = 4422)** **Treatment group (N = 2211)** **Control group (N = 2211)**

| | Mean | SD | P25 | P50 | P75 | Mean | SD | P25 | P50 | P75 | Mean | SD | P25 | P50 | P75 |
|---------------|--------|-------|--------|--------|--------|--------|-------|--------|--------|--------|--------|-------|--------|--------|--------|
| Invention | 1.745 | 1.673 | 0.000 | 1.386 | 2.708 | 1.894 | 1.803 | 0.000 | 1.609 | 2.944 | 1.596 | 1.517 | 0.000 | 1.386 | 2.565 |
| Non-Invention | 1.628 | 1.547 | 0.000 | 1.609 | 2.773 | 1.562 | 1.475 | 0.000 | 1.609 | 2.773 | 1.694 | 1.614 | 0.000 | 1.609 | 2.833 |
| Treat x Post | 0.302 | 0.459 | 0.000 | 0.000 | 1.000 | 0.605 | 0.489 | 0.000 | 1.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Size | 22.196 | 1.194 | 21.380 | 22.082 | 22.866 | 22.206 | 1.201 | 21.344 | 22.122 | 22.884 | 22.185 | 1.186 | 21.415 | 22.054 | 22.844 |
| Age | 2.318 | 0.638 | 1.946 | 2.398 | 2.833 | 2.328 | 0.640 | 1.946 | 2.398 | 2.833 | 2.307 | 0.636 | 1.946 | 2.398 | 2.833 |
| ROA | 0.030 | 0.067 | 0.011 | 0.033 | 0.061 | 0.029 | 0.067 | 0.011 | 0.033 | 0.060 | 0.031 | 0.068 | 0.011 | 0.034 | 0.063 |
| Lev | 0.408 | 0.191 | 0.258 | 0.401 | 0.549 | 0.418 | 0.196 | 0.259 | 0.414 | 0.568 | 0.398 | 0.186 | 0.257 | 0.391 | 0.528 |
| RD | 0.056 | 0.044 | 0.033 | 0.044 | 0.066 | 0.055 | 0.041 | 0.033 | 0.044 | 0.065 | 0.057 | 0.046 | 0.032 | 0.044 | 0.067 |
| Pee | 0.182 | 0.101 | 0.105 | 0.167 | 0.240 | 0.185 | 0.097 | 0.112 | 0.172 | 0.239 | 0.180 | 0.105 | 0.098 | 0.164 | 0.241 |
| Inst | 0.399 | 0.240 | 0.190 | 0.412 | 0.583 | 0.404 | 0.240 | 0.206 | 0.414 | 0.590 | 0.393 | 0.240 | 0.179 | 0.407 | 0.576 |
| HHI | 0.073 | 0.054 | 0.034 | 0.053 | 0.076 | 0.076 | 0.053 | 0.042 | 0.061 | 0.092 | 0.055 | 0.055 | 0.031 | 0.070 | 0.083 |
| KZ | 1.332 | 2.000 | 0.183 | 1.508 | 2.599 | 1.387 | 2.006 | 0.182 | 1.553 | 2.703 | 1.277 | 1.993 | 0.187 | 1.469 | 2.515 |
| CFC | -0.002 | 0.097 | -0.025 | 0.013 | 0.049 | -0.001 | 0.095 | -0.025 | 0.013 | 0.048 | -0.003 | 0.100 | -0.025 | 0.014 | 0.049 |
| Capex | 0.042 | 0.037 | 0.017 | 0.032 | 0.056 | 0.042 | 0.036 | 0.017 | 0.032 | 0.057 | 0.043 | 0.037 | 0.017 | 0.032 | 0.056 |
| NWC | 0.272 | 0.210 | 0.119 | 0.261 | 0.416 | 0.265 | 0.210 | 0.111 | 0.261 | 0.410 | 0.279 | 0.210 | 0.126 | 0.260 | 0.426 |
| SOE | 0.299 | 0.458 | 0.000 | 0.000 | 1.000 | 0.290 | 0.454 | 0.000 | 0.000 | 1.000 | 0.307 | 0.461 | 0.000 | 0.000 | 1.000 |

Table 3 Correlation matrix.

| | Invention | Non-Invention | Treat x Post | Size | Age | ROA | Lev | RD | Pee | Inst | HHI | KZ | CFC | Capex | NWC | SOE |
|---------------|-----------|---------------|--------------|----------|-----------|----------|----------|----------|-----------|----------|----------|-----------|----------|----------|-----------|----------|
| Invention | 1.000 | 0.573*** | 0.077*** | 0.247*** | -0.036** | 0.073** | 0.117*** | 0.193** | -0.040*** | 0.109*** | 0.038** | -0.053*** | 0.037** | 0.062*** | -0.014 | 0.142** |
| Non-Invention | 0.518** | 1.000 | -0.092*** | 0.105** | -0.168*** | 0.030* | 0.074*** | 0.097*** | 0.014 | 0.013 | 0.173** | -0.051*** | 0.02 | 0.058*** | 0.004 | 0.056** |
| Treat x Post | 0.116** | -0.105** | 1.000 | 0.148** | 0.238*** | -0.096** | 0.099** | 0.057*** | -0.023 | -0.028** | 0.005 | 0.110** | -0.023 | -0.110** | -0.084** | -0.009 |
| Size | 0.335** | 0.178** | 0.135** | 1.000 | 0.417*** | 0.026* | 0.487*** | -0.088** | -0.014 | 0.380*** | 0.013 | 0.097*** | 0.028 | 0.057*** | -0.381*** | 0.284** |
| Age | 0.034* | -0.124** | 0.264** | 0.410** | 1.000 | -0.084** | 0.333** | -0.138** | -0.014 | 0.255** | -0.059** | 0.232** | 0.002 | -0.210** | -0.278** | 0.431** |
| ROA | 0.093** | 0.073** | -0.098** | 0.074** | -0.079** | 1.000 | -0.359** | -0.037** | -0.100** | 0.183** | -0.120** | -0.549** | 0.219** | -0.192** | -0.352** | -0.059** |
| Lev | 0.134** | 0.090** | 0.100** | 0.461** | 0.348** | 0.315** | 1.000 | -0.211** | 0.064** | 0.179** | 0.207** | -0.549** | 0.066** | -0.204** | -0.773** | 0.222** |
| RD | 0.130** | 0.039* | 0.028* | -0.100** | -0.122** | -0.106** | -0.218** | 1.000 | -0.076** | -0.104** | -0.150** | -0.077** | -0.032** | -0.040** | 0.195** | -0.076** |
| Pee | -0.070** | -0.014 | -0.031* | -0.044** | -0.042** | -0.090** | 0.058** | -0.109** | 1.000 | 0.01 | 0.041** | 0.043** | 0.023 | 0.036** | -0.332** | -0.043** |
| Inst | 0.141** | 0.053** | -0.028* | 0.402** | 0.212** | 0.185** | 0.167** | -0.117** | 0.01 | 1.000 | 1.000 | 0.002 | 0.013 | 0.054** | -0.107** | 0.414** |
| HHI | 0.031** | 0.125** | -0.048** | 0.062** | -0.032** | -0.032** | 0.169** | -0.175** | 0.089** | 0.073** | 1.000 | 0.124** | -0.017 | 0.012 | -0.155** | 0.070** |
| KZ | -0.041** | -0.055** | 0.113** | 0.063** | 0.254** | -0.493** | 0.653** | -0.046** | 0.064** | -0.02 | 0.068** | 1.000 | -0.094** | -0.093** | -0.557** | 0.128** |
| CFC | 0.062** | 0.036** | 0.003 | 0.065** | 0.051** | -0.493** | 0.653** | -0.041** | 0.033** | 0.01 | 1.000 | 0.001 | 1.000 | -0.051** | -0.090** | 0.015 |
| Capex | 0.019 | 0.041** | -0.111** | 0.007 | -0.239** | 0.122** | -0.043** | 0.062** | 0.351** | -0.01 | 0.039** | 0.001 | 0.001 | 1.000 | -0.128** | -0.149** |
| NWC | -0.024 | -0.009 | -0.091** | -0.354** | -0.328** | 0.328** | -0.775** | 0.206** | -0.366** | -0.101** | -0.162** | -0.567** | -0.121** | -0.133** | 1.000 | -0.141** |
| SOE | 0.152** | 0.077** | -0.009 | 0.289** | 0.400** | 0.007 | 0.225** | -0.066** | -0.043** | 0.410** | 0.105** | 0.123** | 0.041** | -0.152** | -0.148** | 1.000 |

