E Pluribus Unum: Growing TFP From Regional Trade

Weizhe Wang, Zhong Zhao, Xianqiang Zou *

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Abstract

We study how trade shocks shape the distribution and aggregate level of heterogeneous firms' total factor productivity (TFP). By integrating detailed administrative data and utilizing the Urban Integration Policy (UIP) as a policy shock, we demonstrate that the dismantling of local protectionism and the rise of regional trade in China significantly enhanced firms' TFP. However, this growth was accompanied by a decline in patenting activity. We argue that the observed TFP growth is predominantly driven by firms engaging in imitation, consistent with a heterogeneous firm trade model that incorporates an imitation-innovation trade-off. Finally, we show that UIP has contributed to over a 10% increase in China's aggregate productivity, with knowledge diffusion serving as the dominant channel. This finding contributes to the broader understanding of trade's role in shaping productivity dynamics.

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1 Introduction

Total factor productivity (TFP) emerges as a cornerstone in understanding long-term economic growth, shedding light on the intricate mechanisms underpinning economic prosperity (Jorgenson, 1991). At the heart of economic discourse, TFP's influential role has sparked a wealth of theoretical frameworks aimed at deciphering the factors driving its fluctuations (Lagos, 2006; Hsieh and Klenow, 2009; Caliendo and Rossi-Hansberg, 2012; Sraer and Thesmar, 2023). In the forefront of contemporary economic inquiry, a growing perspective investigates the potential of regional trade to sculpt TFP landscapes via channels of innovation (Akcigit and Melitz, 2022; Melitz and Redding, 2023).

A major obstacle complicating the pursuit of a detailed empirical understanding of this topic is the need to systematically analyze the dynamic relationship between trade barriers and firms' innovation incentives. The mainstream literature, including studies by Andersson, Berger and Prawitz (2023) and Donaldson (2018), primarily explores the economic impacts of changes in trade cost from the perspective of transportation infrastructure development. However, in the context of local protectionism, trade costs are not solely determined by the level of infrastructure development but also arise from systemic institutional frictions driven by government policies. These institutional frictions, while intertwined with infrastructure, directly influence firms' innovation strategies, complicating our understanding of the mechanisms by which trade impacts productivity. This complexity represents a significant analytical challenge, as it underscores the necessity of a deeper exploration of the nature of local protectionism to uncover its specific pathways of influence on firms' innovation strategies (Akcigit, Ates and Impullitti, 2018). Such an exploration requires clarifying the specific forms of cross-regional institutional frictions, mapping changes in government policies, and identifying exogenous variations in regional trade to facilitate causal estimation of productivity effects (Eaton and Kortum, 2002; Donaldson, 2015; Desmet, Nagy and Rossi-Hansberg, 2018).

In this paper, we explore an exogenous transition from entrenched local protectionism to regional integration within China. This exploration sheds light on the causal influences, scale, and mechanisms through which regional trade impacts TFP. To support this study, we have collected different datasets covering various aspects of businesses and the government. By combining multiple firm-level databases with business administrative data, we analyze various aspects of firm operations. Adding judicial documents, patent filings, land transaction data, and detailed government action records allows for a clear examination of the key factors shaping TFP growth in the context of local protectionism.

To be specific, we utilize a exogenous shift which referred to as the Urban Integration Policy (UIP). UIP implemented in a staggered manner by local governments in China and aimed at achieving regional integration. In each UIP cluster, it connects a core city with one to two peripheral cities to foster deep cooperation. We find that the policy effectively dismantled entrenched local protectionism and facilitated regional trade flows.

This setting is unique. Historically, China has been deeply entrenched in local protectionism, resulting in significant market segmentation and severe economic distortions (Young, 2000; Poncet, 2003; Bai et al., 2004; Amiti and Javorcik, 2008; Herrmann-Pillatha, Libman and Yu, 2014; Hsieh and Klenow, 2009). In response, at the start of the 21st century, the Chinese central government prioritized regional coordinated development in its strategic agenda. Following the national agenda, local governments began implementing UIP to break the cycle of fragmentation and promote economic integration. Within this context, we transparently reveal the specific shifts in government initiatives induced by UIP to uncover the rise of regional trade flows within UIP clusters. This enables an empirical evaluation of how such trade expansion reshapes the distribution and overall level of firm productivity while clarifying the specific mechanisms driving changes in firms' innovation incentives. Furthermore, the entrenched nature of local protectionism provides a measure to isolate potential network effects between treatment and control groups, which might otherwise impair the empirical

robustness of our results, particularly where extensive treatment effects could inadvertently influence the dynamics of the control group through interconnected production networks.

