Industrial Policy, Congruence, and Innovation: Evidence from "Chinese NASDAQ"

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Abstract

Based on a unique quasi-experimental setting in China, we first document a strong link between firm innovation and endowment-based fundamental factors through the lens of congruence and then examine the effects of a national-level industrial policy on this newly established link. The results suggest that the effect of the "Made in China 2025" (MC2025) industrial policy is nontrivial among small, innovative firms treated in the ten high-tech manufacturing sectors and significantly mitigates the congruence impact. This effect increases bank loans for treated firms and thus has a positive effect on promoting private R&D investments, which works as an effective mechanism to enhance the innovation outcomes measured by both patent numbers and citations. Our analysis implies that MC2025 is a double-edged sword. It helps reduce the power of congruence and generates capital misallocations and policy distortions that may impede long-term innovation capabilities.

Keywords: congruence; industrial policy; innovation; R&D intensity; patents

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1. Introduction

A large body of scholarship in economics examines the role of industrial policy in overcoming market failures and promoting innovation and economic growth at both macro and micro levels (Rodrik, 1996, 2008a, b; Bardhan, 2016; Boeing, 2016; Guo et al., 2016, 2017, 2022; Howell, 2017; Lee and Malerba, 2017; Mu and Lee, 2005). These studies have made important progress by studying both theoretical justifications and economic outcomes of a variety of industry policies that aimed to promote new infant industries or protect selective traditional sectors in different countries, including the provision of tax allowances, loans, grants, education, and training, special organizations, selective investments, government procurement, regulations, and so on (Aghion et al., 2015; Guan and Yam, 2015; Wang and Hua, 2022). Despite opposing theoretical arguments and mixed empirical findings, evidence of the impact of industrial policy on the link between innovation and fundamental factors from the perspective of congruence is still very scant.

In this paper, we conduct empirical analyses using rich microlevel data of Chinese small, innovative firms, which potentially suffer from financing constraints, to provide novel insights into the effects of government interventions on corporate innovations and sectoral development. For a growing economy such as China, which has been gradually losing its comparative advantage in labor-intensive sectors and approaching the world technology frontier, innovation has become an increasingly important driving force for industrial upgrading and economic growth (Wei et al., 2017). China's R&D expenditures in both public and private sectors have been steadily increasing to support "indigenous innovation" (Chen and Naughton, 2016; Wu, 2017).

Over the years, the Chinese government has implemented a variety of industrial policies to encourage firm innovation. One recent example is the "Made in China 2025" Strategic Plan (hereafter, MC2025), which was inspired by Germany's Industry Version 4.0 and launched by the Chinese government to promote industrial development and technology innovation in ten priority sectors[2] in May 2015. As one of the efforts to escape the middle-income trap through technology upgrading, MC2025 aims to boost innovation capabilities in strategic manufacturing industries and transform China from a low-end manufacturer into a high-end producer in the global value chain for the next 10 years. It is an ambitious nationwide strategic plan and has become very controversial internationally, attracting even more attention than the far-reaching national programs officially titled "Five-Year Plans for National Social and Economic Development".

Young and small high-technology firms, especially those in emerging industries, are generally more innovative and contribute more to aggregate growth (Acemoglu et al., 2018) but face more severe financial constraints (Howell, 2017; Chen et al., 2018). Some authors also note that small, innovative companies count on innovation even more than large firms do but are much less capable of appropriating benefits associated with innovation, which results in their underinvestment in R&D (Lerner, 1999).

In transitional economies such as China, private high-technology firms presumably find it even more challenging to obtain financing because state-owned enterprises (SOEs) usually receive more government subsidies than their private counterparts (Wu, 2017). To mitigate this problem, Chinese policy-makers make an earnest effort by adopting a portfolio of instruments to incentivize small, innovative private firms to engage in R&D. One such endeavor is the establishment of the National Equities Exchange and Quotations (NEEQ), the counterpart of NASDAQ in China in 2013[3] that aims to work as an alternative investment market to promote innovation and entrepreneurship for private small and medium-sized firms (SMEs).[4] This provides a good opportunity to empirically investigate how industrial policy affects the

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[2] The ten priority sectors include new generation information technology; advanced numerical control machine tools and robotics; aerospace technology, including aircraft engines and airborne equipment; biopharmaceuticals; high-performance medical equipment; electrical equipment; farming machines; railway equipment; energy-saving and new energy vehicles; and ocean engineering. Source: https://nhglobalpartners.com/made-in-china-2025/

[3] See media coverage at the People's Daily on May 29, 2013 with the Chinese title "The establishment of NEEQ – Chinese Nasdaq Launching", discussing how NEEQ could develop to be the Chinese Nasdaq.

[4] Source: the official website of NEEQ (http://www.neeq.com.cn/en/about_neeq/introduction.html).

innovation behaviors of small, high-technology firms. Therefore, we use the MC2025 industrial policy as a quasi-experiment to evaluate how it affects the innovation behaviors of small and medium-sized firms in the NEEQ market.

Theoretically, when the production factor choice of a firm is more congruent with the factor endowment structure of the region where the firm is located, the production is more cost-effective, and hence, corporate profits are higher (Ju et al., 2015). For example, capital-intensive firms tend to be more profitable in capital-abundant regions than in capital-scarce regions, as capital is relatively inexpensive and labor is relatively expensive when the factor endowment structure is capital-abundant; thus, the relative factor prices favor firms that use capital more intensively, ceteris paribus. This example has two immediate implications for corporate innovations. First, more congruent firms have higher capabilities to mobilize both internal and external financial resources to invest in R&D (including hiring better people to engage in innovation); therefore, both the input and output (such as patents) of R&D are higher. Second, the products newly innovated by more congruent firms also tend to be more cost-effective; therefore, the market value of new patents is higher because the newly innovated products earn more profits. As a result, more congruent firms find it more rewarding to conduct R&D; therefore, they invest more in R&D and obtain more patents. Unfortunately, the analytical angle of factor congruence has been largely ignored in the pertinent literature on firm innovation, although it has been highlighted in the literature on economic development (see Lin 2009).

The analytical focus of this paper is to explore whether the abovementioned congruence effect on innovation is empirically supported for small and medium-sized firms. Moreover, we also quantitatively investigate how the MC2025 industrial policy affects the innovation behaviors of the firms in the NEEQ market, especially through the lens of the congruence effect. We also identify some of the mechanisms that translate the industrial policy impact into innovation outcomes.

Our baseline results show a positive link between the innovation outcomes of small, innovative firms in China and the congruence index, which measures the distance between a firm's factor input structure and the city-industry endowment structure. Evidence on the mechanisms shows that research and development (R&D) intensity, return on equity (ROE), and total factor productivity (TFP) are behind the observed effects.

Our further analyses demonstrate that industrial policy interventions via MC2025 strongly mitigate the determining impact of congruence on firm innovation outcomes, and the main possible channel is through reallocating banking loans and, hence, increasing both the financial leverage and R&D intensity of treated firms. However, we do not identify any significant changes in the government subsidies of treated small, innovative, private firms. This indicates that more subsidies have been allocated to large public companies or SOEs under this strategic layout, which is consistent with previous findings such as those of Boeing (2016) and Wu (2017).

We find that the MC2025 program is a double-edged sword. On the one hand, evidence shows that policy interventions can enhance innovation outcomes by relaxing the requirement of factor congruence and thus helping small, innovative firms overcome financial difficulties even if their input structure is not congruent with the factor endowment structure in the region. On the other hand, the policy may result in capital misallocation across large and small high-technology firms. Small, innovative firms mainly rely on bank loans rather than government subsidies to enhance their innovation outcomes and have higher financial leverage, which may impede their long-term invocation capabilities and sustainable development.

The main policy implications of our study are as follows. First, MC2025 is useful in mitigating the impact of the fundamental economic conditions that are measured by congruence on innovation, but the effectiveness of government interventions depends on firm heterogeneity. Second, the design of industrial policy matters for long-term success. China's MC2025 program could be more effective in capital reallocation by shifting support from SOEs and large, public firms to small, innovative private firms and could be less distortive by employing more equity-based financial instruments, such as venture capital, rather than debt-based instruments, such as bank loans.