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%.

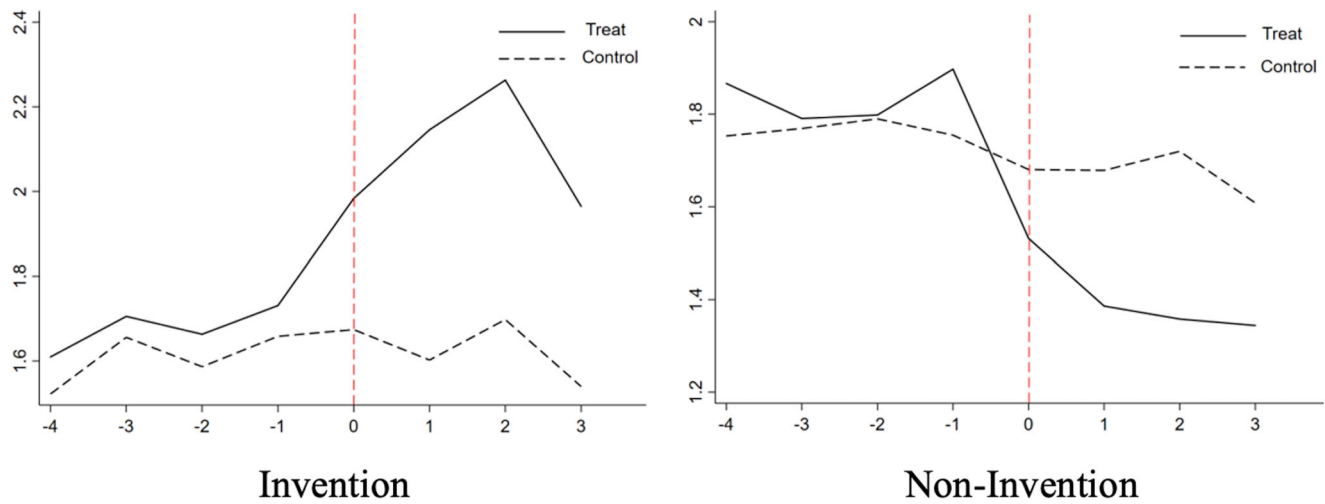


Fig. 3 Trends for the treatment and control groups before and after policy.

| Table 4 Results of MIC 2025 pilot cities and firm innovation. | | |
|---|----------------------------|----------------------------|
| Variables | Invention | Non-invention |
| <i>Treat</i> × <i>Post</i> | 0.395*** (4.549) | −0.325*** (−3.012) |
| Size | 0.135 [†] (1.884) | 0.133 (1.553) |
| Age | −0.099 (−0.681) | 0.278 (1.494) |
| ROA | 0.532 (1.360) | 0.466 (1.460) |
| Lev | 0.419 (1.158) | 0.398 (1.015) |
| RD | 2.346** (2.508) | 1.449* (1.746) |
| Pee | 0.086 (0.216) | 0.882* (1.913) |
| Inst | −0.082 (−0.344) | −0.048 (−0.210) |
| HHI | −1.646 (−1.330) | −2.098 (−1.362) |
| KZ | −0.014 (−0.751) | −0.035** (−2.018) |
| CFC | 0.509** (2.530) | 0.331 [†] (1.871) |
| Capex | 2.150*** (3.021) | 1.360** (2.015) |
| NWC | 0.453 (1.435) | 0.485 (1.419) |
| SOE | −0.169 (−1.087) | −0.046 (−0.302) |
| Constant | −1.544 (−0.932) | −1.932 (−0.992) |
| Year | Yes | Yes |
| Firm | Yes | Yes |
| N | 4422 | 4422 |
| Adj-R ² | 0.037 | 0.047 |

Notes: [†]significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

| Table 5 Results of the parallel trend tests. | | |
|--|----------------------------|----------------------------|
| Variable | Invention | Non-invention |
| <i>Treat</i> × <i>Before</i> ^{−4} | −0.106 (−1.064) | −0.010 (−0.081) |
| <i>Treat</i> × <i>Before</i> ^{−3} | 0.014 (0.171) | −0.054 (−0.451) |
| <i>Treat</i> × <i>Before</i> ^{−2} | −0.045 (−0.716) | −0.083 (−0.908) |
| <i>Treat</i> × <i>Current</i> | 0.263** (2.327) | −0.327*** (−2.601) |
| <i>Treat</i> × <i>After</i> ¹ | 0.419*** (3.021) | −0.411*** (−3.283) |
| <i>Treat</i> × <i>After</i> ² | 0.491*** (3.264) | −0.421*** (−3.095) |
| <i>Treat</i> × <i>After</i> ³ | 0.348** (2.936) | −0.338** (−2.515) |
| Size | 0.135 [†] (1.880) | 0.134 (1.556) |
| Age | −0.098 (−0.678) | 0.278 (1.495) |
| ROA | 0.553 (1.409) | 0.454 (1.424) |
| Lev | 0.435 (1.203) | 0.396 (1.009) |
| RD | 2.350** (2.509) | 1.453 [†] (1.751) |
| Pee | 0.104 (0.259) | 0.878* (1.895) |
| Inst | −0.086 (−0.357) | −0.043 (−0.191) |
| HHI | −1.611 (−1.297) | −2.093 (−1.360) |
| KZ | −0.014 (−0.770) | −0.035** (−2.023) |
| CFC | 0.504** (2.501) | 0.334 [†] (1.892) |
| Capex | 2.115*** (2.964) | 1.363** (2.017) |
| NWC | 0.457 (1.449) | 0.486 (1.416) |
| SOE | −0.170 (−1.085) | −0.045 (−0.294) |
| Constant | −1.500 (−0.906) | −1.936 (−0.992) |
| Year | Yes | Yes |
| Firm | Yes | Yes |
| N | 4422 | 4422 |
| Adj-R ² | 0.037 | 0.046 |