We begin by examining the trajectory of productivity growth in China. Despite starting from a relatively low absolute level, the pace of TFP growth in China since the start of the 21st century has been remarkable. From 2000 to 2013, productivity grew by 30.14% (Figure G.1). When grouped by UIP, our data seem to reveal a distinctive pattern underlying this productivity growth. As depicted in Figure 1, we observed that following the initiation of UIP in 2003, the TFP of firms in treated cities increased significantly compared to control cities. However, their patenting activities were notably suppressed. Additionally, firm dynamics occurred more frequently near the city borders between treated cities, suggesting the critical influence of regional trade (See Figure F.3).

From a theoretical perspective, this stylized fact appears unexpected yet intuitively logical, as China's early developmental lag, uneven distribution of innovative capabilities, and weak intellectual property systems might be more conducive to firms achieving productivity growth through imitation (Spulber, 2008; König et al., 2022). Regional trade flows, actually, facilitate the crucial transition from independent innovation to imitative innovation for the treated firms, resulting in directional firm dynamics. To elucidate this idea, we introduce a tractable model to depict the different margins of TFP growth. The underlying principle emphasizes the UIP's impact on iceberg costs and protectionist measures (government subsidies). As trade costs decrease, competitive pressures compel the least productive firms to exit the market, thereby amplifying overall productivity on the extensive margin. Meanwhile, the knowledge flows induced by trade reduced imitation costs and, coupled with the reduction in subsidies, suppressed subsidy-driven independent innovation. This recalibrated the critical trade-offs in firms' innovation behavior, making the imitation mechanism an endogenous driver of productivity growth on the intensive margin.

In our empirical part, we first demonstrate how UIP reshapes local government behavior to eliminate local protectionism and foster regional trade expansion within UIP clusters. Specifically, we find that UIP induces local governments to shift their focus from industrial policies to regional coordinated development. This shift significantly reduces the intensity of industrial policies, increases public expenditure (particularly on transportation infrastructure), and enhances transparency in the land market. These changes alleviate economic distortions, improve inter-regional labor mobility, and reduce entry barriers associated with local protectionism. In turn, this stimulates a significant increase in inter-regional direct investment in affected cities. With the decline in local protectionism, regional trade expands substantially: firms in treated cities experience notable growth in output, sales revenue, profits, selling expenses, and advertising expenditures. Simultaneously, intensified competition leads to a marked reduction in price markups. While UIP has limited influence on firms' export behavior, it significantly reduces import activities, reflecting the integration of markets within UIP clusters. With UIP's role in reducing local protectionism and promoting regional trade expansion established, we turn to the model's primary implications: whether, to what extent, and through which mechanisms UIP enhances firms' TFP.

Our DID-based findings reveal that, under the influence of the UIP, firms located in treated cities experienced a significant 7.8% increase in TFP compared to those in the control group. This effect grows over time, with the impact exceeding 20% seven years after implementation. Furthermore, we find that this growth is primarily driven by firms that have never applied for patents and are positioned between the 50th and 80th percentiles of TFP. This resonates with the model's prediction that TFP growth primarily emanates from firms engaged in regional trade, benefiting from the intensive margin effects of imitative innovation. This impact carries significant economic implications. Combining formal general equilibrium approaches (Sraer and Thesmar, 2023) with back-of-the-envelope quantifications based on reduced-form estimations indicates that the UIP has contributed to over 10% of the observed aggregate TFP growth in China from 2003 to 2013. Of this, productivity growth driven by

capital reallocation accounts for only 2%, consistent with the baseline results that most productivity growth is driven by the intensive margin effects of knowledge diffusion.

To uncover the specific patterns of productivity growth, we first empirically investigate whether the increase in firms' TFP under regional trade conditions is driven by imitative innovation (Intensive margin) or changes in firm composition (Extensive margin). We then preform extensive robustness checks and further employ an instrumental variable strategy to examine the sources and relative importance of these two mechanisms. Finally, we connect these findings to trade and innovation theories, addressing several unresolved macroeconomic questions.