This paper is related to two strands of the literature. First, our work provides new insights into how industrial policy influences firm innovation behavior and outcomes in emerging countries such as China and thus contributes to the debate in the literature on industrial policy effectiveness. In particular, our paper enriches the literature on the effectiveness of techno-industrial policies on small and medium-sized enterprises (SMEs). One study most related to ours is by Guo et al. (2016), who analyze the impact of Innofund, one of the largest R&D subsidy programs for SMEs in China, on firms' innovation outcomes; the study highlights the role of decentralized governance in enhancing the program's effectiveness. Guo et al. (2022) further find that government R&D support increases firms' access to external funding through the channel of certifying firms' political capital. Related to their study, we examine the potential distortions induced by MC2025, an industry-level innovation policy, through the lens of firms' factor input structure and congruence with local factor endowment structures.

The implementation of China's industrial policies and their impacts have received enormous attention. Aghion et al. (2015) establish that there is complementarity between competition and suitably designed industrial policies in encouraging innovation and productivity growth in China. Hong et al. (2016) explore the function of industrial policy instruments in enhancing innovation activities by using a unique panel dataset of high-tech industries in China and show that excessive government grants exert a significantly negative impact on innovation efficiency. Lin et al. (2021) present empirical evidence that congruence is an important determinant of the success of an industrial policy.

However, there is scant empirical evidence on how industry policies alter the impact of congruence on innovation outcomes. To the best of our knowledge, this paper is among the pioneering research efforts to adopt a quasi-experimental framework to measure the distortive changes brought by industry policies in the link between fundamental factors and firm innovation. We provide novel evidence that MC2025 affects the R&D intensity and patent activities of small, innovative firms by enhancing bank loans rather than providing more government subsidies. This implies that small, innovative firms have the potential to suffer from lower innovation capabilities due to distortions generated by industry policies in the future.

Our research begs a new question for future studies on MC2025 policy impacts as well, namely, whether the specific technique of enhancing bank loans to small, innovative firms translates into higher innovation success in later years.

Second, this paper contributes to the economics literature on the important roles of congruence in innovation. Congruence, which measures the distance between a firm's technology choice (factor input structure) and the city-industry endowment structure, is explored in the literature on growth and development (Leon-Ledesma and Satchi, 2019; Lin et al., 2021). Basu and Weil (1998) highlight that the appropriate technologies for developing countries should be consistent with the factor endowment structure, while Boldrin and Levine (2002) demonstrate how rising wages drive innovation for new vintages of labor-saving capital. Jones (2005) and Caselli and Coleman (2006) study how the properties of the endogenous aggregate production function for developed countries are affected by technology choices that optimally respond to the factor endowment structure.

Most relevantly, Lin (2009) argues that the macroeconomic performance of an economy is significantly affected by the congruence of industrial structure with the comparative advantages determined by the endowment structure. Ju et al. (2015) develop a theory of endowment-driven structural change in explaining shifts in industrial structures, life-cycle industry dynamics, and aggregate economic growth and find that industries that are more congruent with endowment structures tend to have a larger value-added share in the economy. To our knowledge, this paper is the first study to examine the direct effects of congruence on the innovation outcomes of small, innovative firms. Our paper adds to the growth and development literature by showing how the degree of congruence affects the innovation of small and medium-sized firms in China, which has important policy implications.

The remainder of this paper is structured as follows. Section 2 reviews the literature and presents the research hypotheses. Section 3 describes the "Made in China 2025" policy and data sources. Section 4 presents our baseline results on the link between congruence and firm innovation and examines possible mechanisms. Section 5 explores the role played by the MC2025 industrial policy in mitigating the impact of congruence on innovation based on a quasi-experiment approach. Section 6 discusses the heterogeneity and extension. Section 7 concludes.

2. Related Literature and Hypothesis Development

2.1. Identifying the Impact of Congruence on Firm Innovation

Academic studies on congruence can be at least traced back to Lin (1994, 2009), who argues that a wide spectrum of economic development issues can be better understood through the lens of the congruence of the production structures (including industrial and technological structures) with the factor endowment structure of the economy. In this body of literature, the factor endowment structure refers to the composition of production factors, such as labor, physical capital, land, and other natural resources. The core argument is as follows: the economic performance of a firm, an industry, or an economy as a whole would be better, *ceteris paribus*, if the factor intensities of the embodied technologies are more congruent with the factor endowment structure, which is given at a time but changes over time. This is because more congruence implies lower production costs, as production utilizes more abundant and, hence, less expensive factors. In other words, more congruence means higher cost efficiency and higher competitiveness, as the comparative advantage is followed.

More formally, Ju et al. (2015) first use NBER-CES data on the US and UNIDO cross-country data to document the "congruence fact"—namely, the further an industry's capital-labor ratio deviates from the aggregate capital-labor ratio (endowment structure) of the economy, the smaller is the employment (and value-added) share of this industry. Then, they develop a general equilibrium model to formally establish the mechanism by which high congruence translates into the high cost efficiency and market competitiveness of the corresponding industries and hence a higher market share of such industries. Many distortions observed in reality are endogenous consequences of deviations from congruence, which in turn could result from governments' hasty catch-up development strategies, such as the "Great Leap Forward" movement in China in the 1950s (Lin, 2009, 2012).

However, it remains unexplored in the literature how congruence impacts firm innovation. Theoretically, firms in industries that are congruent with the factor endowment structure of the local economy generally have low production costs; therefore, the newly innovated products and services are also cost-efficient and hence profitable to produce. This means that the market values of the patents associated with those innovated products are also high. Thus, firms have stronger incentives to invest more in R&D, and their innovation output is also high. In contrast, industries with too low or too high capital intensities are inconsistent with the comparative advantages of the (local) economy; thus, the newly innovated goods and services have lower production efficiency and profitability, which implies lower market values for such patents, making the shares of both R&D investments and that of patents lower.

The impact of congruence is particularly important in developing countries such as China. This is because, unlike developed countries, developing countries are more plagued with market frictions and distorting policies, making a significant fraction of firms nonviable, as they are incongruent with the factor endowment structure. Small, innovative firms, particularly private firms, would be nonviable if they are in industries incongruent with the factor endowment structure. Such firms cannot operate in a free market but might survive in countries such as China because of government support, including subsidies or entry restrictions on external firms. In contrast, in developed countries, firms are most viable, and industries are generally congruent with factor endowment structures; if not, they would not be able to survive the market competition. Note that markets are mature and more efficient in developed countries, and governments generally do not pursue comparative-advantage-defying, catching-up development strategies.

In summary, we contemplate that small, innovative private firms with higher congruence invest more in research and development (R&D), have higher profitability and production efficiency, and hence produce more patents than those with lower congruence. Thus, we develop our first hypothesis.

Hypothesis 1 *The congruence factor positively affects the innovation performance of small, innovative private firms in China.*

2.2. The Role of Industrial Policy

Industrial policy, despite being controversial in both theory and practice, is widely adopted in both developing and developed economies. Such a policy usually comprises a variety of policy instruments to correct market failures and promote industrial upgrading through forceful policy interventions (Lee and Lim, 2001; Rodrik, 2004; Wu et al., 2019). Theoretical justifications for industry policies include externalities, coordination failures, financial frictions, informational asymmetries, and so on (Romer,1990; Aghion and Howitt,1992; Wu, 2017).

One crucial feature of innovation activities is the high uncertainty, and theoretically, even a firm's successful research projects can face difficulty producing financial returns that can adequately offset the potential failures arising from expensive R&D investments (Wang and Hua, 2022). The key strengths of state interventions include releasing financial constraints, enhancing information efficiency, and conquering the low appropriability issue of many innovation investments that have the characteristics of a public good, namely, non-excludability and non-rivalry (Dimos and Push, 2016; Wu, 2017). Lin (2012) develops the theoretical framework of the new structural economics and emphasizes the important facilitating role of the government in nurturing sectoral development and technology upgrading by actively supporting selective industries.

The government design of industrial policies should be based on the stage of economic development. When the economy is far away from the world technology frontier, imitation and learning are less costly and more effective than is innovation in achieving technological progress; therefore, the industry policy should be to facilitate adopting and adapting the existing technologies. However, as the economy moves closer to the global technological frontier, the focus of the industrial policy should be to facilitate independent innovation on its own (Acemoglu et al., 2006). Somewhat related to this view, it is also argued that the government should take more entrepreneurial risks on a massive scale during early development stages (Mazzucato, 2013), but the private sector should invest more in R&D as the economy approaches the world technological frontier (Aghion and Roulet, 2014).

