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

Xiuping Hua, Yong Wang, Junjie Xia, and Haochen Zhang[1]

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**Abstract**

This paper investigates the association between firm innovation and endowment-based fundamental factors through the lens of congruence and then examines the impact of a national-level industrial policy on this newly established link. Based on a sample of small and innovative firms listed on the National Equities Exchange and Quotations, China's NASDAQ counterpart, we find that firms with greater congruence with local endowment structure tend to have more innovation inputs and outputs. Additionally, in a quasi-experimental setting, we further examine the effect of the "Made in China 2025" (MC2025) industrial policy. Our findings indicate that MC2025 increases bank loans for treated firms and weakens the positive association between congruence and firm innovation. This suggests that MC2025 has a dual impact: while it increases access to capital, it may also lead to capital misallocations and policy distortions, ultimately hindering long-term innovation capabilities.

**Keywords:** Congruence; industrial policy; innovation; R&D intensity; patents

**JEL Classification**: D80, G30, O30, R10

[1]Xiuping Hua is with the University of Nottingham Ningbo China, xiuping.hua@nottingham.edu.cn; Yong Wang is with Peking University, yongwang@nsd.pku.edu.cn; Junjie Xia is with the Central University of Finance and Economics and Peking University, junjiexia@nsd.pku.edu.cn; Haochen Zhang is with Zhejiang University, zhanghaochen@zju.edu.cn.

## 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). These studies have made significant progress by delving into both theoretical justifications and economic outcomes of a variety of industry policies. These policies aim to promote new infant industries or protect selective traditional sectors in different countries through tax allowances, loans, grants, education, and training, special organizations, selective investments, government procurement, regulations, and more (Aghion et al., 2015; Guan and Yam, 2015; Wang and Hua, 2022). Despite conflicting theoretical arguments and mixed empirical findings, there is still limited evidence on how industrial policy impacts the relationship between innovation and fundamental factors through the lens of congruence.

In this paper, we conduct empirical analyses to provide new insights into the effects of government interventions on corporate innovations and sectoral development. We base our research on micro-level data from small and innovative firms in China. 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). Both public and private sectors in China have been steadily increasing R&D expenditures 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

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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/

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 like 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 policymakers 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 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-

[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).

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 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. However, it has been highlighted in the literature on economic development (see Lin (2009)).

This paper analytically focuses on exploring the abovementioned congruence effect on innovation. Furthermore, we quantitatively examine the impact of the MC2025 industrial policy on the innovation behaviors of firms in the NEEQ market. We pay particular attention to the congruence effect. Additionally, we identify mechanisms that translate the impact of industrial policy into innovation outcomes.

In our empirical analysis, 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 positive 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.

The rest of the paper is organized as follows. Section 2 reviews the related literature and introduces the institutional background. Section 3 presents the conceptual framework. Section 4 discusses the main empirical results. Section 5 explores the role of the "Made in China 2025" industrial policy and the underlying mechanism. Section 6 concludes.

## 2. Literature Review and Institutional Background

We now review the related literature and then introduce the institutional background of the "Made in China 2025" (MC2025) industrial policy and the National Equities Exchange and Quotations (NEEQ) platform.

## 2.1. Related Literature

This paper is related to two strands of literature. First, 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.

Broadly speaking, the concept of congruence pertains to the relationship between a firm's internal inputs, their structures, and the external economic environments. Existing studies have explored the determinants of firm innovation through the lens of congruence. They have considered various perspectives such as firms' organization, management, knowledge structure, and input structures including human capital (e.g., Chandler et al., 2000; Kaufmann and Tödtling, 2001; Zahra and George, 2002; Andriopoulos and Lewis, 2009; Lichtenthaler, 2009; De Massis et al., 2015; McGuirk et al., 2015; Fonseca et al., 2019).

Compared to these studies, our paper is the first to empirically examine the direct effects of congruence in terms of firms' factor inputs—capital and labor—on firm innovation. Our focus is especially on small and innovative firms in a developing economy, deriving important policy implications for innovation policy making among developing countries worldwide. To the best of our knowledge, this study is pioneering in its examination of how congruence's role in firm innovation is influenced by nationwide industrial policies. These policies target specific industries to encourage their innovative activities, and the findings on the interactive effect between congruence and industrial policy shed light on the impact of industrial policies on the efficiency of resource allocation in developing countries.

Our paper contributes to a second strand of literature that investigates the impact of industrial policies on firm innovation in the context of emerging markets like China (Choi and Lee, 2017; Wei et al., 2017; Wu, 2017; Wu et al., 2019; Wang and Hua, 2022). Existing studies have examined the impact of industrial policies on innovation in developing countries from multiple perspectives. Some research focuses on policies aimed at specific industries, such as the auto industry and the pharmaceutical industry (Howell et al., 2014; Choi and Lee, 2017; Howell, 2018; Yang et al., 2021), while others explore innovation subsidies across various industries (Aghion et al., 2015; Guo et al., 2016, 2017, 2021). In particular, our paper aligns closely with studies exploring the efficacy of techno-industrial policies on SMEs. For instance, Guo et al. (2016) 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 boosting the program's effectiveness and further, find that government R&D support enhances firms' access to external funding by certifying their political capital.