Intensive Margin of TFP Growth: The evidence suggests that the growth in firms' TFP is largely driven by knowledge spillover effects at the intensive margin. As subsidies and trade costs decreased under the influence of the UIP, firms shifted their innovation strategies from independent innovation to more accessible imitative innovation facilitated by regional trade. Our empirical analysis reveals the role of two types of knowledge spillover effects: *formal learning* and *informal imitation*. First, in treated cities, formal patent transfers increased significantly, with more transfers directed to intra-provincial partner cities, fewer to extra-provincial cities, and a rise in patent citations from core cities. Second, as subsidies declined, firms in affected cities reduced their mislabeling of R&D expenditures to fraudulently claim subsidies (Chen et al., 2021). This led to a notable drop in patenting activities, suggesting a suppression of potential strategic patenting and a shift toward informal imitation (Argente et al., 2020). Our findings show that lower imitation costs and easier access to imitation activities significantly enhance the UIP's positive impact on firms' TFP, while also substituting for independent innovation. This result underscores that, under trade conditions, the optimal level of government R&D subsidies should decrease (Akcigit, Ates and Impullitti, 2018).

Extensive Margin of TFP Growth: Our comprehensive study on the impact of UIP on firms' location choices further provides consistent evidence of the extensive margin effects on overall TFP growth. Under the influence of powerful knowledge diffusion effects, firm dynamics within UIP clusters are exceptionally vibrant (Akcigit and Ates, 2023). Concurrently, due to the intense competition brought about by UIP, it poses significant barriers for some firms seeking market entry, especially those whose productivity is below the optimal level. At the same time, such existing firms are more inclined to relocate to cooperative entities more conducive to organizing production activities, or to exit the market directly. This change in firm composition accelerates the overall improvement in TFP.

We have addressed several potential threats to the validity of our empirical specifications. Our covariate balance, event study estimates and alternative estimates consistently indicate the results are robust. Moreover, baseline results remain robust after controlling for several time-invariant or time-varying controls, using alternative measures of TFP, eliminating of several significant competitive assumptions related to TFP, conducting placebo test for random UIP adoption, applying different data windows and specifications, exploring heterogeneous treatment effect under staggered DID design, and addressing the potential contamination under SUTVA.

We further utilize the dialect similarity between peripheral and core cities, the existence of railway connections between peripheral cities and core cities in 1933, and the presence of post stations in core cities during the Ming Dynasty as instruments for implementing UIP. We prove that baseline results are not influenced by potential selection threats during policy implementation. Concurrently, institution frictions appear to be the fundamental cause of local protectionism. When governments collaborate to eliminate trade barriers, shared cultural traits significantly aid in dismantling local protectionism, enabling knowledge diffusion to become the primary driver of productivity growth. However, predetermined trade conditions and regional productivity levels determine the effectiveness of the knowledge diffusion mechanism. When the iceberg costs of regional trade are inherently low, or when the most productive firms in a region are already numerous, the channels of knowledge dissemination seem negligible. In such cases, productivity growth is primarily driven by favorable

changes in firm composition.

We further address some unresolved macroeconomic questions in the theories of trade and innovation. First, regarding the benefits of trade participation for both parties. we have observed that TFP growth under UIP is primarily driven by peripheral cities. This aligns with the notion that latecomer entities achieve productivity growth through imitative innovation, while early-movers benefit from enhanced resource allocation efficiency resulting from changes in firm composition. Second, concerning the issue of specialization based on comparative advantage. Under the variations in firm composition, core-periphery relationships drive industries to relocate to peripheral cities that facilitate organized production, shaping an industrial structure that aligns with local comparative advantages. These industries dominate TFP growth.

This paper contributes to several strands of literature. First, it contributes to the study of local protectionism (Fang, Li and Wu, 2022; Barwick, Cao and Li, 2021; Liu et al., 2022). We examine how resolving institutional frictions enables trade to drive long-term national economic development through knowledge diffusion (Wolf, 2000; Sonin, 2010; Froot, Kim and Rogoff, 2019). While previous studies have primarily focused on the role of infrastructure improvements (Donaldson, 2018; Andersson, Berger and Prawitz, 2023), this paper identifies institutional frictions as a significant source of iceberg costs in the context of local protectionism. This emphasis helps to understand firms' innovation choices and economic outcomes under trade shocks, offering new insights into how trade influences dynamic economic welfare through innovation channels (Akcigit and Melitz, 2022; Melitz and Redding, 2023). Furthermore, as an initial effort to uncover the causal relationship between local protectionism and macro-level productivity dynamics, this paper enriches the body of literature on the determinants of TFP (Gai et al., 2021; Brandt and Zhu, 2010; Hsieh and Klenow, 2009; Sraer and Thesmar, 2023). In terms of policy implications, our findings strongly support the view that optimal R&D subsidies should decrease with increasing trade openness (Akcigit, Ates and Impullitti, 2018). This suggests that addressing local protectionism and facilitating a transition from industrial policies to regional policies could be effective tools for achieving long-term growth in developing countries.