Empirically, the findings on the impact of industrial policies are rather mixed. On the one hand, some studies have found that industry policies promote industrial development and technology innovation in specially treated sectors or companies. A large share of the recent growth in high-technology industries in Korea, Japan, and Singapore has also been attributed to government interventions through active industry and innovation policies (Branstetter and Sakakibara, 1998; Lerner, 1999; Doh and Kim, 2014; Lazzarini, 2015; Choi and Lee, 2017). For instance, Choi and Lee (2017) explore the impact of government R&D subsidies on private R&D investments in the Korean pharmaceutical industry and identify a stimulating rather than crowding-out effect. Dimos and Pugh (2016) investigate 52 microlevel evaluation studies on public R&D subsidies and find that government subsidies contribute to correcting market failures by increasing both R&D inputs and outputs in subsidized firms.

However, several studies challenge the effectiveness of industrial policies and argue that all such policies have shortcomings and difficulties when implemented in the real world (Rodrik, 2008a). Potential shortcomings of industrial policies are well discussed in Dixit (1997), Lazzarini (2015), and Nishimura and Okamuro (2018). Some papers find that industrial policies crowd out private R&D investments. Wallsten (2000) indicates that in some circumstances, industrial policies have no impact on a firm's R&D activities and sometimes even crowd out private investments; thus, the government is not capable of finding effective ways to rectify market failures. Boeing (2016) examines the allocation and effectiveness of Chinese public subsidies and finds that government support crowds out private R&D investments. Similar crowding-out effects of public programs are also documented in the French case in Marino et al. (2016).

As previous studies have noted, the justifications of industrial policy also include challenges in the financing of young and high-tech entrepreneurial companies. As such firms are rather vulnerable to the liability of originality and usually disclose little information to the public, external investors are disadvantageous in assessing the prospects and risks of firms, which makes raising external finance very difficult (Stuart et al., 1999; Chen et al., 2018). Nevertheless, more benefits of industrial policy in various countries went to large or public firms. For instance, since the early 1960s, Japanese policy support for R&D projects has mainly focused on large private firms in several specific industries (Nishimura and Okamuro, 2018). It is also well reported that for government capital allocations, the Chinese government tends to favor SOEs or large firms that have strong ties to the state (Wu, 2017).

China has experienced remarkable economic growth and industrial development since 1978. To solve problems such as a shrinking workforce and higher labor costs, China must move to a growth model that is based more on innovation than it has in the past and embrace a shift to a more innovative economy (Wei et al., 2017). To encourage growth in emerging or innovation-driven sectors, China has proactively adopted a series of national programs to pick particular industries for preferential treatment, such as the far-reaching national "Five Year Plans" that provide targets and measures for the country's next five years of economic development and industry upgrading. By resource reallocation, Chinese governments at both the central and local levels identify strategic sectors and attempt to influence industrial development and technological sovereignty in the short and long terms (Wu et al., 2019; Wang and Hua, 2022). Among them, MC2025 is a very ambitious endeavor and represents the Chinese version of the German government's "Industry 4.0", targeting the promotion of the country's manufacturing capabilities through rapid automation and supply chain upgrading.

As discussed, the role played by congruence in firm innovation is mainly through its effects on both profitability and production efficiency. In a competitive market, firms with factor input structures deviating greatly from local endowment structures usually suffer from higher production costs and lower profitability, which weakens their incentives to make R&D investments. The MC2025 policy is a strategic plan to promote R&D commitment and innovation capability in ten high-tech manufacturing industries. The policy helps ease financial constraints, increase the likelihood of raising external financing, and thus mitigate the potential underinvestment risks in technology innovations due to the endowment structure. We expect that treated firms in these strategic areas increase their R&D investments significantly after the policy intervention, which distorts the link between congruence and innovation.

Firms with state ownership usually enjoy financial support, access to information on policies and regulations, and shortcuts to exclusive favorable treatments by governments at various levels (Chen et al., 2018). Using a comprehensive dataset of large and medium firms in China, Aghion et al. (2015) document that industrial policies that target competitive sectors or that help foster competition in a treated sector can increase productivity growth. He emphasizes that more benefits could be generated if such policies were allocated to younger and more competitive firms. As highlighted by Wu (2017), although the Chinese government has increased capital allocation to R&D expenditures in specially treated industries, state-owned enterprises receive more subsidies than do private enterprises. Boeing (2016) examines the issue of government subsidy allocation and finds that firm selection is mainly determined by prior grants, high-quality inventions, and minority state ownership, while the majority of small, innovative private firms meet such selection requirements.

In the MC2025 strategic plan, financial resources consist of large, low-interest loans from development banks, state-owned commercial banks, and investment funds, and extensive R&D subsidies. Based on the previous authors' findings, government subsidies are mainly allocated to SOEs or large, public, innovative private companies with trackable innovation experience rather than small, private firms that lack adequate historical innovation records. Similar to other industrial policy programs, part of the MC2025 program aims to provide direct and indirect government support in high-tech manufacturing segments; however, China's governments at both central and provincial levels mainly provide subsidies to finance SOEs or large, public firms to achieve their ambitious objectives rather than directly allocate more subsidies to small, innovative firms in the NEEQ market.

Thus, for the R&D investments in our data, in terms of being supported through which policy instruments, we distinguish between low-interest bank loans and government subsidies. Given that the majority of NEEQ firms in the 10 strategic sectors are private enterprises with a small size relative to SOEs or listed firms in the main stock markets, we contemplate that the impact of congruence on innovation outputs is reduced mainly through the mechanism of increasing bank loans rather than allocating more government subsidies. The second hypothesis is listed as follows.

Hypothesis 2 *The industrial policy of MC2025 significantly mitigates the impact of congruence on the innovation performance of small, innovative private firms in China through the channel of bank loans.*

3. Institutional Background and Data

We start by introducing the institutional background of the “Made in China 2025” (MC2025) industrial policy and the National Equities Exchange and Quotations (NEEQ) platform. We then describe the data used in our paper.

3.1. Industrial Policy of “Made in China 2025”

While the role of industrial policy on economic growth is controversial, industrial policy can often be found globally. Developed economies, such as South Korea, Japan, and Singapore, occasionally use industrial policy to strategically protect and promote certain industries. Industrial policy is more prevalent in developing countries, especially those adopting communist systems. China is well known for overtly employing economy-wide industrial policies. The market-led but state-controlled economy has been combined with various industrial policies to promote and guide economic development in past decades.

In contrast to traditional industrial policies targeting labor-intensive sectors, in May 2015, the Chinese government announced a nationwide industrial policy—the “Made in China 2025”—to modernize capital-intensive sectors and enhance their future competitiveness. In particular, MC2025 targeted ten high-tech manufacturing sectors and selected approximately 30 pilot cities mostly in the eastern and coastal areas of China. These ten targeted sectors include information technology, numerical control and robotics, aerospace equipment, railway equipment, power equipment, green vehicles, marine engineering and high-tech ships, agricultural machinery, new materials, and biomedicine and medical devices. These ten targeted industries are central to the “Fourth Industrial Revolution”, which refers to the ongoing integration of big data, cloud computing, and other emerging digital technologies in this century.

Digital technology innovations are becoming integral to the global manufacturing supply chain and are thus central to China's economic development and industrial upgrading.

The MC2025 program also provided a ten-year guideline and goals for targeted sectors; for example, the R&D expenditures to sales ratio increased from 0.95% in 2015 to 1.68% in 2025, and the proportion of firms adopting automation increased from 33% in 2015 to 64% in 2025.[5] To achieve these targets, China's state has committed to devoting more resources and strengthening centralized policy planning by fostering coordination between its governments and innovative companies. The initiative combines publicly released policies and more local-level measures. For example, the Beijing municipal government started a $300-billion investment fund to cultivate R&D activities, while SOEs have been guided to increase their R&D spending by 10% annually.[6]

Innovation is one of the most important components of the MC2025 policy. It has been mentioned 101 times in the official report entitled "Made in China 2025" released by the Chinese State Council on May 08, 2015. According to the report, the program was inclined to provide financial support to improve the innovation ability and efficiency of Chinese manufacturing firms in the targeted sectors, including large, low-interest loans from development banks, state-owned commercial banks and investment funds, extensive R&D subsidies, government venture capital, and so on.