Our paper also closely relates another line of research on industrial policy. This research studies the heterogeneous effects of such policies, including their interaction with economic environments, such as market competition and vertical integration (Aghion et al., 2015; Wu, 2017; Lin et al., 2021). Specifically, several studies question the effectiveness of industrial policies, arguing that these policies invariably have shortcomings and encounter implementation challenges (Rodrik, 2008a; Hong et al., 2016). Potential shortcomings of industrial policies are well discussed in Dixit (1997), Lazzarini (2015), and Nishimura and Okamuro (2018). Some research suggests that industrial policies can 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, finding that government support tends to crowd out private R&D investments. Marino et al. (2016) also document similar crowding-out effects of public programs in a French context.

Our paper also contributes to the literature on industrial and innovation policies through the lens of the MC2025 policy in China. Wen and Zhao (2021) and Chen et al. (2024) investigate the effects of MC2025 using data on publicly listed companies. While Wen and Zhao (2021) document increased R&D spending but limited innovation output in the short term, Chen et al. (2024) highlight enhanced innovation in pilot cities through mechanisms such as tax incentives and subsidies. Complementary to these studies, our analysis focuses on small and medium-sized technological enterprises (SMTEs), which often face tighter credit constraints than publicly listed firms. Their technological choices—particularly the congruence of their factor input structure with local endowment structures—may significantly influence innovation outcomes, making our findings especially relevant for developing economies where SMTEs are key drivers of innovation.

Additionally, our paper provides a new perspective by examining the interactive effects of industrial policy and firms' factor structure on innovation outcomes, with a particular focus on congruence with local endowment structure. Distinct from Wen and Zhao (2021), who discuss the potential misallocation effects of MC2025 from the perspective of firm ownership, we offer new evidence of industrial policy-induced distortions through the lens of comparative advantage and factor structures. This underscores the critical importance of aligning industrial policies with local comparative advantages to maximize policy effectiveness and minimize resource misallocation.

Our findings also enrich the understanding of comparative advantage and congruence theories in the context of industrial policy. By examining the interplay between firm-level congruence to local endowments and state-led industrial policy, our work demonstrates how deviations from comparative advantage can lead to distortions, thereby advancing the discourse on the adaptability of economic frameworks under policy-driven settings.

## 2.2. Institutional Background

## A. 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. The 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 sectors 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

[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.

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, and larger tax deductions. 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 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.

## B. 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.

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[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.

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 state-owned enterprises (SOEs) choose to raise funds on 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 for improving the understanding of innovation behavior and outcomes of small and innovative firms in China, and it helps provide strong policy implications.

# 3. Conceptual Framework

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 higher congruence implies lower production costs, as production utilizes more abundant and, hence, less expensive factors. In other words, higher 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 innovative 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 those of patents lower. This yields the first hypothesis for our empirical analysis:

**Hypothesis 1 (Congruence and Firm Innovation):** *Firms with factor input structures that are more congruent with the local factor endowment structure will, on average, invest more in R&D and have more patents.*

We then investigate the impact of an industrial policy. We consider a capital subsidy for the more capital-intensive industry, as promoted by the 'Made in China 2025' (MC2025) policy aimed at boosting the development of ten targeted industries in China, all of which are capital-intensive. Without the subsidy, firms with varying levels of congruence face the same factor prices. However, if the policy provides high subsidies for capital-intensive industries to lower their financing costs, then patent values in these industries would be larger, so the effect of congruence would be weakened. This yields the second hypothesis for our empirical analysis:

**Hypothesis 2 (The Impact of MC2025):** *If capital-intensive industries receive credit subsidies, as stipulated in the MC2025 policy, the positive association between congruence with local factor endowment structure and firm innovation will weaken.*

In Appendix A, we develop a model of firm innovation decisions to mathematically express this conceptual framework. The model formally demonstrates the relationship between congruence, innovation, and the role of industrial policy. We derive model propositions corresponding to our empirical hypotheses described in this section.

# 4. Empirical Analysis on Congruence and Innovation

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

## 4.1. Data Source and Sample

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

[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.

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]

This sample is suitable for our hypothesis examination for four reasons. First, firms on NEEQ are relatively smaller than listed companies in China and receive fewer policy protections from the government. This amplifies the effect of congruence on their innovative activities. Second, most firms on NEEQ are high-tech firms and actively conduct innovations, which provides a rich variation in firm innovation activities for our empirical analysis. Third, the NEEQ sample encompasses firms from various industries, spanning most manufacturing and service sectors in China, which lends support to the economywide representativeness of the sample and provides rich variations in factor input structures among industries that facilitate our empirical identification. Fourth, SMEs constitute a significant portion of the economy and play an important role in technological innovation, not just in China but also in other developing countries.[10] The study based on an equities exchange and quotations platform of SMEs has strong implications for industrial, technology, and innovation policies in developing countries, strengthening the external validity of our empirical findings in this paper.