In theoretical aspects, drawing upon the insights of Aghion et al. (2021); Akcigit and Melitz (2022); Melitz and Redding (2023), we connect to an emerging body of literature that integrates trade theory with innovation to quantify the dynamic economic benefits of regional trade and distinguish the relative importance of different mechanisms. Contrary to the perspective of Bau and Matray (2023), we find that trade flows not only relate to improvements in resource misallocation but also profoundly reshape firms' innovation incentives. This finding complements the results of Bloom, Draca and Van Reenen (2015), which demonstrate that trade expansion enhances innovation incentives in developed economies. In contrast, our findings emphasize a novel trade-off between imitation and innovation under trade conditions, showing that for countries distant from the knowledge frontier, knowledge diffusion through trade fosters greater reliance on imitation, leading to greater firm dynamism and significant improvements in TFP. These findings align with macroeconomic research suggesting that imitation drove China's early economic growth, while a decline in knowledge diffusion contributed to the stagnation of firm dynamics in the United States (König et al., 2022; Akcigit and Ates, 2023). Furthermore, our evidence shows that under regional trade conditions, even as governments reduce the intensity of industrial policies, leading to a decline in patenting activities, TFP still increases. This highlights concerns in the literature about the welfare-reducing effects of strategic patenting activities (Argente et al., 2020; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020; Akcigit and Ates, 2023).

From an empirical perspective, by introducing exogenous shocks, we address the longstanding challenge of rigorously investigating the causal impact of regional trade due to the limitations of SUTVA (Eaton and Kortum, 2002; Donaldson, 2015). This approach reveals the specific operational mechanisms of key predictions in trade theory within the context of regional trade expansion (Melitz, 2003;

Bernard, Redding and Schott, 2007; Melitz and Redding, 2014; Caliendo et al., 2017). Specifically, we document the sources, impacts, and relative importance of knowledge diffusion and firm composition under regional trade, addressing how trade participants benefit (Waugh, 2010; Uy, Yi and Zhang, 2013; Święcki, 2017), and resolving several outstanding issues related to comparative advantage, market size, and resource allocation (Bernard, Redding and Schott, 2007; Melitz and Redding, 2023; Akcigit and Melitz, 2022; Hsieh and Klenow, 2009). Essentially, our research findings are a crucial component of integrating heterogeneous firm trade models with innovation models, confirming that incorporating a knowledge diffusion function into quantitative spatial models to characterize productivity dynamics represents a substantive innovation (Desmet and Rossi-Hansberg, 2014; Desmet, Nagy and Rossi-Hansberg, 2018) and further emphasizing the endogenous and customized design of the knowledge diffusion function.

2 Policy Background and Conceptual Framework

2.1 Policy Background

The objective of this paper is to empirically investigate the changes in both the distribution and aggregate level of firm TFP under regional trade conditions. For this purpose, we focus on China, owing to a key characteristic: historically, China has faced significant local protectionist measures. However, since the early 21st century, we observe that Chinese local governments have increasingly dismantled these protectionist barriers, providing a well-defined exogenous shock to the emergence of regional trade. This development offers a solid foundation for estimating causal effects.

2.1.1 Local Protectionism in China

Local protectionism in China is deeply rooted in its historical context. On one hand, a pivotal aspect of China's history is its developmental trajectory spanning over 5,000 years, marked by dynastic changes initiated across different regions by various ethnic groups. This dynastic evolution, driven by cultural divergences, led to significant familial separations and competition, engendering pronounced protectionism at the territorial level. To this day, China encompasses 56 distinct ethnic groups and more than 80 different languages[1]. On the other hand, many scholars argue that China's decentralized administrative system has fostered a competitive milieu among local governments, contributing to market fragmentation. The term "*razor's edge*" (Young, 2000) symbolizes this perspective, highlighting the competition among local autonomous entities triggered by the devolution of various powers from the central government. This competition is also perceived as a foundational element of local protectionism.

In the late 20th century, Deng Xiaoping's economic philosophy of *allowing some people and regions to become prosperous first, then gradually achieve common prosperity* becomingly cope with the local protectionism stemming from historical roots. This was particularly the case during the nascent period of industrialization when internal market demand was strong and often did not require external incentives. Consequently, major provincial cities representing advanced regions experienced early development, supporting the preliminary growth during the initial stages of China's economic reform.