Notes: [†]significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

in non-invention patents. Combined, the graphical evidence in Fig. 4 suggests that the DID model satisfies the parallel trend assumption.

Robustness tests. To ensure the robustness of the results, we further conducted robustness tests by various methods.

Placebo tests. First, to exclude the impact of random time trends, a placebo test is used. We randomly selected the same number of firm-year observations to be the placebo-treated group. The number is 1337, which equals the sample size 4422 multiplied by the mean of *Treat* × *Post* 0.302 in the baseline model. The remaining samples are the new control group. Figure 5 indicates that the estimated coefficients of placebo *Treat* × *Post* in 1000 times bootstraps are located near zero. It suggests that the innovation effect of MIC 2025 on focal firms is caused by the MIC 2025 policy, not random time trends.

Endogeneity tests. Second, to test the endogeneity of the selection of MIC 2025 pilot cities, this study first checks whether city-specific economic factors result in different probabilities of pilot city selection using the Logit model.

The dependent variable of the Logit model is *Treat*, describing whether a city is being selected as the MIC 2025 pilot city at time *t*. The independent variables are city-specific variables one year before the cities' selection at time *t*−1. Table 6 shows that all city-specific variables are insignificant and do not endogenously promote the probability of being selected as a MIC 2025 pilot city.

It further analyzes whether other non-economic factors (such as political connections) result in different probabilities of pilot city selections. Political connections with powerful politicians,

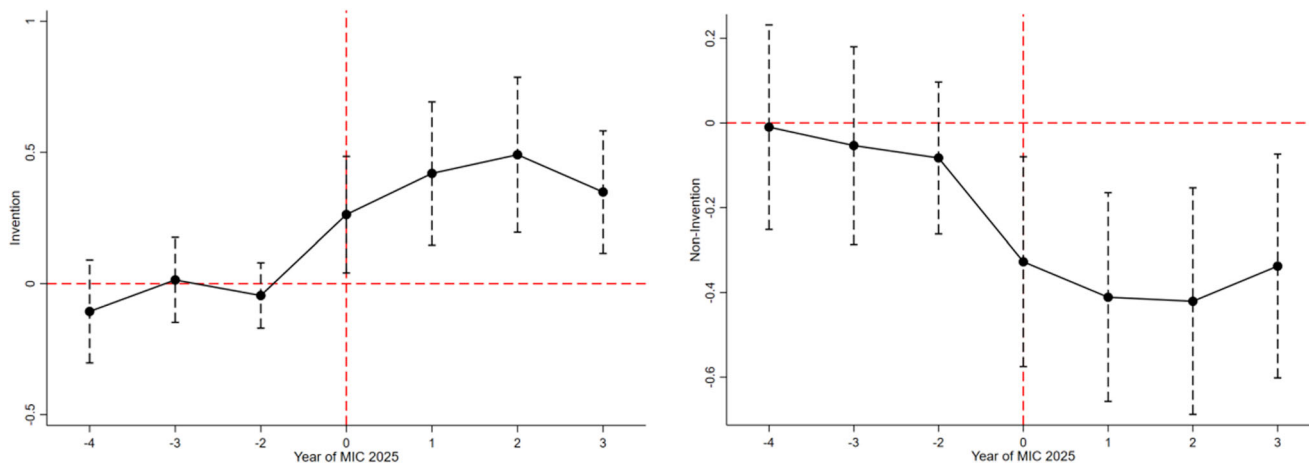


Fig. 4 Parallel trend tests.

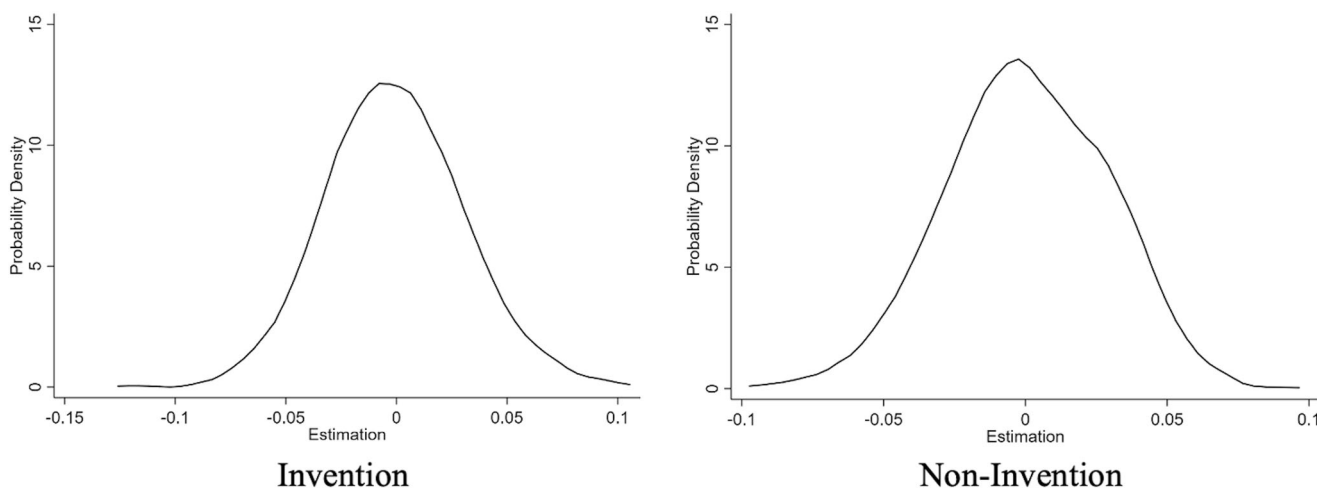


Fig. 5 Placebo test.