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.[11] 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.[12] In terms of firm performance, the average ROA and ROE are 4.76% and 4.72%, respectively.

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[9] There are in total 97 two-digit industries in China.

[10] According to the China Ministry of Industry and Information Technology, SMEs contributes up to 60% of GDP and 70% of technological innovation in 2020.

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

[12] 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.

**[Insert Table 1 about here]**

## 4.2. Empirical Method and Baseline Results

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; $\varphi_{ct}$, $\theta_{st}$ and $\lambda_{sc}$ are city-year, industry-year, and city-industry fixed effects, respectively; and $\varepsilon_{isct}$ is the error term. The mathematical expression of the congruence index is as follows.

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

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

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*.[13] 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.[14]

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., city, industry, and year fixed effects. In Column (4), we further control for the three interactive

[13] City-level factor endowments are drawn from the China City Statistical Yearbook.
[14] In the regressions, congruence is standardized with a mean of zero and a standard deviation of 1.

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%.[15]

**[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]**

## Robustness Analysis

We now conduct sensitivity analyses regarding the positive association between congruence and firm innovation, as documented above in two respects. Firstly, we conduct sensitivity analysis using alternative construction methods for the congruence index. Secondly, we use multiple methods to address potential concerns of reverse causality and omitted variables.

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[15] We obtain similar results when estimating Equation (1) for different types of patents, including invention, utility model, and industrial design. Table B1 in the appendix provides corresponding results, which suggest that the type of utility model is more sensitive to congruence.

In the first set of robustness checks, we conduct three sensitivity analyses by adjusting the congruence index constructed in Equation (2). 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.[16] 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 B2 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.[17]

In the second set of robustness checks, we conduct three analyses to address the potential concern of reverse causality and omitted variables. Firstly, in addition to using the time-invariant congruence index as described above, we use the one-year lagged term of the congruence index, helping us address the concern about the possibility that more innovative firms are more likely to establish a high level of congruence. Secondly, we control for other dimensions of "congruence" for firms. This includes (i) the congruence between a firm's human

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

[17] The estimated coefficient of city-by-industry-level congruence on firm invention patent applications is small and insignificant (Appendix Table B2, 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.

capital structure and the regional human capital abundance; (ii) the congruence between a firm's occupational structure and the regional occupational structure; (iii) the congruence between a firm's technology structure (measured using patent classifications) and the regional technology structure;[18] (iv) the congruence between a firm's industry and the regional input-output production network. We formally define these measurements in Appendix C. Thirdly, to address potential omitted variable bias arising from unobservable entrepreneurs' ability, we additionally control for the demographic characteristics—including gender, age, and schooling years—of the chairman and CEO of a firm.[19] Appendix Table B3 reports the results of the three sensitivity analyses, where we find that the estimated coefficients on congruence are largely consistent with those in the baseline results. This suggests that our baseline results are less likely to suffer from severe biases arising from reverse causality or omitted variables.

## 4.3. 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:

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

where $Firm_{isct}$ stands for firm-level characteristics, including R&D intensity, ROE, and TFP. We focus on the coefficient $\alpha$, 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

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[18] As we do not have measures of occupational structure and technology structure at the firm level, we use industry-level measures as a proxy.

[19] We note that there are many missing values in the variables of chairmen and CEOs' characteristics. Thus, the results with these controls (Panel C of Appendix Table B3) might not be comparable with our baseline results. This caution should be kept in mind when interpreting the results with these controls.

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.[20]

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.

# 5. Empirical Analysis on the Impact of 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:

[20] We also obtain similar results for patent citations (See Appendix Table B4).

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

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 $\alpha_1$, the average effect of the MC2025 policy, we do not control for industry-by-year fixed effects ($\theta_{st}$).

In Equation (4), $\alpha_3$ 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; $\alpha_1$ 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; $\alpha_2$ 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. $\beta^{y}$ captures the difference in the effect of congruence on firm innovation between MC2025 industries and the other industries in year $y$. $\alpha^{y}$ captures the yearly main effects of congruence. We use industry-by-year fixed effects $\theta_{st}$ 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 $\beta^{y}$ and study the dynamic effects of congruence. The estimates for $\beta^{y}$ 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.[21]

**[Insert Figure 1 about here]**

One potential concern regarding the above results is that our findings of the moderating effect of the MC2025 policy on the role of congruence might be confounded by changes in

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

international trade environment, especially given that MC2025 was implemented during a period of increasing trade tensions. To address this concern, we augment our regression specification in Equation (4) by incorporating two trade variables at the industry-by-year level: (i) the logarithm of industry-level exports, which captures the overall external demand at the industry level, and (ii) the U.S. tariff rates on Chinese products, which specifically reflects the changes in export environment due to U.S.-China trade tensions.[22] We include these variables using their one-year lagged terms as controls. We also control for their interaction terms with congruence. As shown in Appendix Table B6, the negative interaction effect between MC2025 and congruence remains statistically significant after controlling for these trade-related factors and their interactions with congruence. This suggests that our key finding about the interactive effect of industrial policy and congruence is less likely to be confounded by concurrent changes in the international trade environment.