Entering the new millennium, divergent situations emerged. As these advanced regions achieved significant economic growth, regional disparities in wealth widened further, and the people's pursuit of diversity urgently demanded entry into a phase of common prosperity. Simultaneously, this localism paradoxically inhibited the product diversification that urban integration would bring. For this reason, central policies promoting coordinated regional development were introduced. Specifically, clear

[1]The extent of dialectal isolation is such that it impedes effective communication among many ethnic communities.

policy divergences appeared between the Tenth Five-Year Plan and the Ninth Five-Year Plan. The Tenth Five-Year Plan underscored the importance of *breaking administrative segmentation*, *leveraging regional comparative advantages*, and fostering the *rational construction of the urban system*. These priorities highlight the central government's increasing commitment to dismantling local protectionism and promoting economic growth.

2.1.2 The Emergence of UIP

Against the backdrop of the central government's initiative to promote coordinated regional development, local governments have been actively dismantling local protectionism to align with central directives. The UIP serves as a cornerstone in achieving this goal. Its fundamental principle is to transform local governments' protectionist competition, rooted in industrial policies, into a cooperative model based on regional policies. By forming city clusters of 2–3 cities, the UIP aims to foster the emergence of regional trade within the clusters.

Regarding the specific content of the UIP, our review of policy documents reveals that all UIPs emphasize the necessity of strengthening intercity cooperation. Specifically, this is reflected in three key measures: reducing local protectionist practices to dismantle trade barriers, enhancing the construction of transportation networks to lower iceberg costs, and fostering regional industrial linkages to upgrade the industrial structure. Collectively, these measures have directly contributed to the rise of regional trade among cities within the clusters. In the empirical analysis, we will provide evidence that directly aligns with these objectives, illustrating the reduction of local protectionism and the development of regional trade facilitated by the UIP.[2]

Regarding the selection of cities for UIP implementation, we argue that historically determined cultural ties are key factors influencing this decision. Specifically, we find that cities sharing similar dialect attributes in history are more likely to form cooperative clusters. A representative case illustrating the essence of the UIP is the cluster formed by Guangzhou and Foshan. As shown in Figure F.3, Guangzhou is adjacent to both Foshan and Dongguan. However, Guangzhou cooperated with Foshan rather than Dongguan. A core reason is the shared dialect affiliation between Guangzhou and Foshan, which differs from that of Dongguan. In the subsequent analysis, we employ this cultural attribute as an IV for UIP to demonstrate that the observed effects of UIP are causal, not driven by pre-existing economic conditions. Supporting this claim, as shown in Tables C.3 and C.4, all important and relevant factors remain balanced between the treatment and control groups before the implementation of UIP.

With respect to the geographic structure and the impacts of the UIP, by 2013, a total of 14 provinces—including Hunan, Guangdong, Henan, Liaoning, Xinjiang, Anhui, Gansu, Jilin, Jiangsu, Fujian, Guizhou, and Hubei—had implemented UIP, covering 34 cities throughout our sample period (Appendix A outlines the detailed progression of UIP implementation). Regarding provinces, those included in the UIP constitute 43.75% (14/32) of all provinces in China, inclusive of independent regions and municipalities directly under the central government. Pertaining to prefecture-level cities, the cities included in the UIP constitute 12% (34/283) of all cities in China, illustrating the expansive influence of UIP on local protectionism in China. It is worth noting that the provinces that have adopted UIP represent 45.5%, 50%, and 41.7% in the eastern, central, and western provinces of China, respectively. This suggests a suitable control group with similar attributes to the treatment group (see Figure C in Appendix C for reference), thereby providing a solid base for our empirical study.

[2] A typical case of UIP is reported in Appendix A, demonstrating the specific measures of UIP. Furthermore, we also detail the specific circumstances of UIP adoption in all treated cities.

2.2 Conceptual Framework

To elucidate the intricate relationship between UIP and TFP growth, as revealed by the patterned facts, and to provide rigorous guidance for empirical work, we endeavor to construct a simple model. This model aims to clarify the role of extensive margins related to firm entry-exit dynamics and intensive margins associated with firm innovation behavior in influencing aggregate TFP and its distribution. With this objective in mind, we build upon the seminal work of Melitz (2003) and integrate the strategic model related to firm innovative behavior as proposed by König et al. (2022). This approach endogenizes the fluctuations in firm-level productivity. For simplicity, the main text presents only the theoretical intuition and key implications of the model, while the full model can be found in Appendix I.