While these targeted sectors have the potential to deviate from China's comparative advantage in traditional labor-intensive sectors, such as textile and furniture,[7] the program promised to support firms in these sectors with higher subsidies, lower financing costs, larger tax deductions, etc. Taking the example of automation, the program offered subsidies to eligible firms that purchased robotic and semi-automatic machines with a value ranging from 3% to

[5] Source: an official report titled "Made in China 2025" released by Chinese State Council on May 08, 2015. Relate link: http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm.

[6] Source: See media coverage of FDI China on June 22, 2022 with the title of "Made in China 2025: the Plan to Dominate Manufacturing and High-Tech Industries".
Relate link: https://www.fdichina.com/blog/made-in-China-2025-plan-to-dominate-manufacturing/.

[7] Using firm level data from the Annual Survey of Industrial Enterprises conducted by China National Bureau of Statistics, Liu et al. (2022) show that the national average capital to labor ratio is approximately 253, while this ratio for the ten sectors targeted by MC2025 is approximately 393.

10% of the purchase price of machines. Overall, the MC2025 industrial policy aimed to provide support to firms in these targeted capital-intensive manufacturing sectors and increase firms' competitiveness by allocating more resources to them.

3.2. National Equities Exchange and Quotations

The National Equities Exchange and Quotations (NEEQ), the counterpart of the NASDAQ in China and known as the New Third Board Market, was officially established in 2013 and under the supervision of the China Securities Regulatory Commission. The NEEQ aims to serve micro, small, and medium-sized enterprises (hereafter, MSMEs) to enhance innovation and entrepreneurship and energize new drivers of economic growth.

The Chinese government has conducted several rounds of reforms to the NEEQ. For example, on September 3, 2021, Chinese President Xi Jinping announced a new reform—the formation of a Beijing Stock Exchange to better and more effectively steer investments into innovation. The recent development of NEEQ has gradually boosted the financial and innovation practice of MSMEs by offering trading systems and infrastructures, improving market liquidity, enhancing information disclosure quality, and so on.

There are many rules and criteria for entering the NEEQ. In brief, firms successfully listed on NEEQ are considered to have well-organized corporate governance, lawful and regulated operations, and a well-defined shareholding structure. However, unlike initial public offerings on the Shanghai and Shenzhen Stock Exchanges, there is no particular requirement for financial indicators when listing on the NEEQ. In other words, the NEEQ is inclined to provide better funding opportunities to relatively small private enterprises. Very few SOEs choose to raise funds in the NEEQ market.

In summary, NEEQ is an important platform for promoting alternative investments in the innovation activities of private firms in China. Studying innovation behaviors for firms listed on the NEEQ is useful to improve the understanding of innovation behavior and outcomes of small, innovative firms in China and helps provide strong policy implications.

3.3. Data

Our sample consists of yearly data on all listed firms available on NEEQ from 2013 to 2019. A firm's balance sheet information is manually collected from two professional Chinese enterprise databases: CSMAR and Wind. Patent data are collected from the official website of the China National Intellectual Property Administration (CNIPA) and the Incopat Database. There are three types of patents in China: invention, utility model, and design. To construct other measures in our empirical analysis, our paper also relies on three other sources: 1) enterprises' income tax records from the Chinese State Administration of Tax (CSAT),[8] 2) the China City Statistical Yearbook, and 3) the China Population Census. Our final dataset contains 88 two-digit level industries and covers most manufacturing and service sectors.[9]

Following recent studies on innovation (e.g., Chuluun et al., 2017), we use two methods to measure innovation performance: one is the number of granted patent applications measuring the number of innovation outputs, and the other is the number of patent citations measuring the quality of innovation outputs. We also study the innovation input and process by using R&D intensity—the ratio of R&D expenditures to total assets.

Table 1 reports the statistical summary of all variables used in our paper.[10] In terms of innovation performance, the average number of patent applications per firm is 3.26 and that of patent citations is 2.23. In terms of innovation input, the average R&D expenditure is 5.34% of total assets.[11] In terms of firm performance, the average ROA and ROE are 4.76% and 4.72%, respectively.

[Insert Table 1 about here]

[8] CSAT is the counter of the IRS in China and is responsible for firm tax collection and auditing. The income tax records cover firms in the manufacturing, service and construction sectors and survey firm-level information on sales, production inputs and outputs, tax payment, subsidies, etc.

[9] There are in total 97 two-digit industries in China. Table A2 in the appendix lists firm distribution in the top 20 industries.

[10] To lessen the influence of outliers, we winsorize all variables at the 1st and 99th percentiles.

[11] For the comparison, publicly traded firms, which are considered to be larger, have lower R&D intensity. The average R&D expenditures is 1.59% of total assets.

4. Baseline Analysis without Industrial Policy

In this section, we first discuss a scenario without an industrial policy. More specifically, we show how fundamental economic factors captured by the factor of congruence affect firm innovation performance and then examine the possible mechanisms behind the observed link.

4.1. Innovation and Congruence

To investigate the connection between firm innovation and fundamental economic factors, we follow Ju et al. (2015) and Lin et al. (2021) and construct a firm-level congruence index using two fundamental variables: capital and labor. This index essentially captures the distance between the local factor endowment structure and the firm factor input structure. Therefore, we estimate the following equation.

$$y_{isct} = \beta Congruence_{isct} + \rho X_{isct} + \varphi_{ct} + \theta_{st} + \lambda_{sc} + \varepsilon_{isct}, \tag{1}$$

where i indices firm; s indices industry; c indices city; t indices time (i.e., year); y_{isct} represents dependent variables of interest (e.g., patent applications and citations); X_{isct} represents firm-level control variables, including size, age, leverage, and profitability; φ_{ct}, θ_{st} and λ_{sc} are city-year, industry-year, and city-industry fixed effects, respectively; and ε_{isct} is the error term. The mathematical expression of the congruence index is as follows.

$$congruence_{sc} = -\left[\,\left|\log\left(\frac{K_{isct}/L_{isct}}{K_s/L_s}\right) - \log\left(\frac{\overline{K_c}/\overline{L_c}}{\bar{K}/\bar{L}}\right)\right|\,\right], \tag{2}$$

with $\bar{K} \equiv \sum_c \overline{K_c}$ and $\bar{L} \equiv \sum_c \overline{L_c}$.

In the first term of Equation (2), K_{isct} and L_{isct} are the fixed assets and employment for firm i of industry s in city c in year t. Thus, $\frac{K_{isct}}{L_{isct}}$ measures the factor input structure (or technology choice) of the firm. K_s and L_s are total fixed assets and employment in industry s at the national aggregate level, respectively; therefore, K_s/L_s measures the national average level of the factor input structure (technology choice) of industry s. We calculate the nationwide industry-level factor intensity using enterprises' income tax records from CSAT. $\frac{K_{isct}/L_{isct}}{K_s/L_s}$ measures the capital intensity of firm i relative to the national average.

Note that within the same industry, there exist heterogeneous subsectors, products, and tasks depending on the disaggregated level, and their capital intensities can be different. For example, in capital-abundant cities such as Shanghai, we could still find some labor-intensive industries, such as apparel and shoes; however, firms in Shanghai may choose more capital-intensive technologies or specialize in more capital-intensive products/tasks than firms in the same industry but in capital-scarce cities, such as Lanzhou in the western part of China.

In the second term of Equation (2), $\overline{K_c}$ refers to the total fixed assets of city *c,* and $\overline{L_c}$ refers to the total employment of city *c*; therefore, $\overline{K_c}/\overline{L_c}$ measures the factor endowment structure of city *c*.[12] Likewise, $\overline{K}/\overline{L}$ measures the factor endowment structure at the national level. $\frac{\overline{K_c}/\overline{L_c}}{\overline{K}/\overline{L}}$ then represents the endowment structure of city *c* relative to the national average. As a result, $\left|\log\left(\frac{K_{isct}/L_{isct}}{K_s/L_s}\right) - \log\left(\frac{\overline{K_c}/\overline{L_c}}{\overline{K}/\overline{L}}\right)\right|$ captures the congruence of the *relative* technological choice (capital intensities) of firm i in industry *s* in city *c* with the *relative* endowment structure of city *c*. A larger absolute value of the difference indicates less congruence. For convenience, we add a negative sign before the absolute value for the congruence index. In other words, the higher is the congruence index, the more congruent firm i is with its local endowment structure.[13]

The fixed effects estimation approach of Equation (1) captures both cross-sectional and time-series variations between congruence and firm innovation. The city-year fixed effects absorb time-varying city characteristics, e.g., local government policies, city-wide reforms, and economic differences; industry-year fixed effects absorb the effects of industrial variations, and city-industry fixed effects absorb any time-invariant factors that affect the spatial distribution of industries and the performance of an industry in a city. These interacted fixed effects allow us to control for a wide array of omitted variables (see a similar approach used in Rajan and Zingales, 1998; Hsu et al., 2014).