## 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:

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

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 $\mu_i$ and $\eta_t$ 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.

[22] The industry-level export data are obtained from UN Comtrade Database, while the U.S. tariff rates on Chinese products are from World Bank's WITS (World Integrated Trade Solution) Database. Both datasets are originally at the HS 6-digit product level. We aggregate these data at the 3-digit China Industry Classification code level to merge with our main dataset.

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)).[23]

**[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 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 $\alpha_1$, 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

[23] 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.

interaction term, where the variable $MC2025_{st}$ is absorbed by the industry-by-year fixed effects ($\theta_{st}$).

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 $\alpha_1$ 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 B5.

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. Discussion and Conclusion

In this paper, we empirically analyze a lesser-known factor that determines firms' innovation activities, namely, the congruence between firms' input structures and local endowment structures as captured by capital-labor ratios. We find that firms with higher congruence to local endowment structure tend to have better performance in innovation, as evidenced by their R&D investments, patent applications, and citations. Furthermore, using a quasi-experimental framework, we investigate the impact of the MC2025 policy—an industrial policy aimed at promoting innovation in capital-intensive sectors—on the association between congruence and firm innovation and find that the MC2025 policy significantly mitigates this positive association. The mechanism analysis suggests that this mitigation effect is possibly due to the increase in bank loans for firms in the targeted industries after the implementation of MC2025, which potentially makes firms with lower congruence more capable of conducting innovations. In sum, 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.

Our findings have important implications for innovation and industrial policies, both theoretically and empirically. We identify a novel determinant of firm innovation. The findings on the congruence effect highlight the importance of complying with local comparative advantage determined by local factor endowment structures in boosting innovations. This provides new insights into the theory of development and growth for developing countries. As many of the most advanced technologies are in capital-intensive sectors, and developing countries typically have relatively scarce capital and more abundant labor, firms in capital-intensive sectors tend to have lower incentives to conduct innovation in a free market. In that case, catching-up development strategies aimed at promoting capital-intensive sector development can lower the overall efficiency of the economy and increase resource misallocations in innovation activities due to the high production costs and low profitability arising from the large deviation from comparative advantages.

On the policy front, our findings help derive profound implications for China and other developing countries. Nowadays, in the new wave of rapid technological progress, developing countries such as China seek effective industrial policy tools to enhance their indigenous innovation capabilities. At the same time, developing economies are typically dominated by small and medium-sized firms (SMEs). Our analysis is based on a sample of innovative SMEs listed on NEEQ in China. This provides important insights into the potential impact of industrial policies on the innovations of SMTEs in other developing countries. In developing countries where a well-functioning financial system is less developed, SMEs tend to suffer from financial constraints, whereby industrial policy tools can exert an effect in relaxing such constraints and fostering firm innovation. Nevertheless, our findings emphasize that it is important to take into account comparative advantages across sectors when selecting industries to be supported. Supporting industries with large deviations from local comparative advantage would lower the effectiveness of industrial policies and induce further distortions.

We conclude by discussing some limitations of the current paper and providing suggestions for future studies. First, while our conceptual framework is generally applicable and not specifically restricted to small firms, our empirical analysis is based on a sample of innovative SMEs in China. It is worth exploring whether the findings in the current paper can be generalized to larger firms for whom financial constraints tend to be less of a concern. Second, we only examine the impact of MC2025 in the relatively short run, while 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. Third, both our conceptual framework and empirics are essentially partial equilibrium analyses, based on which we derive some suggestive implications for resource allocation efficiency. In the future, a general equilibrium analysis combined with quantitative work would substantially improve the analysis. This approach would help derive more concrete conclusions on the welfare implications of congruence, the role of industrial policy, and the design of an optimal industrial policy program.

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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: Mechanisms