2.2.1 Setup

Environment

We begin with an economic framework comprised of n_c cities, where the municipal governments operate within a decision set $\Psi\{pi(o), \tau(1-o)\}$ and $o \in (0,1)$. Within this parameter space, authorities allocate a portfolio of fiscal expenditures, the pivotal distinction being whether or not to implement local protectionist measures. These policy decisions are exogenously dictated in alignment with the overarching guidelines articulated by the central government. The primary objective of these fiscal choices involves optimizing two representative types of public expenditure: firm subsidies (denoted as τ) and public investment (denoted as pi), aimed at reducing institutional frictions (ι) that influence iceberg costs in regional trade, where $\iota = 1/pi$. We introduce o to define the government's fiscal allocation ratio. Under the adoption of UIP, o increases, reducing subsidies to firms while increasing public investment aimed at alleviating iceberg costs.

Heterogeneous Innovation

We first conceptualize productivity growth on the intensive margin under trade conditions, driven by heterogeneous innovation. Within the two-period innovation decision framework of König et al. (2022), firms can achieve TFP improvement $\tilde{g}$ through both imitative innovation and independent innovation. These are characterized by $m(\iota)$ and I, respectively, as realization probabilities, where $m'(\iota) = 0 \; if \; a < a^x, m'(\iota) < 0 \; if \; a >= a^x$, where a^x is the regional trade cut-off point will be introduced formally later[3], and I is randomly drawn from an i.i.d.- c.d.f $B : (0, \bar{I}]$, and $\bar{I} \leq 1$. To simplify the analysis, the firm's individual productivity is defined in a step-like discrete ranking form represented by a_r, where both successful imitative innovation and independent innovation can increase a_r by one level. If $\mathcal{T}$ is defined as the productivity level for each a_r, the productivity c.d.f. up to a_r can be written as F_{a_r}.

For firms initially opting for independent innovation, there exists the opportunity to pivot toward imitative innovation in the event of failure, with the probability of realization, $c(\tau)m(\iota)(1 - F_{a_r})$. However, this entails an opportunity cost, $c(\tau)$. If $c(\tau) > 1$, it indicates that engaging in independent innovation is advantageous for better realizing imitative innovation, and vice versa if $c(\tau) < 1$. We have $c'(\tau) > 0$ and $c(\tau) < 1$, implying that subsidies serve to enhance the incentives for firms to undertake independent innovation. Firms will only engage in independent innovation activities if the return of independent innovation exceeds that of imitative innovation. Therefore, the probability of successful innovation realization must satisfy the following condition:

[3]The economic intuition is straightforward: higher iceberg costs impede regional trade for firms, making it less likely for low-productivity firms to encounter firms with higher productivity levels (as typically only higher-productivity firms can afford to engage in trade).

$$I_i > T(a, \tau, \iota; \mathfrak{T}) \equiv \frac{m(\iota)(1 - c(\tau))(1 - F_{a_r})}{1 - c(\tau)m(\iota)(1 - F_{a_r})} \tag{1}$$

We set a threshold T such that independent innovation occurs only when the expected probability of innovation exceeds T. This threshold is defined by a firm's own productivity level a, iceberg costs ι, and subsidies τ. Clearly, $\frac{\partial T}{\partial a} < 0$, as defined by König et al. (2022), indicating that higher-productivity firms are more likely to rely on independent innovation. Concurrently, the higher the productivity level, the harder it is to encounter firms with higher productivity levels for realizing imitative innovation, and the lower the subsidy, the more it harms the firm's long-term profits and suppresses independent innovation activities. We then use χ_{im} and χ_{in} to define a firm's innovation decisions, i.e., undertaking imitative innovation and independent innovation, respectively.

$$\chi_{\text{im}}(a, I, \tau, \iota; \mathfrak{T}) = 1 - \chi_{\text{in}}(a, I, \tau, \iota; \mathfrak{T}) = \begin{cases} 1 & \text{if } I \leq T(a, \tau, \iota; \mathfrak{T}) \\ 0 & \text{if } I > T(a, \tau, \iota; \mathfrak{T}) \end{cases} \tag{2}$$

Since innovation is costless, heterogeneous firms simply trade off between the two forms of innovation to achieve the optimal productivity level in the second period. This allows us to directly integrate the framework into the static trade model of Melitz (2003). When doing so, heterogeneous firms choose their optimal innovation strategies based on government policies, which determine the equilibrium productivity distribution and aggregate level. This provides testable empirical implications.