Table 2 presents the estimates of Equation (1). The coefficient of the *Congruence* variable is of primary interest. All regressions include city-year fixed effects and industry-year fixed effects. Column (1) of Table 2 includes only the variable of congruence, which has a positive and significant coefficient. Column (2) includes firm-level controls, such as size, leverage, profitability, and firm age. We use the lagged terms of the firm-level controls to mitigate the concern of bad controls. Column (3) further includes three one-dimensional fixed effects, i.e.,

[12] City-level factor endowments are drawn from the China City Statistical Yearbook.

[13] In the regressions, congruence is standardized with a mean of zero and a standard deviation of 1.

city, industry, and year fixed effects. In Column (4), we further control for the three interactive fixed effects, i.e., city-industry, city-year, and industry-year fixed effects. All columns show that congruence is positive and statistically significant at better than the 1% level. In terms of magnitude, using the result in Column (4), we find that the coefficient for congruence is 0.083, suggesting that an increase in congruence by one standard deviation on average increases patent applications by 8.3%.[14]

[Insert Table 2 about here]

To further confirm the positive association between congruence and innovation performance, we examine an alternative measure of innovation performance—patent citations. Patents with higher citations are often considered to be of higher quality. Table 3 presents the estimates of total patent citations and citations of invention patents and provides similar results to those in Table 2. The coefficient of congruence remains economically and statistically significant in all columns. In terms of magnitude, considering the result in Column (3), conditional on firm-level covariates and the fixed effects, one standard deviation higher in congruence is on average associated with 4.5% more citations of the patents applied for by a firm in a year. This magnitude is comparable to that for patent applications (Column (4) in Table 2). The estimated coefficients for citations to invention patents are smaller than those for all citations, indicating that congruence might also have positive effects on the other two types of patents. Overall, the results for citations suggest that the role of congruence enhances the quality of firm innovation outputs.

[Insert Table 3 about here]

As robustness checks, we show that the finding of the positive association between congruence and firm innovation remains robust across alternative construction methods for the congruence index. In particular, we conduct three sensitivity analyses by adjusting the congruence index constructed in Equation (2).

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[14] We obtain similar results when estimating Equation (1) for different types of patents, including invention, utility model, and industrial design. Table A1 in the appendix provides corresponding results, which suggest that the type of utility model is more sensitive to congruence.

First, we measure congruence at the city-by-industry level instead of the firm level. Specifically, we replace firm-level capita intensity ($\frac{K_{isct}}{L_{isct}}$) in Equation (2) with city-by-industry level capital intensity ($\frac{K_{sc}}{L_{sc}}$), holding other parts unchanged.[15] Although this measure is less precise due to the loss of firm-level variations, it helps alleviate the concern over confounding factors at the firm level that might be associated with both capital intensity and firm innovation. Second, we use firm-level congruence that does not vary across time—the initial level of congruence for each firm in the sample period—to minimize potential reverse causality concerns in estimating Equation (1). Third, we construct the congruence index in Equation (2) using the province-level capital abundance, i.e., replacing $\frac{\overline{K_c}}{\overline{L_c}}$ with $\frac{\overline{K_p}}{\overline{L_p}}$, where p denotes provinces. This helps mitigate the concern over flows of capital and labor across regions, as such flows are much lower across provinces than cities. Thus, the province-level endowment structure is more stable, although it might make the measure of congruence less precise. Appendix Table A2 presents the estimates of Equation (1) in the three sensitivity analyses, where we find that the estimated coefficients on congruence are mostly positive and significant, which confirms the robustness of our construction method for congruence.[16]

4.2. Mechanism Analysis for the Effect of Congruence

To enrich our understanding of the underlying mechanisms behind the role of congruence in firm innovation performance, we next study several dimensions of heterogeneity using regressions with interactions. Specifically, we add interaction terms between congruence and firm-level characteristics, including research and development (R&D) intensity, return on equity (ROE), and total factor productivity (TFP), into the specification of Equation (1). Therefore, we estimate the following regression:

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[15] The city-by-industry level capital intensity is measured by aggregating firm-level fixed assets and employment using the CSAT data in 2011.

[16] The estimated coefficient of city-by-industry-level congruence on firm invention patent applications is small and insignificant (Appendix Table A2, Panel A, Column (2)). This is possibly because the city-by-industry-level measure does not capture firm-level variations in technology choice. We find significantly positive effects of the city-by-industry-level congruence on total patent applications and utility model patent applications.

$$y_{isct} = \beta_1 Firm_{isct} + \beta_2 Congruence_{isct} + \alpha Congruence_{isct} \times Firm_{isct} + \rho X_{isct} + \varphi_{ct} + \theta_{st} + \lambda_{sc} + \varepsilon_{isct}, \quad (3)$$

where $Firm_{isct}$ stands for firm-level characteristics, including R&D intensity, ROE, and TFP. We focus on the coefficient α, which captures the interactive role of congruence and firm-level characteristics.

Table 4 presents the results for patent applications, including all patents (Columns (1)-(3)) and invention patents (Columns (4)-(6)). For the convenience of interpreting the estimated coefficients, all firm characteristics variables, i.e., $Firm_{isct}$ in Equation (3), are demeaned. Column (1) indicates that firms with higher R&D intensity tend to have more patent applications, and higher congruence can magnify the effect of R&D intensity on patent applications. This result suggests that congruence boosts firm innovation by enhancing the efficacy of innovation inputs, i.e., R&D investments. Intuitively, when a firm has a higher degree of congruence, the benefit of higher expected profitability from R&D investments is more prominent; thus, it is easier for a firm to have more profitable opportunities for innovation.

[Insert Table 4 about here]

Columns (2) and (3) show that firms with higher profitability (ROE) and production efficiency (TFP) tend to apply for more patents, and the effect of congruence is significantly larger for these firms relative to the others. These findings are consistent with our hypothesized mechanism. First, higher firm profitability means more resources or potential expenditures for innovation; thus, the higher cost efficiency and larger expected profits from innovation can be more likely to be transformed into more patent outputs. Second, a reduction in factor input costs induced by a higher level of congruence is more beneficial for firms with higher TFP than other firms; for these firms, the improvement in expected profitability from innovation is larger, and congruence has stronger positive associations with patent applications. Finally, as shown in Columns (4)-(6), our results continue to hold for invention patents.[17]

In summary, the fundamental economic condition measured by the congruence between firm factor input structure and local factor endowment structure is important for firm innovation performance.

[17] We also obtain similar results for patent citations (See Appendix Table A3).

5. Empirical Analysis with Industrial Policy

5.1. The Role of Industrial Policy

We now investigate how industrial policy distorts the link between fundamental factors and innovation performance. Using the MC2025 policy as an external shock, we employ a difference-in-differences approach to estimate the following equation:

$$y_{isct} = \alpha_1 MC2025_{st} + \alpha_2 Congruence_{isct} + \alpha_3 Congruence_{isct} \times MC2025_{st} + \rho X_{isct} + \varphi_{ct} + \lambda_{sc} + \varepsilon_{isct}, \quad (4)$$

where i indices firm; s indices industry; c indices city; t indices time (i.e., year); y_{isct} represents dependent variables of interest (e.g., patent applications and citations); $MC2025_{st}$ is a dummy variable indicating whether an industry is treated by the MC2025 policy in a given year and equals one if industry *s* belongs to the targeted industries and year *t* is after 2015 (the year of MC2025 policy announcement). The other notations are the same as those in Equation (1). To estimate α_1, the average effect of the MC2025 policy, we do not control for industry-by-year fixed effects (θ_{st}).

In Equation (4), α_3 captures the moderating effect of the MC2025 policy on the role of congruence, i.e., the difference between the effects of congruence in the industry-years treated by the policy and those not affected; α_1 captures the average effect of the MC2025 policy on firm innovation, as the congruence variable is standardized in the regression with a mean of 0 and a standard deviation of 1; α_2 captures the effect of congruence for the industry-years not affected by MC2025.