| | 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 |

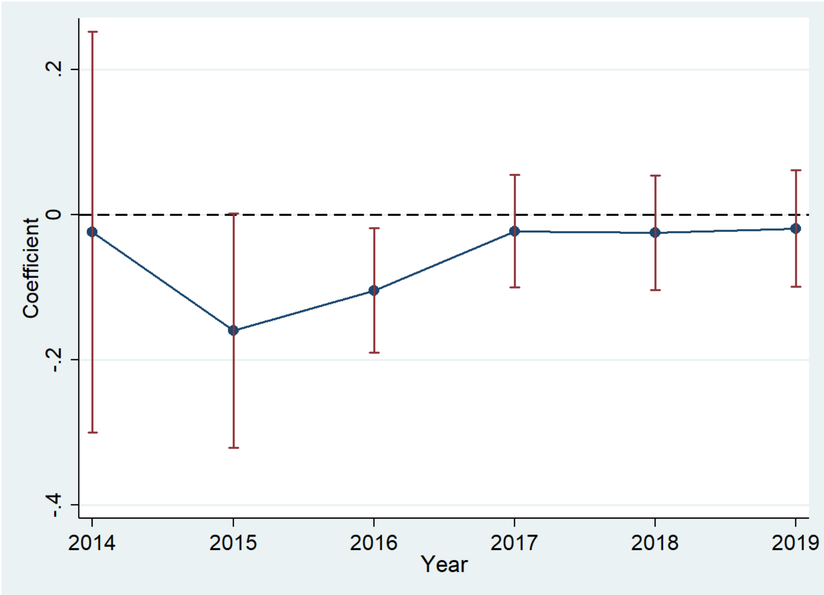
Note: The dependent variable is patent applications, referring to the nature logarithm of one plus the number of granted patent applications of a firm in a year. Congruence is constructed by Equation (2) and is standardized with a mean of zero and a standard deviation of one. MC2025 is an indicator equaling 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 $\beta^{y}$ in Equation (5). Standard errors are clustered at the firm level.

# Appendix

## A. Model Appendix

In this appendix section, we develop a model to theoretically formalize the hypothesized mechanism about how congruence might affect firm innovation. Moreover, we also explore how the relationship between factor congruence and firms' innovation would be affected by the MC2025 policy. The intuition of the model is outlined in Section 3 in the main text.

### Model Setup

Consider an economy consisting of multiple industries, which are heterogeneous in capital intensities. Industries are indexed by $\alpha$. The production function of industry $\alpha$ is given by

$$Y = A_i K^{\alpha} L^{1-\alpha},$$

where $Y$, $K$ and $L$ denote output, capital, and labor, respectively. $A_i$ is the total factor productivity (TFP) after the $i$th innovation. Thus, in our model, an innovation means an increase in the TFP. Obviously, according to the production function, the marginal cost ($MC_i$) is equal to the average cost ($AC_i$):

$$MC_i = AC_i = \frac{r^{\alpha} w^{1-\alpha}}{A_i \alpha^{\alpha} (1-\alpha)^{1-\alpha}},$$

where $r$ and $w$ stand for the prices of capital and labor, respectively, relative to the price of the final product, which is normalized as 1.

When a firm is successful in its innovation so that it obtains the state-of-the-art technology (that is, it achieves the highest TFP level in its industry), it would monopolize the market. As a monopolist producer, it maximizes the profit by choosing the optimal price ($P$) subject to the demand function $D(P) = \eta P^{-\varepsilon}$, which the firm takes as exogenous:

$$\max_{P} \ [PD - MC_i D]$$

$$\text{s.t.} \quad D(P) = \eta P^{-\varepsilon},$$

where the price elasticity $\varepsilon > 1$ and $\eta$ is the demand shifter. It is straightforward to derive the equilibrium price and monopoly profit as follows:

$$P_i = MC_i \frac{\varepsilon}{\varepsilon - 1},$$

$$\Pi_i = \eta \varepsilon^{-\varepsilon} \left[ \frac{r^{\alpha} w^{1-\alpha}}{(\varepsilon - 1) A_i \alpha^{\alpha} (1-\alpha)^{1-\alpha}} \right]^{1-\varepsilon}.$$

Suppose that the duration of each patent is *T* years, then the market value of this patent in industry $\alpha$ is nothing but the total sum of the discounted monopoly profits when the patent is still valid. Let $\delta$ denote the discount factor for a firm. For simplicity, suppose factor prices remain constant over time. We obtain the market value of the *i*th patent as follows:

$$PV(\alpha) = \sum_{t=1}^{T} \delta^{t-1} \Pi_i = \frac{1-\delta^T}{1-\delta} \eta \varepsilon^{-\varepsilon} \left[ \frac{r^{\alpha} w^{1-\alpha}}{(\varepsilon - 1) A_i \alpha^{\alpha} (1-\alpha)^{1-\alpha}} \right]^{1-\varepsilon}.$$

Similarly, for another industry indexed by $\beta$, the *i*th successful innovation (that is, the *i*th vintage of technology for that industry) yields the following production function

$$Y = B_i K^{\beta} L^{1-\beta},$$

where $B_i$ is the TFP and $\beta$ is the capital intensity of industry $\beta$. Thus, the corresponding patent value can be written as

$$PV(\beta) = \frac{1-\delta^T}{1-\delta} \eta \varepsilon^{-\varepsilon} \left[ \frac{r^{\beta} w^{1-\beta}}{(\varepsilon - 1) B_i \beta^{\beta} (1-\beta)^{1-\beta}} \right]^{1-\varepsilon}.$$

Without loss of generality, we assume that $0 < \alpha < \beta < 1$. This indicates that industry $\alpha$ is less capital-intensive than industry $\beta$. Furthermore, we normalize the units of output such that $A_i = B_i$, then we have $PV(\alpha) > PV(\beta)$ if and only if

$$\frac{r}{w} > \left[ \frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}{\beta^{\beta}(1-\beta)^{1-\beta}} \right]^{\frac{1}{\alpha-\beta}} \equiv \Omega. \qquad (*)$$