2.2.2 Equilibrium Under UIP: Extensive Margin

We now describe the extensive margin growth of productivity in trade equilibrium. Following Melitz (2003), the marginal productivity levels for firms entering the market and engaging in trade can be denoted as a^e and a^x, respectively. These two thresholds satisfy a given relationship, weighted by the elasticity of substitution, the iceberg cost ι, and regional fixed trade cost f_x, divided by the entry cost f:

$$a^e, a^x = \begin{cases} a^e = \inf\{a : V(a) > 0\} & \text{if Successful Entry} \\ a^x = \inf\{a : a > a^e, \quad \pi_x(a) > 0\} & \text{if Regional Trade} \end{cases} \tag{3}$$

$$a^x = a^e \iota \left(\frac{f_x}{f}\right)^{\frac{1}{\sigma - 1}} \tag{4}$$

Next, we present the market aggregation function defined over the equilibrium distribution of productivity $F(a)$, which endogenously determines the final form of firm TFP dynamics. The average productivity of the economy, $\tilde{a}_t$, is given by the following expression, defined as a form of CES aggregation of the productivity of incumbent non-trading firms and trading firms:

$$\tilde{a}_t = \left(\frac{1}{M_t}\left[M\tilde{a}(a^e)^{\sigma-1} + nM_x\left(\tau^{-1}\tilde{a}(a^x)\right)^{\sigma-1}\right]\right)^{\frac{1}{\sigma-1}}, \quad M_t = M + nM_x = M + nx_rM \tag{5}$$

Implications

We are concerned with how the government's selection regarding o will impact the variations in aggregate TFP, as well as its transmission mechanisms (cut-off points). This shift is anticipated to elevate the mean TFP primarily due to the exit of low-productivity firms from the market, attributable to heightened competition, denoted as the extensive margin:

$$\frac{\alpha a^e}{\alpha o} > 0, \frac{\alpha a^x}{\alpha o} < 0, \frac{\tilde{a}}{\alpha o} > 0 \tag{6}$$

Proof. See Appendix I

Proposition 1 *If the UIP eliminates local protectionism, the government would channel public investment into infrastructure development, thereby reducing iceberg costs and fostering inter-regional trade. This policy shift would engender three pivotal changes along the extensive margin: (1) a rightward shift in the firm entry cutoff a^e, leading to the exit of more low-productivity firms from the market; (2) a leftward shift in the cutoff for firms participating in regional trade, enabling a larger number of firms to engage in such activities; and (3) an enhancement in aggregate TFP.*

2.2.3 Equilibrium Under UIP: Intensive Margin

Subsequently, we delve into the internal innovation trade-offs within firms that lead to the equilibrium dynamics of TFP at the intensive margin. Analogous to the model proposed by König et al. (2022), we posit the existence of an innovation threshold a^i, such that firms with $a > a^i$ engage in independent innovation, while those with $a \leq a^i$ partake in costless imitative innovation. Intuitively, a decrease in iceberg costs ι—making imitative innovation more accessible—and a decrease in subsidies τ—escalating the challenge of independent innovation activities—both contribute to a rightward shift in the equilibrium of independent innovation cut-off point. We define this as a function positively correlated with a threshold T along the TFP equilibrium growth trajectory, $\alpha a^i/\alpha T > 0$[4].

Implications

We investigate how alterations in the government's allocation function influence the critical trade-offs in firm innovation behavior by modifying iceberg costs and subsidies, thereby affecting the growth of firm productivity along the intensive margin:

$$\frac{\alpha a^i}{\alpha o} > 0, \quad \frac{\alpha v}{\alpha o} = \begin{cases} = 0 & \text{if } a < a^x \\ > 0 & \text{if } a^x <= a < a^i \\ < 0 & \text{if } a >= a^i \end{cases} \tag{7}$$

Proof. See Appendix I

Proposition 2 *The breakdown of local protectionism will enhance TFP growth along the intensive margin. This emanates from a rightward shift in the independent innovation cutoff point a^i due to reductions in subsidies and iceberg costs, as well as a leftward shift in the regional trade cutoff point a^x. These shifts collectively enable a larger number of firms to benefit from imitative innovation, thereby accelerating TFP advancement. Along this trajectory, independent innovation activities are subdued.*

2.2.4 Comparative Static and Explanations

To elucidate the implications of the model, we conduct a comparative static analysis of three distinct equilibrium, as depicted in Figure 4. These equilibrium are represented by the cumulative distribution

[4]The economic intuition behind this assumption is clear: since the probability of achieving independent innovation is randomly drawn from an exogenously given distribution, an increase in T implies that only firms with much higher productivity find it more profitable to pursue independent innovation over imitation, given the probability drawn for successful innovation. Consequently, in the dynamics of the productivity distribution, a^i will shift to the right, indicating that more firms will rely on imitation to enhance productivity.