Table 6 Endogeneity test: city-specific factors Logit model.

| Variables | Treat |
|------------------------|-----------------|
| GDP per capita | -0.122 (-0.299) |
| GDP growth rate | 11.578 (1.033) |
| Science and Technology | 45.341 (0.432) |
| LnPopulation | 0.284 (0.709) |
| Research_Employment | 16.197 (0.269) |
| Infra_Spending | -1.642 (-1.544) |
| Apply_Patent | -0.381 (-0.566) |
| Obtain_Patent | 0.740 (1.080) |
| Constant | -5.321 (-1.072) |
| N | 290 |
| Pseudo-R ² | 0.144 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets.

especially national leadership, highly influence economic growth and corporate behaviors (Jones and Olken, 2005; Cohen et al., 2011; Fan et al., 2016). MIC 2025 was proposed by the Chinese state council. Thus, whether local cities have political connections with the premier and vice-premiers in the state council and the state president and vice president (through work or birth place) may endogenously affect the selection of pilot cities. Table 7 provides intergroup comparisons of the probability of being

selected as a MIC 2025 pilot city, using a *t*-test. The results show that cities with political connections actually gain a lower probability of being selected as MIC 2025 pilot cities, compared with the groups without political connections. The differences are also statistically significant. This finding suggests that political connections do not endogenously promote the probability of being selected as a MIC 2025 pilot city.

Excluding other industrial policies. In order to exclude influences from other industrial policies, we consider whether the firm is in the main industries supported by the central government (*IMPIND*) and whether or not the firm is identified as a high-tech firm (*High-tech*) (Chen and Kim, 2023). Table 8 shows that by adding these variables, the coefficients of *Treat* × *Post* are still significantly positive in *Invention* and significantly negative in *Non-Invention*, which supports the results in the baseline model.

Change of model designs and samples. According to Baker et al. (2022), the time-varying DID model may result in inefficient estimators. We further use *did_multipligt* command in Stata to test the time-varying DID model with a heterogenous treatment effect (De Chaisemartin and d’Haultfoeuille, 2020). Table 9 shows the results of the DIDM model. Moreover, considering the independent variables are based on patent application

Table 7 Endogeneity test: political connection.

| Type of political connections | Group with political connections | Group without political connections | Intergroup difference |
|---------------------------------------|----------------------------------|-------------------------------------|-----------------------|
| Once worked now State Council leaders | 0.343 | 0.589 | 0.246*** |
| Once worked now State leaders | 0.321 | 0.615 | 0.294*** |
| State Council leaders' birth place | 0.339 | 0.594 | 0.255*** |
| State leaders' birth place | 0.321 | 0.615 | 0.294*** |

Notes: ***significant at 1%.

Table 8 Robustness test excluding other industrial policies.

| Variable | Invention | Non-invention |
|----------------------------|------------------|--------------------|
| <i>Treat</i> × <i>Post</i> | 0.411*** (4.656) | -0.325*** (-2.995) |
| Size | 0.133* (1.854) | 0.133 (1.553) |
| Age | -0.119 (-0.830) | 0.279 (1.493) |
| ROA | 0.559 (1.417) | 0.456 (1.425) |
| Lev | 0.432 (1.195) | 0.398 (1.016) |
| RD | 2.306** (2.459) | 1.440* (1.735) |
| Pee | 0.111 (0.277) | 0.887* (1.924) |
| Inst | -0.086 (-0.362) | -0.046 (-0.205) |
| HHI | -1.753 (-1.424) | -2.101 (-1.365) |
| KZ | -0.013 (-0.714) | -0.034** (-2.008) |
| CFC | 0.503** (2.491) | 0.342* (1.926) |
| Capex | 2.170*** (3.077) | 1.385** (2.045) |
| NWC | 0.475 (1.501) | 0.494 (1.440) |
| SOE | -0.169 (-1.078) | -0.047 (-0.305) |
| IMPIND | 0.531 (1.476) | 0.030 (0.261) |
| High-Tech | 0.005 (0.104) | -0.041 (-1.002) |
| Constant | -1.510 (-0.917) | -1.912 (-0.981) |
| Year | Yes | Yes |
| Firm | Yes | Yes |
| N | 4422 | 4422 |
| Adj-R ² | 0.039 | 0.047 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

Table 9 Robustness tests: DIDM.

| Variables | Invention | Non-Invention |
|----------------------------|-----------------|--------------------|
| <i>Treat</i> × <i>Post</i> | 0.246** (2.217) | -0.316*** (-2.744) |
| Controls | Yes | Yes |
| Year | Yes | Yes |
| Firm | Yes | Yes |
| N | 673 | 673 |

Notes: **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level. The number of bootstrap replicates is 10 to be used in the computation of estimators' standard errors. The seed is set to be equal to 1000 in the bootstrap replications, to ensure results can be reproduced.

numbers, we further use the Poisson model for robustness tests. Table 10 provides the results of the Poisson regression. The results of the DIDM and Poisson model are both robust, which supports H1.

To exclude the potential influence from COVID-19, we use data from 2012 to 2019. Table 11 shows the results after excluding the potential influence from COVID-19. The results are also robust.

Further analysis

Mechanism analysis. The analysis of the mediation effect is in Table 12. The independent variable is *Invention*. The mediators

Table 10 Robustness tests: Poisson model.

| Variables | Invention | Non-invention |
|----------------------------|--------------------|--------------------|
| <i>Treat</i> × <i>Post</i> | 0.216*** (6.652) | -0.199*** (-5.792) |
| Size | 0.108*** (2.834) | 0.101*** (2.976) |
| Age | -0.054 (-0.899) | 0.217*** (3.414) |
| ROA | 0.437 (1.514) | 0.464** (1.993) |
| Lev | 0.302 (1.483) | 0.238 (1.280) |
| RD | 1.596*** (2.908) | 1.155** (2.499) |
| Pee | 0.076 (0.305) | 0.702*** (3.252) |
| Inst | -0.040 (-0.328) | -0.027 (-0.259) |
| HHI | -1.108* (-1.935) | -1.658*** (-3.013) |
| KZ | -0.009 (-0.882) | -0.025** (-2.487) |
| CFC | 0.355*** (2.838) | 0.233*** (2.046) |
| Capex | 1.363*** (3.656) | 0.926*** (2.649) |
| NWC | 0.342** (2.097) | 0.294* (1.887) |
| SOE | -0.089 (-1.338) | -0.005 (-0.076) |
| Constant | -2.950*** (-3.235) | -2.682*** (-3.015) |
| Year | Yes | Yes |
| Firm | Yes | Yes |
| N | 4422 | 4422 |
| Pseudo R ² | 0.268 | 0.303 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets.