To interpret this condition, we recognize that in equilibrium, the relative factor price is determined by the relative abundance of factor endowments in an economy, i.e., a higher rental-wage ratio ($\frac{r}{w}$) corresponds to a factor endowment structure with higher labor abundance relative to capital. Thus, condition (*) indicates that the market value of a patent in a labor-intensive industry ($\alpha$) would be higher than that in a capital-intensive one ($\beta$) if and only if the relative price of capital ($\frac{r}{w}$) is sufficiently high, which is equivalent to the condition that the labor is sufficiently abundant relative to capital. Therefore, in an economy abundant in labor, patents tend to have higher market values in more labor-intensive industries. Alternatively speaking, when an industry is more congruent with the local factor endowment structure, the market value of a patent within the industry would be higher on average.

## Firm R&D Decision

Consider a firm's incentive to conduct R&D. Let $\theta$ denote the probability of success in an innovation. We assume that $\theta'(M) > 0$, where $M$ stands for R&D expenditure, and that $\theta''(M) < 0$. That is, higher R&D expenditure makes innovation more likely to succeed, but the marginal effect is diminishing. Now consider an innovative firm in industry $\alpha$, which chooses $M$ to maximize the expected net profit of conducting R&D:

$$\max_{M} \ [\theta(M) \cdot PV(\alpha) - M]$$

The first order condition is given by $\theta'(M) \cdot PV(\alpha) = 1$, which uniquely determines an optimal level of R&D expenditure, $M^*$. Clearly, we have

$$\frac{\mathrm{d}M^*}{\mathrm{d}\, PV(\alpha)} > 0.$$

That is, higher patent values induce a firm to increase its R&D expenditure; this further implies that the probability of success would also be higher, i.e., $\frac{\mathrm{d}\theta}{\mathrm{d}\, PV(\alpha)} > 0$. Higher R&D expenditure and a higher probability of innovation success jointly indicate more patents will be produced.

We summarize the above discussions as the following proposition:

**Proposition 1 (Congruence and Firm Innovation):** *If industry $\alpha$ is more congruent with local factor endowment structure than industry $\beta$, i.e., when* (*) *is satisfied, then firms in industry $\alpha$ will on average invest more in R&D than their counterparts in industry $\beta$. Moreover, on average more patents will be produced in firms in industry $\alpha$ than in industry $\beta$.*

## Model Extensions

In the baseline model, each firm only produces one product and conduct one innovation each period. In reality, a firm could produce multiple products and hence have several lines to do innovation, therefore multiple patents. To this end, we can extend our baseline model to the following more general setting:

A firm in industry $\alpha$ can produce multiple products, i.e., it has several product lines. Its production function is given by

$$Y = \left[ \int_0^n Y_\phi^\sigma d\phi \right]^{\frac{1}{\sigma}},$$

where $n$ denotes the measure of product lines for a firm. For each line, the firm decides whether to conduct an innovation or not. Thus, $n$ is endogenous.

For product line $\phi$, its expected gain from innovation is given by

$$\theta(M^*) \cdot PV(\alpha, \phi, n) - M^*.$$

Since products of the *n* lines are imperfectly substitutable, standard monopolistic competition model implies that $PV(\alpha, \phi, n)$ is a strictly decreasing function of *n*. In equilibrium, *n* must satisfy the "free entry" condition, $n[\theta(M^*) \cdot PV(\alpha, \phi, n) - M^*] = 0$, which, in nontrivial cases, indicates that $\theta(M^*) \cdot PV(\alpha, \phi, n) - M^* = 0$. Therefore, when industry $\alpha$ is more congruent than industry $\beta$, we have $n^*(\alpha) > n^*(\beta)$; that is, a firm in industry $\alpha$ produces more patents than its counterpart in industry $\beta$.

## The Impact of an Industrial Policy

We now consider the "Made in China 2025" (MC2025) policy, which aims to promote the development of ten targeted industries in China. It turns out that all of these targeted industries are capital-intensive. Thus, MC2025 provides capital subsidies for the targeted industries. Without this industrial subsidy, a firm in industry $\alpha$ faces the same factor prices $(r, w)$ as a firm in industry $\beta$. Suppose that the local endowment structure is sufficiently labor abundant such that the corresponding factor prices $(r, w)$ is more favorable to the labor-intensive industry $\alpha$. In contrast, when the MIC2025 policy is at play, capital-intensive industry $\beta$ becomes a targeted industry, so firms in industry $\beta$ now pay the factor prices $((1-\tau)r, w)$, where $\tau$ denotes the credit supply rate. In this case, the market value of a patent in industry $\beta$ becomes

$$\widetilde{PV}(\beta) = \frac{1-\delta^T}{1-\delta}\eta\varepsilon^{-\varepsilon}\left[\frac{[(1-\tau)r]^{\beta}w^{1-\beta}}{(\varepsilon-1)B_i\beta^{\beta}(1-\beta)^{1-\beta}}\right]^{1-\varepsilon}.$$