Table 5 presents the estimates of patent applications and citations. All firm-level controls and interactive fixed effects are included in the regressions. We have two major findings in Table 5. First, we find that the estimates of the effect of the MC2025 policy are all statistically insignificant. This indicates that the policy itself may have little effect on promoting firm innovation. Second, we find significant and negative coefficient estimates for the interactive effect between MC2025 and congruence, which indicates that the MC2025 policy significantly weakens the association between congruence and firm innovation. The role of congruence in the treated industries and years, $(\alpha_1 + \alpha_2)$ in Equation (4), is not significantly different from zero in F tests, and the coefficient $(\alpha_1 + \alpha_2)$ is negative in regressions in Columns (2)-(4). This result indicates that MC2025 nullified the association between congruence and firm innovation.

[Insert Table 5 about here]

According to our hypothesis, congruence plays a role in firm innovation through its effect on factor input cost efficiency. In an open and competitive market, firms with factor input structures deviating substantially from local endowment structures suffer from higher production costs and lower profitability. This weakens their incentives to engage in innovation. However, we find no significant role of congruence for firms supported by the MC2025 policy, which might suggest a distortion induced by the MC2025 policy even though it may not enhance firm innovation performance.

To further investigate how the moderating role of MC2025 changes over time, we estimate the following regression:

$$y_{isct} = \sum_{y=2014}^{2019} \beta^y \, Congruence_{isct} \times MC\ Industry_s \times 1\{t = y\} +$$

$$\sum_{y=2014}^{2019} \alpha^y \, Congruence_{isct} \times 1\{t = y\} + X_{isct} + \varphi_{ct} + \lambda_{sc} + \theta_{st} + \varepsilon_{isct}, \quad (5)$$

where $MC\ Industry_s$ is an industry-level indicator for the industries treated by the MC2025 policy; $1\{t = y\}$ denotes indicators for years. β^y captures the difference in the effect of congruence on firm innovation between MC2025 industries and the other industries in year y. α^y captures the yearly main effects of congruence. We use industry-by-year fixed effects θ_{st} to absorb the interactive effects between $MC\ Industry_s$ and year dummies. The other notations are the same as those in Equation (4).

In the above equation, we aim to estimate β^y and study the dynamic effects of congruence. The estimates for β^y are presented in Figure 1, in which we find that the estimated coefficient for 2014 is small and insignificant, i.e., before the release of the MC2025 policy. This also provides support for the parallel trend assumption. The role of the MC2025 policy in reducing the effect of congruence is significant in 2015 and 2016, i.e., right after the release of the policy. Since 2017, the effect has shrunk and has become insignificant. This result indicates that the moderating effect of the MC2025 policy is temporary instead of long-lasting.[18]

[18] This result on temporary effect is also consistent with the finding in Liu et al. (2022).

[Insert Figure 1 about here]

5.2 Mechanism Analysis for the Effect of the MC2025 Policy

What are the potential mechanisms that lead to such consequences? Given that the industries targeted by MC2025 diverge significantly from China's average factor endowment structure, the government is expected to provide certain types of support to these firms to overcome this "natural" disadvantage. We therefore explore whether these treated firms received additional government subsidies (subsidy to sales ratio) and had better access to external financing (debt to assets ratio) after the implementation of MC2025. We estimate the following regression:

$$Y_{isct} = \delta MC2025_{st} + \rho X_{isct} + \mu_i + \eta_t + \phi_s \times t + \varepsilon_{isct}, \quad (6)$$

where the dependent variable Y_{isct} represents the firm's overall debt-to-assets ratio, short-term debt-to-assets ratio, and subsidy-to-sales ratio; $MC2025_{st}$ is the indicator for treatment by the MC2025 policy; and μ_i and η_t are firm and year fixed effects, respectively. We also control for industry-specific linear trends, $\phi_s \times t$, to allow for different time trends across industries. We cluster standard errors at the firm level.

Table 6 presents the estimation results. We find that on average, the MC2025 policy significantly improves firms' leverage ratio by 2.0 percentage points (Column (1)). The result indicates that the MC2025 policy allows firms in the targeted industries to have better access to external financing, such as loans from banks, which can potentially compensate for the lower profitability and tighter liquidity constraints caused by low congruence, thus mitigating the role of congruence on firm innovation. Using the information on subsidies reported by firms, we do not find significant results from the role of subsidies in mitigating the congruence effect (Table 6, Column (2)).[19]

[Insert Table 6 about here]

Therefore, the MC2025 industrial policy provides extra financial support to firms with low congruence, suggesting a certain degree of resource misallocation. In other words, to

[19] It is also possible that firms in targeted industries may receive additional direct government purchase orders; unfortunately, we cannot obtain the related data to conduct a similar analysis.

promote firm innovation in highly capital-intensive industries, the policy tends to allocate more financial resources to firms with lower efficiency and profitability due to the deviation from the comparative advantages determined by factor endowment structures. In this case, industrial policy mitigates the role of congruence through the relocation of financial resources.

We have documented that the MC2025 policy increases the leverage of treated firms, which might be the channel through which the policy reduces the effect of congruence. To further explore the role of MC2025 and firm leverage, we estimate the following regression with a triple interaction term among MC2025, firm leverage, and congruence.

$$y_{isct} = \alpha_1 Congruence_{isct} \times MC2025_{st} \times Leverage_{isc,t-1} + \alpha_2 Congruence_{isct} \times MC2025_{st} + \alpha_3 Congruence_{isct} \times Leverage_{isc,t-1} + \alpha_4 MC2025_{st} \times Leverage_{isc,t-1} + \alpha_5 Congruence_{isct} + \alpha_6 Leverage_{isc,t-1} + \rho X_{isct} + \varphi_{ct} + \lambda_{sc} + \theta_{st} + \varepsilon_{isct}, \quad (7)$$

where $Leverage_{isc,t-1}$ denotes firms' leverage ratio in the previous year, and the other notations have the same meaning as in Equation (4). We aim to estimate α_1, which captures how the moderating effect of MC2025 on the association between congruence and firm innovation varies with firms' leverage. We control for all lower-order terms of the triple interaction term, where the variable $MC2025_{st}$ is absorbed by the industry-by-year fixed effects (θ_{st}).

Table 7 reports the estimates of Equation (7), with granted total patent applications and invention patent applications as dependent variables. We find that the estimated α_1 in Equation (7) is negative and statistically significant, indicating that the effect of MC2025 on weakening the role of congruence is stronger for firms with higher leverage. This also suggests that the MC2025 policy reduces the effect of congruence on firm innovation by providing financial support for firms, represented by higher leverage ratios. Combined with the finding in the estimation of the dynamic effects of MC2025 in the regression in Equation (5), the results imply that the MC2025 policy relaxes firms' financial constraints through a short-term policy signaling effect, which weakens the role of congruence and makes it easier for firms that deviate from local endowment-determined comparative advantages to engage in innovation.

[Insert Table 7 about here]

In addition, another concern is that firms with higher levels of congruence might obtain more benefits from the policy through external financing or direct subsidies, which can affect our interpretation of the estimated moderating effects of MC2025 on the congruence effect. For example, if firms with higher congruence receive more subsidies, then MC2025 reduces the effect of congruence simply because it enables lower-congruence firms to receive more subsidies, which has nothing to do with the fundamental factor input cost mechanism. To alleviate this concern, we examine the correlation of firm congruence with the measures of firm leverage and subsidies and do not find significant correlations, as shown in Appendix Table A4.

Thus far, we have focused on firms' innovation output—patent applications—as the main dependent variables when studying the role of congruence and the MC2025 policy. To supplement the above analysis, we also estimate Equations (1) and (4) using firms' R&D intensity, measured by the ratio of R&D expenditures to total assets or sales, as dependent variables. R&D intensity captures firms' innovation inputs. The findings presented in Table 8 are consistent with what we have obtained for the measures of innovation output (patent applications and citations). First, firms' R&D intensity is positively associated with congruence. Second, the MC2025 policy itself does not have a significant effect on firm R&D intensity. Third, the MC2025 policy significantly reduces the effect of congruence on firm innovation. This result demonstrates that congruence and MC2025 affect firm innovation outputs—patent applications—through their effect on firm innovation inputs. This is consistent with our hypothesis that higher congruence implies higher expected profits from innovation and more financial resources for R&D activities through higher cost efficiency, which further suggests stronger incentives for firms to increase innovation inputs.