Table 11 Robustness tests: excluding COVID-19.

| Variables | Invention | Non-invention |
|----------------------------|------------------|--------------------|
| <i>Treat</i> × <i>Post</i> | 0.414*** (4.688) | -0.320*** (-3.108) |
| Size | 0.145* (1.785) | 0.082 (0.825) |
| Age | -0.016 (-0.094) | 0.363* (1.824) |
| ROA | 0.535 (1.059) | 0.523 (1.378) |
| Lev | 0.264 (0.637) | 0.284 (0.679) |
| RD | 4.234*** (3.722) | 1.889* (1.927) |
| Pee | 0.680 (1.455) | 1.129** (2.346) |
| Inst | 0.007 (0.026) | -0.073 (-0.301) |
| HHI | -1.725 (-1.224) | -4.743*** (-2.662) |
| KZ | -0.002 (-0.089) | -0.036* (-1.876) |
| CFC | 0.598*** (3.004) | 0.355* (1.738) |
| Capex | 1.588** (2.089) | 1.128* (1.686) |
| NWC | 0.496 (1.389) | 0.408 (1.148) |
| SOE | -0.282 (-1.533) | -0.104 (-0.633) |
| Constant | -2.051 (-1.098) | -0.677 (-0.306) |
| Year | Yes | Yes |
| Firm | Yes | Yes |
| N | 3216 | 3216 |
| Adj-R ² | 0.044 | 0.037 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on firm level.

are *Tax*, *Subsidy*, *Financing*, *Collaboration* and *Talent*. For each mediator, we first analyze how *Treat* × *Post* influences the mediator. Then, we add both *Treat* × *Post* and the mediator in the regression to check whether the estimated coefficients of *Treat* × *Post* are lower than that in the baseline model. For

Table 12 Mechanism analysis.

| Variable | Tax | Invention | Subsidy | Invention | Financing | Invention | Collaboration | Invention | Talent | Invention |
|--------------------|---------------------|----------------------|---------------------|---------------------|-------------------|---------------------|--------------------|---------------------|--------------------|---------------------|
| Treat × Post | -0.023* (-2.005) | 0.390*** (4.501) | 0.002*** (3.358) | 0.379*** (4.348) | 0.013* (2.525) | 0.373*** (4.351) | 0.081** (2.507) | 0.372*** (4.239) | 0.017** (2.450) | 0.382*** (4.421) |
| Mediators | | | | | | | | | | |
| | | -0.238** (-2.036) | | 9.502*** | | 1.738*** | | 0.284*** (2.679) | | 0.728** (2.298) |
| Size | 0.002 | 0.135* | -0.001 | 0.140** | -0.016*** | 0.163** | 0.041* | 0.123* | 0.003 | 0.132* |
| Age | (0.208) | (1.875) | (-1.453) | (1.971) | (-3.165) | (2.314) | (1.806) | (1.706) | (0.602) | (1.865) |
| | -0.009 | -0.101 | 0.002*** | -0.122 | -0.009 | -0.083 | 0.021 (0.388) | -0.105 | 0.030** | -0.121 |
| ROA | (0.619***) | (-0.696) | (3.015) | (-0.844) | (-1.052) | (-0.570) | | (-0.726) | (2.587) | (-0.830) |
| | (9.822) | (1.762) | (0.003) | (0.502) | (-0.028) | (0.581) | 0.026 | (0.525) | (-0.033) | (0.557) |
| Lev | (-0.014) | (1.762) | (1.364) | (1.278) | (-1.140) | (1.499) | (0.264) | (1.336) | (-1.018) | (1.438) |
| | (-0.280) | (1.147) | (2.151) | (1.055) | (6.180) | (0.543) | (-0.169) | (1.285) | (-0.013) | (0.428) |
| RD | (-0.032) | (2.338**) | (0.008) | (2.267**) | (0.002) | (2.343**) | (0.141 (0.503)) | (2.306**) | (-0.459) | (1.194) |
| | (-0.176) | (2.496) | (1.330) | (2.412) | (0.034) | (2.538) | | (2.467) | (0.126) | (2.254**) |
| Peo | (0.068) | (0.102) | (0.008***) | (0.010) | (-0.091***) | (0.245) | (-0.067) | (0.105) | (1.218) | (2.388) |
| | (1.087) | (0.257) | (3.561) | (0.026) | (-3.766) | (0.616) | (-0.0487) | (0.264) | (-0.083**) | (0.147) |
| Inst | (-0.086**) | (-0.103) | (-0.000) | (-0.081) | (-0.016) | (-0.055) | (-0.138**) | (-0.043) | (-0.022) | (-0.066) |
| | (-2.513) | (-0.427) | (-0.154) | (-0.339) | (-1.101) | (-0.229) | (-2.100) | (-0.180) | (-1.357) | (-0.277) |
| HHI | (0.247) | (-1.587) | (-0.013**) | (-1.523) | (-0.078) | (-1.510) | (0.150 (0.415)) | (-1.689) | (0.037) | (-1.673) |
| | (1.267) | (-1.275) | (-2.156) | (-1.234) | (-1.115) | (-1.226) | | (-1.371) | (0.433) | (-1.368) |
| KZ | (0.004) | (-0.013) | (0.000) | (-0.014) | (0.003***) | (-0.019) | (-0.002) | (-0.014) | (0.001) | (-0.015) |
| | (1.453) | (-0.701) | (0.180) | (-0.762) | (3.364) | (-1.034) | (-0.311) | (-0.730) | (0.979) | (-0.808) |
| CFC | (-0.073*) | (0.492**) | (0.002) | (0.494**) | (-0.007) | (0.521**) | (-0.041) | (0.521***) | (-0.028) | (0.529***) |
| | (-1.745) | (2.451) | (1.203) | (2.439) | (-0.460) | (2.581) | (-0.830) | (2.597) | (-1.504) | (2.635) |
| Capex | (-0.227*) | (2.096***) | (0.009**) | (2.066***) | (-0.093*) | (2.312**) | (0.020 (0.107)) | (2.144**) | (0.006) | (2.145***) |
| | (-1.904) | (2.935) | (2.113) | (2.893) | (-2.234) | (3.272) | | (3.042) | (0.155) | (3.028) |
| NWC | (-0.036) | (0.445) | (0.004**) | (0.413) | (-0.126***) | (0.672**) | (-0.109) | (0.484) | (-0.051**) | (0.490) |
| | (-0.825) | (1.404) | (3.026) | (1.291) | (-6.727) | (2.066) | (-1.110) | (1.527) | (-2.127) | (1.557) |
| SOE | (0.012) | (-0.166) | (-0.001*) | (-0.157) | (-0.006) | (-0.158) | (-0.032) | (-0.160) | (0.003) | (-0.171) |
| | (0.552) | (-1.070) | (-1.743) | (-1.013) | (-0.873) | (-1.009) | (-0.770) | (-1.022) | (0.232) | (-1.098) |
| Constant | (0.109) | (-1.518) | (0.011) | (-1.652) | (0.471***) | (-2.363) | (-0.666) | (-1.355) | (-0.080) | (-1.486) |
| | (0.427) | (-0.908) | (1.275) | (-1.002) | (4.056) | (-1.442) | (-1.306) | (-0.812) | (-0.645) | (-0.904) |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 4422 | 4422 | 4422 | 4422 | 4422 | 4422 | 4422 | 4422 | 4422 | 4422 |
| Adj-R ² | 0.048 | 0.039 | 0.039 | 0.040 | 0.170 | 0.045 | 0.179 | 0.040 | 0.585 | 0.039 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

example, Column 1 shows that $Treat \times Post$ has a significantly negative effect on Tax . Column 2 shows that located in MIC 2025 cities promote firm innovation through lowering tax rates. According to Wang et al. (2022) and Jebran et al. (2023), it calculates the mediation effects by the percentage change of the new estimated coefficient of $Treat \times Post$ compared with that in the baseline model (which is 0.395). The mediation effect of Tax is 1.266% (which is calculated by $(0.395 - 0.390) / 0.395$).