Then we have $PV(\alpha) > \widetilde{PV}(\beta)$ if and only if

$$\frac{r}{w} > \left[\frac{A_i(1-\tau)^{\beta}}{B_i}\right]^{\frac{1}{\alpha-\beta}}\left[\frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}{\beta^{\beta}(1-\beta)^{1-\beta}}\right]^{\frac{1}{\alpha-\beta}}.$$

When $A_i = B_i$ as in the baseline setting, the condition is equivalent to

$$\frac{r}{w} > (1-\tau)^{\frac{\beta}{\alpha-\beta}}\left[\frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}{\beta^{\beta}(1-\beta)^{1-\beta}}\right]^{\frac{1}{\alpha-\beta}} = (1-\tau)^{\frac{\beta}{\alpha-\beta}}\Omega, \qquad (**)$$

where $\Omega$ is defined as in (*).

From conditions (*) and (**), we obtain the following result: when $\Omega < \frac{r}{w} \leq (1-\tau)^{\frac{\beta}{\alpha-\beta}}\Omega$, firms in industry $\alpha$ would have higher patent values than firms in industry $\beta$ before MC2025, but the opposite is true after MC2025 is implemented. In particular, if the credit subsidy rate $\tau$ is sufficiently large, e.g., close to 1, then $(1-\tau)^{\frac{\beta}{\alpha-\beta}} \to +\infty$. That is, if MC2025 provides very high subsidies for industry $\beta$, then patent values in industry $\beta$ would be still higher even though this industry is not congruent with factor endowment structure, so the effect of congruence on innovation, both input and output, would be weakened. It yields the following proposition:

**Proposition 2 (The Impact of MC2025):** *If the capital-intensive industry $\beta$ receives credit subsidies, as is stipulated in the MC2025 policy, the positive correlation between congruence with local factor endowment structure and firm innovation would become weaker.*

# B. Additional Figures and Tables

Table B1: 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 B2: 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 B3: Robustness Checks with Alternative Constructions of Congruence

| | Dependent Variable: Patent Applications | |
|---|---|---|
| | All | Invention |
| | (1) | (2) |
| *A. Lagged Congruence Index* | | |
| Congruence (t-1) | 0.077*** | 0.025*** |
| | (0.008) | (0.004) |
| Observations | 31,918 | 31,918 |
| Adjusted R-squared | 0.278 | 0.147 |
| *B. Controlling for Additional Dimensions of Congruence* | | |
| Congruence | 0.068*** | 0.028*** |
| | (0.008) | (0.004) |
| Congruence (human capital) | 0.018* | 0.019*** |
| | (0.010) | (0.005) |
| Congruence (technology) | 0.018* | 0.005 |
| | (0.011) | (0.006) |
| Congruence (occupation) | 0.032* | 0.002 |
| | (0.018) | (0.009) |
| Congruence (vertical integration) | -0.016 | -0.017** |
| | (0.014) | (0.008) |
| Observations | 32,894 | 32,561 |
| Adjusted R-squared | 0.289 | 0.153 |
| *C. Controlling for Demographic Characteristics of Chairmen and CEOs* | | |
| Congruence | 0.076*** | 0.028*** |
| | (0.009) | (0.005) |
| Male (chairman) | 0.027 | 0.012 |
| | (0.029) | (0.014) |
| Male (CEO) | -0.004 | -0.011 |
| | (0.028) | (0.014) |
| Age (chairman) | -0.002 | -0.000 |
| | (0.001) | (0.001) |
| Age (CEO) | -0.002* | -0.001 |
| | (0.001) | (0.001) |
| Schooling years (chairman) | -0.001 | 0.006* |
| | (0.005) | (0.003) |
| Schooling years (CEO) | 0.004 | -0.001 |
| | (0.006) | (0.003) |
| Observations | 26,760 | 26,272 |
| Adjusted R-squared | 0.294 | 0.160 |

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 measures about congruence are standardized with a mean of zero and a standard deviation of one. In all regressions, we include industry-year and city-year fixed effects and firm level controls, which 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. The congruence variables used in Panel B are formally defined in Appendix C.

Table B4: 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 B5: 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.

Table B6: MC2025 Industrial Policy and Congruence: Incorporating Trade-related Variables