[Insert Table 8 about here]

6. Conclusion

At present, China seeks effective industrial policy tools to enhance its indigenous innovation capabilities. Our paper provides new insights into the effectiveness of the national-level policy tool MC2025. We first document the positive influences of endowment structure on innovation outcomes, such as R&D intensity and patent activity. We then find significant mitigation effects of MC2025 on the impact of congruence on innovation mainly through the channel of increasing bank loans. These findings demonstrate that industrial policy is capable of playing an important role in developing short-term innovation capabilities in strategic sectors.

The policy relevance of our research findings is apparent. First, we have contributed evidence of a nonnegligible long-term impact of economic fundamentals proxied by congruence on innovation at the firm level. Second, our estimates shed light on the extent to which industrial policy, mainly through the redistribution of financial resources, may provide effective policy instruments to address the financial constraints encountered by small, innovative firms in short-term innovation activities. Our estimates also suggest differences in the policy support for large and small innovative firms, and evidence shows that small, innovative private firms mainly receive funding from bank loans to enhance R&D intensity and patent activities after the implementation of MC2025.

However, our analysis implies that MC2025 is a double-edged sword. It helps reduce the power of congruence but also generates capital misallocations and policy distortions that may hurt long-term innovation capabilities. Thus, in the longer term, whether industrial policy's distortive impact on the link between congruence and firm innovation creates sustainable development for Chinese firms begs future research efforts. Another valuable point of future research would be to design an optimal industrial policy program to insure small, innovative firms against the risks of excessive financial leverage.

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Table 1: Summary Statistics of Main Variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Number of patent applications (all)	49,823	3.26	5.96	0	32
Number of patent applications (invention)	49,823	0.61	1.91	0	12
Number of patent citations (all)	49,823	2.23	6.11	0	43
Number of patent citations (invention)	49,823	1.38	4.49	0	33
ROA (%)	43,328	4.76	16.20	-64.42	50.24
ROE (%)	42,824	4.72	29.89	-147.90	93.20
R&D expenditure / Assets (%)	43,206	5.34	8.35	0.00	37.78
TFP	43,053	0.00	0.87	-2.25	2.53
Age	49,823	11.70	5.14	1.00	54.00
Employment	49,823	214.71	314.86	9	2390
Subsidy / Sales (%)	43,189	2.41	4.45	0.00	25.50
Debt / Asset (%)	43,110	42.21	22.84	3.04	146.90
Short-term debt / Asset (%)	43,206	38.27	21.33	0.00	97.84

Note: Data sources include (i) firm balance sheet information from two professional Chinese enterprise databases: CSMAR and Wind, and (ii) patent data from China National Intellectual Property Administration (CNIPA) and Incopat Database. Each observation is a firm in a year. Congruence is defined in Section 4.1. All variables are winsorized at the 1st and 99th percentiles.

Table 2: Congruence and Patent Applications

	Dependent Variable: Patent Applications			
	(1)	(2)	(3)	(4)
Congruence	0.227***	0.194***	0.069***	0.083***
	(0.007)	(0.007)	(0.008)	(0.010)
$Size_{t-1}$		0.195***	0.183***	0.170***
		(0.009)	(0.008)	(0.009)
$Leverage_{t-1}$		0.002***	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
$Profitability_{t-1}$		0.005***	0.004***	0.003***
		(0.000)	(0.000)	(0.000)
Age		-0.017	-0.062***	-0.061***
		(0.020)	(0.018)	(0.023)
City FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
City-year FE	No	No	No	Yes
Industry-year FE	No	No	No	Yes
City-industry FE	No	No	No	Yes
Observations	39,866	35,007	34,997	34,121
Adjusted R-squared	0.045	0.093	0.285	0.383

Note: The dependent variable is patent applications, referring to the nature logarithm of one plus the number of granted patent applications of a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. Size refers to the nature logarithm of total employment. Leverage is the ratio of total debt to total assets. Profitability is return on assets. Age is the current minus firm founding year. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 3: Congruence and Patent Citations

	All Patent Citations			Invention Patent Citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Congruence	0.134***	0.117***	0.045***	0.083***	0.072***	0.029***
	(0.006)	(0.006)	(0.008)	(0.005)	(0.005)	(0.007)
Firm-level Controls	No	Yes	Yes	No	Yes	Yes
City-year FE	No	No	Yes	No	No	Yes
Industry-year FE	No	No	Yes	No	No	Yes
City-industry FE	No	No	Yes	No	No	Yes
Observations	39,866	35,007	34,121	39,866	35,007	34,121
Adjusted R-squared	0.020	0.048	0.310	0.011	0.033	0.236

Note: The dependent variable is patent citations, referring to the nature logarithm of one plus the number of citations by the end of 2019 to the granted patents applied by a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. Control variables include size, leverage, profitability, and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 4: Mechanism

	Patent Applications			Invention Patent Applications		
	(1)	(2)	(3)	(4)	(5)	(6)
Congruence	0.110***	0.080***	0.082***	0.037***	0.026***	0.026***
	(0.012)	(0.010)	(0.010)	(0.007)	(0.005)	(0.005)
R&D Intensity	0.022***			0.005***		
	(0.001)			(0.001)		
Congruence×R&D Intensity	0.005***			0.002***		
	(0.001)			(0.000)		
ROE		0.198***			0.044***	
		(0.021)			(0.011)	
Congruence×ROE		0.104***			0.019***	
		(0.013)			(0.007)	
TFP			0.076***			0.027***
			(0.010)			(0.006)
Congruence×TFP			0.018***			0.007**
			(0.006)			(0.003)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,040	33,777	34,029	34,040	33,777	34,029
Adjusted R-squared	0.389	0.384	0.385	0.224	0.222	0.223

Note: The dependent variable is patent applications, referring to the nature logarithm of one plus the number of granted patent applications of a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. R&D intensity refers to the ratio of R&D expenditure to sales revenue. ROE is return to equity. TFP is estimated total factor productivity. Control variables include size, leverage, profitability, and age. R&D intensity, ROE, and TFP are demeaned. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 5: MC2025 Industrial Policy and Congruence

	Patent Applications		Patent Citations	
	All	Invention	All	Invention
	(1)	(2)	(3)	(4)
Congruence	0.090***	0.029***	0.054***	0.037***
	(0.010)	(0.005)	(0.009)	(0.008)
MC2025	0.136	-0.091	0.044	0.092
	(0.089)	(0.060)	(0.102)	(0.088)
Congruence×MC2025	-0.050*	-0.032**	-0.069***	-0.055***
	(0.028)	(0.015)	(0.024)	(0.021)
Firm-level Controls	Yes	Yes	Yes	Yes
City-by-year FE	Yes	Yes	Yes	Yes
City-by-industry FE	Yes	Yes	Yes	Yes
Observations	34,373	34,373	34,373	34,373
Adjusted R-squared	0.385	0.207	0.296	0.226

Note: Dependent variables are patent applications and patent citations. Patent applications are the nature logarithm of one plus the number of granted patent applications of a firm in a year. Patent citations are the nature logarithm of one plus the number of citations by the end of 2019 to the granted patents applied by a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. MC2025 is an indicator equaling one for the firm-year observations in the targeted industries in the years after 2015. Control variables include firm size, leverage, profitability, and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 6: Effects of MC2025 Policy on Firm Characteristics

	Debt / Assets	Subsidy / Sales
	(1)	(2)
MC2025	0.020**	-0.002
	(0.009)	(0.002)
Firm-level controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry-specific year trend	Yes	Yes
Observations	41,854	41,942
Adjusted R-squared	0.811	0.561

Note: MC2025 is an indicator equaling one for the firm-year observations in the targeted industries in the years after 2015. Control variables include firm size, profitability, and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 7: Congruence, MC2025, and Firm Leverage