For the remaining mediators, the results in Table 12 indicate that $Treat \times Post$ has a significantly positive effect on $Subsidy$, $Financing$, $Collaboration$, and $Talent$, which shows that located in MIC 2025 cities promote firm innovation by improving public subsidies, convenient financing, academic collaboration, and talent incentives. Moreover, the mediation effect of $Subsidy$ is 4.051%. The mediation effect of $Financing$ is 5.570%. The mediation effect of $Collaboration$ is 5.823%. The mediation effect of $Talent$ is 3.291%. The overall mediation effect of the five mediators is 20%. The mechanisms of convenient financing and academic collaborations are more important than other mediators during the implementation of MIC 2025 pilot cities.

Heterogeneity analysis. Pilot cities are different in terms of geographical locations. We use whether pilot cities are located in eastern, middle, or western China to check for city heterogeneity. The results of the heterogeneity are provided in Table 13. Results show that location in MIC 2025 has a significantly larger effect on firm innovation in Western China cities, compared with eastern or middle China cities. The intergroup difference test of the estimated coefficients supports this result.

Moreover, in order to test industry heterogeneity, we divide the samples into two subgroups, by whether a focal firm is in high-tech sectors or not. Results show that located in MIC 2025 has a stronger effect on firm innovation in high-tech industries but the intergroup difference is not significant. For firm heterogeneity, we consider firm size and ownership differences. We test the innovation effect for SOEs versus non-SOEs, as well as large-size firms versus small-size firms. It divides the full sample into the large-size subgroup and the small-size subgroup, by the median of firm size of the full sample. Results show that compared with non-SOEs, located in MIC 2025 pilot cities better promote SOEs' innovation. There exist significant intergroup differences between the SOEs and non-SOEs. However, the difference between the large-size firms and small-size firms is not significant.

Economic performance analysis. We are also interested in whether MIC 2025 pilot cities influence firms' economic performance. We first use Tobin's Q (TQ) and TFP (TFP_{LP}) as the independent variable in the baseline model. Table 14 shows that being located in MIC 2025 cities significantly promotes firm innovation and further increases firms' Tobin's Q and TFP.

To test whether MIC 2025 pilot cities have a spillover effect, which increases the innovation of firms located in the nearby cities, we define the cities border on MIC 2025 pilot cities to be the new treatment group, while the remaining cities that do not border on MIC 2025 cities as the new control group. We regress $Invention_t$, $Invention_{t+1}$, $Invention_{t+2}$, $Invention_{t+3}$ on the newly established independent variable $Border \times Post$. Table 15 shows that in periods t and $t + 1$, MIC 2025 does not increase firm innovation, which is located in cities bordering on MIC 2025 cities. The spillover effect starts in periods $t + 2$ and $t + 3$. Results show that MIC 2025 promotes firm innovation, which is located in cities bordering MIC 2025 significantly at $t + 2$ and $t + 3$.

Discussion and conclusion

How industrial policy affects firm innovation is a heated topic, especially in transitional economies, such as China. Previous studies focus more on the debate of whether China's central government's selective industrial policy has good economic consequences (Aghion et al., 2015; Howell, 2017). Regarded as a techno-nationalist industrial policy (Petricevic and Teece, 2019), policymakers and scholars have widely focused on how MIC 2025 influences China's OFDI; the welfare impact of MIC 2025 subsidies (Zhao and Lee, 2021; Ju et al., 2021) has also been analyzed. However, as an innovation-oriented industrial policy, it is still not clear whether and how MIC 2025 influences firm innovation.

On the perspective of the resource-based view (RBV) (Barney, 1991; Wernerfelt, 1984), we proposed that located in MIC 2025 creates resource incentives and competitive incentives, which relax the resource constraints for firm innovation. This study investigates MIC 2025's influence on firm innovation using MIC 2025 pilot cities as a quasi-natural experiment. Using the PSM-DID model, this study demonstrates that located in MIC 2025 pilot cities promote firm high-quality innovation. Mechanism analysis shows that it promotes firm innovation through tax incentives, public subsidies, convenient financing, academic collaboration, and talent incentives.

Our paper contributes to and extends industrial policy literature regarding how place-based policy experimentation implements the sector-based industrial policy in China. Previous studies of MIC 2025 on firm innovation regard MIC 2025 as a sector-based industrial policy and ignore the policy implementation by the local governments (Wen and Zhao, 2021; Branstetter and Li, 2022). These studies regard the ten preferred sectors in MIC 2025 as a treatment group in the quasi-natural experiment settings. In fact, several industrial policies are implemented by the local governments during place-based policy experimentation in China (Chen, 2023). The policy text of MIC 2025 clearly states that local governments from the MIC 2025 pilot cities provide various policy supports to facilitate MIC 2025 implementation. China's sector-based or place-based industrial policies are the top-down model. Of them, the central government's "picking the winners" may result in low efficiencies (Rodrik, 2008), and local governments as policy-takers have little embedded autonomy (Chen, 2023; Ling et al., 2023). We proposed that although MIC 2025 has clear sector preferences, it relies heavily on the support of local governments in the pilot cities during the policy experimentation. The effectiveness of MIC 2025 depends on the design of policy supported by the MIC 2025 pilot cities.

Our paper also contributes to how MIC 2025 influences firm innovation. We contribute to MIC 2025 literature by moving from "whether MIC 2025 should be implemented" to "how MIC 2025 is implemented". Previous studies evaluating industrial policies focused on the treatment effect, which is the first layer of industrial policies. It usually ignores the second layer, the implementation of the policy (Juhász et al., 2023). For example, scholars usually identify the treatment group by whether the core business is the preferred sector of the policy (Feng, 2019; Branstetter and Li, 2022). Our paper empirically tests how MIC 2025 pilot cities promote firm innovation using mechanism analysis. Evidence shows that being located in MIC 2025 cities can promote firm innovation by tax incentives, public subsidies, convenient financing, academic collaboration, and talent incentives. Through policy experiments, the intention of the central government is transferred to pilot cities and performed by participation in the form of policy support from the local governments.