| Dep. var.: Patent applications | All | Invention | All | Invention | All | Invention |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (3) | (4) |
| Congruence | 0.119*** | 0.052*** | 0.126*** | 0.048*** | 0.114*** | 0.046*** |
| | (0.030) | (0.017) | (0.031) | (0.018) | (0.031) | (0.017) |
| MC2025 | 0.173 | -0.061 | 0.182 | -0.065 | 0.171 | -0.065 |
| | (0.118) | (0.077) | (0.119) | (0.077) | (0.118) | (0.077) |
| Congruence×MC2025 | -0.107*** | -0.062** | -0.134*** | -0.047* | -0.095** | -0.044** |
| | (0.039) | (0.023) | (0.045) | (0.025) | (0.042) | (0.022) |
| Export (t-1) | -0.161** | -0.130*** | -0.165** | -0.127** | -0.160** | -0.128** |
| | (0.072) | (0.051) | (0.072) | (0.051) | (0.072) | (0.051) |
| Tariff (t-1) | -0.004 | -0.000 | -0.004 | 0.000 | -0.008 | -0.006 |
| | (0.012) | (0.008) | (0.012) | (0.008) | (0.013) | (0.008) |
| Congruence×Export (t-1) | | | 0.018 | -0.010 | | |
| | | | (0.013) | (0.006) | | |
| Congruence×Tariff (t-1) | | | | | 0.009 | 0.013** |
| | | | | | (0.013) | (0.006) |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| City-by-year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| City-by-industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 17,300 | 17,300 | 17,300 | 17,300 | 17,300 | 17,300 |
| Adjusted R-squared | 0.276 | 0.210 | 0.277 | 0.210 | 0.276 | 0.210 |

Note: Dependent variables are patent applications, defined as 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. Export (t-1) represents one-year lagged industry-level export in logarithm. Tariff (t-1) represents one-year lagged U.S. tariff rates (in percentage points) on Chinese products at the industry level. 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.

# C. Additional Variable Constructions

In this section, we describe how we construct the measures of additional dimensions of congruence as discussed in the Robustness Analyses in Section 4.2.

1) *Human capital congruence.* The definition is analogous to that for congruence in the capital-labor ratios. The congruence in human capital structure is defined as

$$congruence\_HC_{sc} = -\left[\,\left|\log\left(\frac{H_{isct}/L_{isct}}{H_s/L_s}\right) - \log\left(\frac{\overline{H_c}/\overline{H_c}}{\bar{H}/\bar{L}}\right)\right|\,\right], \quad (2)$$

with $\bar{K} \equiv \sum_c \overline{K_c}$ and $\bar{L} \equiv \sum_c \overline{L_c}$. In the above equation, $H_{isct}$ and $L_{isct}$ are the number of employees with and without college education completion, respectively, for firm $i$ of industry *s* in city *c* in year *t*. Thus, $\frac{H_{isct}}{L_{isct}}$ measures the human capital structure of the firm. $H_s$ and $L_s$ are total high-skill and low-skill employment in industry *s* at the national aggregate level, respectively, defined using the cutoff of college education completion; therefore, $H_s/L_s$ measures the national average level of the human capital structure of industry *s*. $\overline{H_c}$ and $\overline{L_c}$ are high-skill and low-skill employment in city *c*, respectively. We calculate the city-level and industry-level H/L ratios based on the Chinese population census data in 2010.

2) *Occupational structure congruence.* Based on population census data in 2010, we calculate the occupational structure of each city as a vector. For city *c*, the vector is $occ_c = (s_c^1, \ldots, s_c^{409})$, where $s_c^n$ refers to the employment share of occupation *n* in city *c*. We use three-digit occupation codes, and there are 409 occupations in the population census data in 2010. Similarly, we calculate the occupational vector for an industry countrywide, $occ_s = (s_s^1, \ldots, s_s^{409})$, where $s_s^n$ refers to the employment share of occupation *n* in industry *s*. Then for firms in industry *s* in city *c*, the congruence in occupational structure is defined as the correlation between the two vectors, $occ_c$ and $occ_s$.

3) *Technology structure congruence.* We merge the patent data collected from CSMAR and Incopat with the firm data from CSAT based on firm names. Then we can calculate the shares of patents across technological classifications (125 3-digit IPC codes) for each industry. For city *c*, the vector is $tech_c = (s_c^1, \ldots, s_c^{125})$, where $s_c^n$ refers to the share of IPC code $n$ in patents in city $c$. Similarly, we calculate the occupational vector for an

industry countrywide, $tech_s = (s_s^1, \ldots, s_s^{125})$, where $s_s^n$ refers to the share of IPC code *n* in patents in industry *s*. Then for firms in industry *s* in city *c*, the congruence in technology structure is defined as the correlation between the two vectors, $tech_c$ and $tech_s$.

4) *Production network congruence*. We measure production network congruence—in another word, vertical integration—for firms in an industry in a city by combining city-level industry compositions and inter-industry input-output linkages. For industry *s* in city *c*, its integration with vertically related industries is defined as $Upstream_{sc} = \sum_j w_{s\leftarrow j} \times \frac{E_{jc}}{E_c}$ and $Downstream_{sc} = \sum_j w_{s\rightarrow j} \times \frac{E_{jc}}{E_c}$, where $E_{jc}$ denotes the employment in industry *j* in prefecture *c*, and $E_c$ is the total employment in city *c* in China; $w_{s\leftarrow j}$ and $w_{s\rightarrow j}$ are weights constructed based on the input-output table published by National Bureau of Statistics in China in 2012. The production network congruence at the city-industry level is defined as the maximum of $Upstream_{sc}$ and $Downstream_{sc}$.