	Dependent variable: Patent Applications	
	All Patent Applications	Invention Patent Applications
	(1)	(2)
Congruence × MC2025 × $Leverage_{t-1}$	-0.227**	-0.118**
	(0.115)	(0.060)
Congruence × MC2025	0.054	0.017
	(0.057)	(0.031)
Congruence × $Leverage_{t-1}$	-0.009	-0.012
	(0.027)	(0.015)
MC2025 × $Leverage_{t-1}$	0.119	0.089*
	(0.104)	(0.054)
Congruence	0.096***	0.036***
	(0.016)	(0.009)
MC2025	0.829**	0.829**
	(0.369)	(0.369)
$Leverage_{t-1}$	0.013	-0.033
	(0.042)	(0.023)
Firm-level Controls	Yes	Yes
City-by-year FE	Yes	Yes
Industry-by-year FE	Yes	Yes
City-by-industry FE	Yes	Yes
Observations	27,454	27,454
Adjusted R-squared	0.384	0.384

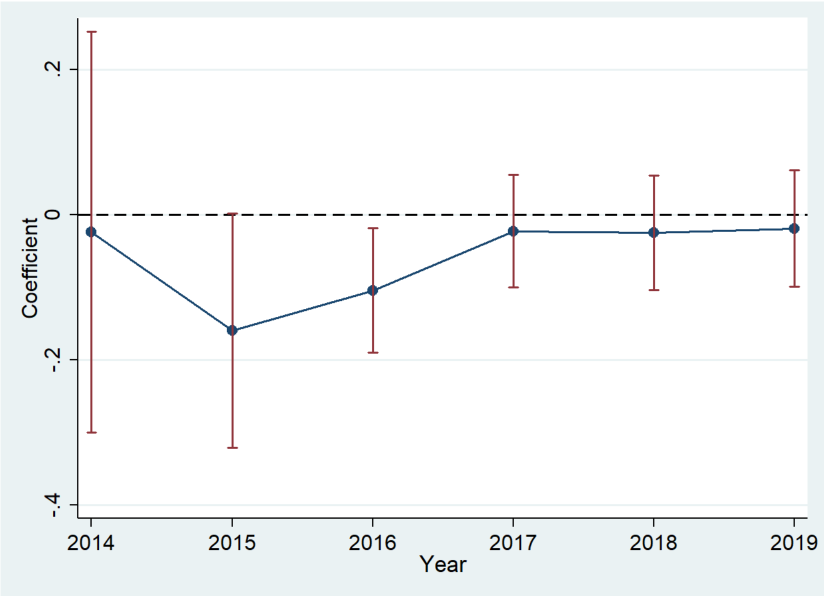
Note: The dependent variable is patent applications, referring to the nature logarithm of one plus the number of granted patent applications of a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. MC2025 is an indicator equaling one for the firm-year observations in the targeted industries in the years after 2015. Leverage is the ratio of total debt to total assets. Control variables include size, profitability, and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 8: R&D Intensity

	R&D / Assets		R&D Sales	
	(1)	(2)	(3)	(4)
Congruence	0.132**	0.169**	0.250***	0.299***
	(0.059)	(0.069)	(0.058)	(0.068)
MC2025		0.509		0.600
		(0.393)		(0.403)
Congruence × MC2025		-0.210*		-0.281***
		(0.110)		(0.105)
$Size_{t-1}$	0.660***	0.665***	0.558***	0.564***
	(0.055)	(0.055)	(0.054)	(0.054)
$Leverage_{t-1}$	-0.013***	-0.013***	-0.019***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
$Profitability_{t-1}$	0.002	0.002	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.559***	-0.560***	-0.493***	-0.494***
	(0.136)	(0.136)	(0.135)	(0.135)
City-by-year FE	Yes	Yes	Yes	Yes
City-by-industry FE	Yes	Yes	Yes	Yes
Observations	34,292	34,292	34,280	34,280
Adjusted R-squared	0.589	0.589	0.594	0.594

Note: Dependent variables are the nature logarithm of one plus the ratio of R&D expenditure to total assets (sales) of a firm in a year in Columns (1) and (2) (Columns (3) and (4)). Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. MC2025 is an indicator equaling one for the firm-year observations in the targeted industries in the years after 2015. Size refers to the nature logarithm of total employment. Leverage is the ratio of total debt to total assets. Profitability is return on assets. Age is the current minus firm founding year. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Figure 1: Dynamic Interactive Effects of Congruence and the MC2025 Industrial Policy



Note: This graph plots estimated coefficients with 95% confidence intervals of β^y in Equation (5). Standard errors are clustered at the firm level.

Appendix: Additional Figures and Tables

Table A1: Congruence and Patent Applications – Three Types

	Dependent Variable: Patent Applications		
	Invention	Utility Model	Industrial Design
	(1)	(2)	(3)
Congruence	0.026***	0.060***	0.016***
	(0.005)	(0.008)	(0.005)
Firm-level Controls	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
City-industry FE	Yes	Yes	Yes
Observations	34,121	34,121	34,121
Adjusted R-squared	0.222	0.385	0.234

Note: The dependent variable is patent applications, referring to the nature logarithm of one plus the number of granted patent applications of a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of 0 and a standard deviation of 1. Control variables include size, leverage, profitability and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table A2: Robustness Checks with Alternative Constructions of Congruence

	Dependent Variable: Patent Applications	
	All	Invention
	(1)	(2)
A. City-by-Industry Level Congruence		
Congruence	0.024***	0.003
	(0.009)	(0.005)
Firm-level Controls	Yes	Yes
Industry-by-year FE	Yes	Yes
City-by-year FE	Yes	Yes
Observations	38,454	38,454
Adjusted R-squared	0.279	0.157
B. Firm-level Congruence (Time-invariant)		
Congruence	0.079***	0.024***
	(0.010)	(0.005)
Firm-level Controls	Yes	Yes
Industry-by-year FE	Yes	Yes
City-by-year FE	Yes	Yes
City-by-industry FE	Yes	Yes
Observations	41,524	41,524
Adjusted R-squared	0.386	0.218
C. Firm-level Congruence (Province-level Endowment)		
Congruence	0.086***	0.028***
	(0.009)	(0.005)
Firm-level Controls	Yes	Yes
Industry-by-year FE	Yes	Yes
City-by-year FE	Yes	Yes
City-by-industry FE	Yes	Yes
Observations	34,141	34,141
Adjusted R-squared	0.387	0.222

Note: The dependent variable is patent applications, referring to the nature logarithm of one plus the number of granted patent applications of a firm in a year. All three measures of congruence are standardized with a mean of zero and a standard deviation of one. Control variables include size, leverage, profitability, and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table A3: Mechanism (Patent Citations)

	All Citations			Citations to Inventions		
	(1)	(2)	(3)	(4)	(5)	(6)
Congruence	0.067***	0.043***	0.045***	0.046***	0.028***	0.029***
	(0.011)	(0.008)	(0.008)	(0.010)	(0.007)	(0.007)
R&D Intensity	0.014***			0.010***		
	(0.001)			(0.001)		
Congruence×R&D Intensity	0.004***			0.003***		
	(0.001)			(0.001)		
ROE		0.028			0.006	
		(0.020)			(0.018)	
Congruence×ROE		0.029**			0.008	
		(0.013)			(0.012)	
TFP			0.037***			0.026***
			(0.009)			(0.008)
Congruence×TFP			0.002			-0.002
			(0.005)			(0.005)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
City-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-by-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,040	33,777	34,029	34,040	33,777	34,040
Adjusted R-squared	0.313	0.309	0.311	0.238	0.236	0.313

Note: The dependent variable is patent citations, referring to the nature logarithm of one plus the number of citations by the end of 2019 to the granted patents applied by a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of mean and a standard deviation of 1. R&D intensity refers to the ratio of R&D expenditure to sales revenue. ROE is return to equity. TFP is estimated total factor productivity. Control variables include size, leverage, profitability, and age. R&D intensity, ROE, and TFP are demeaned. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table A4: Correlations between Congruence and Firms' Leverage and Subsidies

	Debt / Assets	Subsidy / Sales
	(1)	(2)
Congruence	-0.010	0.000
	(0.007)	(0.001)
Firm-level controls	Yes	Yes
City-by-year FE	Yes	Yes
Industry-by-year FE	Yes	Yes
City-by-industry FE	Yes	Yes
Observations	10,029	8,793
Adjusted R-squared	0.281	0.305

Note: The sample is restricted to firms in the ten industries affected by MC2025. Congruence is constructed by Equation (2) and is standardized with a mean of mean and a standard deviation of 1. Control variables include firm size, profitability, and age. The standard errors in parentheses are clustered at the firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.