It has some implications for policymakers and firms. First, it provides policy implications for the central government to

Table 13 Heterogeneity analysis.

| Variables | City heterogeneity | | Industry heterogeneity | | Ownership heterogeneity | | Size heterogeneity | | |
|-----------------------|---------------------|--------------------|------------------------|---------------------|-------------------------|---------------------|---------------------|---------------------|---------------------|
| | Eastern China | Middle China | Western China | High-tech | Non High-tech | SOE | Non-SOE | Large size | Small size |
| Treat × Post | 0.394*** (3.432) | 0.340** (2.146) | 0.760*** (2.797) | 0.432*** (4.061) | 0.302** (2.167) | 0.596*** (3.467) | 0.337*** (3.367) | 0.391*** (3.332) | 0.439*** (3.350) |
| Size | 0.141 (1.621) | 0.160 (1.170) | 0.176 (0.899) | 0.204** (2.232) | 0.013 (0.118) | 0.048 (0.344) | 0.166** (2.000) | 0.159 (1.521) | 0.160 (1.564) |
| Age | 0.097 (0.490) | -0.377 (-1.524) | -0.400 (-1.147) | -0.067 (-0.389) | -0.187 (-0.706) | -0.712* (-1.708) | 0.095 (0.548) | -0.278 (-1.342) | -0.151 (-0.641) |
| ROA | 0.107 (0.216) | 1.678** (2.328) | -0.929 (-0.671) | 0.840* (1.679) | -0.036 (-0.063) | 0.975 (1.237) | 0.484 (1.104) | 0.976 (1.390) | 0.207 (0.452) |
| Lev | 0.082 (0.179) | 1.178 (1.788) | 0.212 (0.173) | 1.069** (2.287) | -0.575 (-1.226) | 0.465 (0.634) | 0.350 (0.824) | 0.282 (0.575) | 0.437 (0.818) |
| RD | 2.054* (1.716) | 5.591** (2.596) | -1.044 (-0.503) | 2.826** (2.239) | 2.169* (1.659) | 2.287 (0.799) | 2.167** (2.160) | 0.717 (0.499) | 3.166*** (2.697) |
| Pee | 0.351 (0.648) | 0.047 (0.062) | -1.352 (-1.416) | 0.531 (0.975) | -0.646 (-1.384) | 0.006 (0.007) | 0.055 (0.118) | -0.550 (-1.008) | 0.901 (1.427) |
| Inst | 0.116 (0.418) | -0.380 (-0.672) | 0.202 (0.284) | 0.039 (0.143) | -0.339 (-0.804) | -0.470 (-0.752) | -0.045 (-0.171) | 0.058 (0.170) | -0.225 (-0.669) |
| HHI | -3.303* (-1.845) | 0.591 (0.254) | 0.110 (0.049) | -1.462 (-0.898) | -1.376 (-0.729) | -2.953 (-1.319) | -0.899 (-0.587) | -3.392** (-2.196) | 0.650 (0.332) |
| KZ | -0.012 (-0.478) | -0.009 (-0.265) | -0.059 (-0.819) | -0.020 (-0.849) | -0.008 (-0.242) | -0.064 (-1.627) | 0.001 (0.033) | -0.017 (-0.550) | -0.016 (-0.682) |
| CFC | 0.631** (2.573) | 0.018 (0.041) | 0.854 (1.502) | 0.505* (1.928) | 0.531* (1.835) | -0.076 (-0.168) | 0.606*** (2.645) | 0.434 (1.438) | 0.548** (1.972) |
| Capex | 2.069** (2.429) | 2.451 (1.647) | 2.201 (1.169) | 2.901*** (3.332) | 0.626 (0.531) | 2.579 (1.286) | 2.118** (2.724) | 2.049** (2.037) | 1.822* (1.839) |
| NWC | 0.351 (0.845) | 0.517 (1.060) | 0.825 (0.801) | 0.835** (2.000) | -0.135 (-0.346) | -0.287 (-0.431) | 0.624* (1.728) | 0.093 (0.218) | 0.576 (1.196) |
| SOE | -0.316* (-1.955) | -0.035 (-0.110) | 0.420 (0.621) | -0.246 (-1.156) | -0.043 (-0.190) | (-0.431) | (-0.431) | 0.056 (0.273) | -0.307 (-1.385) |
| Constant | -1.856 (-0.917) | -2.125 (-0.684) | -1.855 (-0.388) | -3.579* (-1.668) | 1.835 (0.771) | 2.771 (0.770) | -2.793 (-1.464) | -1.077 (-0.445) | -2.656 (-1.127) |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2601 | 1323 | 498 | 3124 | 1298 | 1265 | 3157 | 2211 | 2211 |
| Adj-R ² | 0.039 | 0.035 | 0.057 | 0.041 | 0.030 | 0.062 | 0.029 | 0.033 | 0.046 |
| Intergroup difference | 0.079* | | | 0.314 | | 0.041** | | 0.749 | |
| | | 0.050** | | | | | | | |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

Table 14 Economic performance analysis: Tobin's Q and TFP.

| Variables | TQ | TQ | TFP_LP | TFP_LP |
|--------------------------|--------------------|--------------------|--------------------|--------------------|
| <i>Treat × Post</i> | 0.203*** (3.023) | 0.171*** (2.596) | 0.110*** (2.631) | 0.091** (2.155) |
| <i>Invention</i> | | 0.081*** (2.735) | | 0.048*** (2.675) |
| <i>Size</i> | -0.521*** (-8.630) | -0.532*** (-8.753) | 0.417*** (11.958) | 0.410*** (11.600) |
| <i>Age</i> | 0.337*** (2.779) | 0.345*** (2.857) | 0.150* (1.953) | 0.155** (1.989) |
| <i>ROA</i> | 2.333*** (5.454) | 2.290*** (5.377) | 0.808*** (4.722) | 0.783*** (4.568) |
| <i>Lev</i> | 0.194 (0.715) | 0.161 (0.592) | 0.633*** (3.875) | 0.613*** (3.744) |
| <i>RD</i> | -3.086*** (-3.494) | -3.276*** (-3.694) | -3.366*** (-5.147) | -3.477*** (-5.411) |
| <i>Pee</i> | 0.153 (0.425) | 0.147 (0.404) | -1.159*** (-6.107) | -1.163*** (-6.037) |
| <i>Inst</i> | 1.706*** (8.731) | 1.713*** (8.748) | 0.363*** (3.940) | 0.366*** (3.981) |
| <i>HHI</i> | 0.070 (0.078) | 0.203 (0.230) | 3.145*** (3.263) | 3.224*** (3.322) |
| <i>KZ</i> | 0.187*** (8.474) | 0.188*** (8.471) | 0.009 (1.099) | 0.009 (1.177) |
| <i>CFC</i> | -0.030 (-0.160) | -0.071 (-0.376) | 0.130 (1.420) | 0.106 (1.178) |
| <i>Capex</i> | 1.842*** (3.038) | 1.668*** (2.721) | 0.180 (0.811) | 0.077 (0.336) |
| <i>NWC</i> | 0.555** (2.169) | 0.518** (1.989) | 0.460*** (3.460) | 0.439*** (3.335) |
| <i>SOE</i> | -0.223** (-2.008) | -0.210* (-1.897) | -0.051 (-0.868) | -0.043 (-0.768) |
| <i>Constant</i> | 10.921*** (8.202) | 11.045*** (8.204) | -1.766** (-2.325) | -1.693** (-2.210) |
| <i>Year</i> | Yes | Yes | Yes | Yes |
| <i>Firm</i> | Yes | Yes | Yes | Yes |
| <i>N</i> | 4422 | 4422 | 4422 | 4422 |
| <i>Adj-R²</i> | 0.287 | 0.294 | 0.391 | 0.400 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

Table 15 Economic performance analysis: spillover effect.

| Variables | <i>Invention_t</i> | <i>Invention_{t+1}</i> | <i>Invention_{t+2}</i> | <i>Invention_{t+3}</i> |
|--------------------------|------------------------------|--------------------------------|--------------------------------|--------------------------------|
| <i>Border × Post</i> | 0.102 (1.175) | 0.117 (1.355) | 0.187** (2.072) | 0.252** (2.457) |
| <i>Size</i> | 0.172** (2.163) | -0.035 (-0.424) | -0.126 (-1.562) | -0.253*** (-3.138) |
| <i>Age</i> | -0.175 (-1.147) | -0.217 (-1.395) | -0.116 (-0.628) | -0.301* (-1.701) |
| <i>ROA</i> | 0.182 (0.562) | 0.365 (0.781) | -0.069 (-0.174) | 0.377 (0.782) |
| <i>Lev</i> | -0.004 (-0.012) | 0.096 (0.292) | 0.180 (0.540) | 0.105 (0.294) |
| <i>RD</i> | 0.873 (0.874) | -0.590 (-0.555) | -0.600 (-0.487) | 0.237 (0.168) |
| <i>Pee</i> | 0.270 (0.733) | -0.130 (-0.277) | 0.298 (0.628) | 0.445 (0.968) |
| <i>Inst</i> | 0.217 (0.935) | 0.452* (1.876) | 0.207 (0.813) | 0.204 (0.850) |
| <i>HHI</i> | -2.263* (-1.890) | -1.702 (-1.405) | -2.277 (-1.441) | -0.197 (-0.113) |
| <i>KZ</i> | -0.005 (-0.318) | 0.005 (0.231) | 0.006 (0.272) | -0.020 (-0.935) |
| <i>CFC</i> | 0.189 (1.113) | 0.093 (0.489) | 0.106 (0.531) | 0.032 (0.151) |
| <i>Capex</i> | 1.410** (2.478) | 0.176 (0.266) | -0.166 (-0.219) | -1.383** (-1.989) |
| <i>NWC</i> | 0.048 (0.183) | 0.077 (0.297) | 0.337 (1.239) | -0.128 (-0.403) |
| <i>SOE</i> | 0.022 (0.171) | 0.067 (0.515) | 0.239 (1.609) | 0.131 (1.048) |
| <i>Constant</i> | -2.201 (-1.215) | 2.385 (1.301) | 4.139** (2.328) | 7.307*** (4.050) |
| <i>Year</i> | Yes | Yes | Yes | Yes |
| <i>Firm</i> | Yes | Yes | Yes | Yes |
| <i>N</i> | 3454 | 3454 | 3454 | 3454 |
| <i>Adj-R²</i> | 0.026 | 0.151 | 0.179 | 0.220 |

Notes: *significant at 10%, **significant at 5%, ***significant at 1%; t-values are in the brackets. Standard errors are clustered on a firm level.

integrate both sector-based and place-based policies during industrial policy experimentation. Integrating sector-based and place-based policies provides more accurate incentives for both manufacturing firms and local governments to upgrade key technologies urgently needed in the local region. MIC 2025 pilot cities not only target key sectors but also incentivize the local governments to provide policy support. Establishing better central-local interactions is vital for the success of policy experiments in China. Pilot city policy experiments provide embedded autonomy for the local governments, which mitigates government failure in central government decision-making.

Second, the local governments should provide various kinds of policy instruments during policy experimentation. Apart from traditional policy instruments, such as tax incentives or public subsidies, the local government should provide more convenient

financing, academic collaboration, and talent incentives to reduce resource constraints and create a better competition environment. Policymakers of the local governments should target high-quality innovation and provide iterative public-private collaborations during policy experimentation. Third, during policy implementation, firms in the supported sectors of MIC 2025 need to improve their R&D ability and competition incentives by deeper collaborations with academics, which together form a better innovation ecosystem. Firms should also upgrade their technologies to intelligent manufacturing and highlight the cultivation of engineering and technical talents.

This study also has some limitations. First, due to data limitations, this study evaluates only the innovation effect of MIC 2025 by firm-level data. City-level data based on local policy documents for MIC 2025 will provide evidence about how local

governments respond to the central government during policy experimentation. Meanwhile, future studies can analyze whether there exists policy learning during policy experimentations across the cities and bring new insights into policy implementation. Second, the sample is listed as manufacturing firms. This study uses patent applications of the firms' head offices to modify the innovation effect. Future studies should increase the sample size by using patent applications of unlisted firms and test whether MIC 2025 has a heterogeneous effect between bigger firms and smaller firms. Moreover, since MIC 2025 also has goals such as green transformation and intelligent manufacturing, future studies can further test whether MIC 2025 influences green innovation or digital innovation (Chen and Hao, 2022). Third, this study focuses on ten manufacturing sectors supported by MIC 2025, the effect of MIC 2025 on different manufacturing sectors remains unclear. Future studies should analyze whether MIC 2025 has sectoral effects and inter-sector spillover effects to provide a sectoral implication of MIC 2025.

Data availability

The data that support the findings of this study are in the supplementary.

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Note

1 MIC 2025 highlights the following ten priority sectors: (1) New advanced information technology; (2) automated machine tools & robotics; (3) aerospace and aeronautical equipment; (4) maritime equipment and high-tech shipping; (5) modern rail transport equipment; (6) new-energy vehicles and equipment; (7) power equipment; (8) agricultural equipment; (9) new materials, and (10) biopharma and advanced medical products.

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Author contributions

Authors are arranged alphabetically, and all coauthors have made equal contributions to the paper.

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The authors declare no competing interests.

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