of firms in relation to their productivity levels. Initially, a gray line delineates an equilibrium devoid of both regional trade and innovative activities. Subsequently, a black line demarcates an equilibrium characterized by the presence of innovative undertakings, distinguished by the independent innovation cutoff point a^i. Finally, an equilibrium encompassing both regional trade and innovation under a UIP framework is identified, marked by a shifted independent innovation cutoff point $a^{i(\text{UIP})}$, a regional trade cutoff point $a^{x(\text{UIP})}$, relative to a counterfactual regional trade cutoff point a^x in a no-innovation scenario, a firm exit cutoff point $a^{e(\text{UIP})}$ and corresponding counterfactual exit cutoff point a^e. And the explanations for the dynamics are provided in the figure's annotations.

3 Empirical Strategy and Data

3.1 Empirical Strategy

We use the Difference-in-Differences estimator to identify the causal effect. This model is specified in equation (8).

$$TFP_{ict} = \alpha + \beta \times UIP_{ct} + X_{ict} + \gamma_t + (\lambda_i \quad or \quad \theta_c) + \varepsilon_{ict} \tag{8}$$

Where TFP_{ict} is the total factor productivity of firm i in year t of city c, measuring the firm's ability to transform the same inputs into outputs, in other words, the efficiency of its production technology. We measure it by adopting the method from Ackerberg, Caves and Frazer (2015) in baseline estimation. We further adopt the method from Olley and Pakes (1996); Levinsohn and Petrin (2003); Gandhi, Navarro and Rivers (2020) for robustness check (See Appendix B.4 for further details on the measurement). UIP_{ct} is a dummy variable for measuring if a firm is affected by UIP (1 after UIP, otherwise 0). We focus on β, which captures the Average Treatment Effect on the Treated (ATT) of UIP on firm's TFP.

We also include control variables that capture firm-level and city-level attributes in our regression. We include firm's age, which is measured as the logarithm of the time elapsed between its registration year and the survey year. The firm's history of successful Research & Development (R&D) activities is another control variable, symbolized by the dummy variable denoting whether the firm sought patents during its early stages. A firm's export status, marked by a dummy variable indicating its engagement in export activities, is also included. Additionally, three pre-determined city characteristics [5]—population size, per capita GDP, and the citywide share of the secondary industry—interacted with the annual trend are also included. We also include time-fixed effects γ_t, firm-fixed effects λ_i, or city-fixed effects θ_c. When firm fixed effects are accounted for, the coefficient for UIP_{ct} can be interpreted as the intramural variation in TFP within firms, denoting the intensive margin effects of the UIP. Conversely, when controlling for city fixed effects, it represents the mean shift in TFP at the city level, encapsulating a confluence of both intensive and extensive margin effects of the UIP. Lastly, ε_{ict} represents the error term and are clustered at the city-year level.

For the Difference-in-Differences (DID) specification to yield a valid estimate of the causal effect of the UIP, it is necessary to verify that the treatment and control groups exhibit parallel trends in a firm's TFP during the pre-treatment period. To test the assumption of a common trend, and to account for the potential time-varying effects of the UIP, we estimate the following event study analysis (ESA) specification. We create a set of year dummies and interacting them with an indicator for whether a firm is located in a city that received the treatment (Sarah, Norman and Laura, 2021):

[5] Values from 2002, before the initial adoption of UIP.

$$TFP_{ict} = \beta_0 + \sum_{d=-5}^{7} \delta_d \cdot \mathbb{I}(Year_{ct} = t + d) \cdot UIP_{ic} + X_{ict} + \gamma_t + (\lambda_i \quad or \quad \theta_c) + \epsilon_{ict} \tag{9}$$

Where $\mathbb{I}$ is an indicator function, $Year_t$ indicates the year of observation for firm i in city c, and δ_d captures the difference between the firms located in treated cities and the firms located in control cities in year $t + d$. The rest of the variables are defined in the same way as those in equation (8).

3.2 Data

A key advantage in studying changes in China's TFP is the availability of extensive data sources, including the China Industrial Enterprise Database. This database includes a wide range of industrial firms across various regions of China[6], and incorporates specific details such as output, costs, firm characteristics, subsidies, etc.

We also utilize the registered business records from the Administration for Industry and Commerce in China. We integrate micro-level data from diverse sources-China Industrial Enterprise, Customs, and Patent Databases-based on geographic coordinates, and create unique micro-panels. Moreover, we construct innovative panels to analyze urban, judicial, and land system features, enabling a detailed examination of firm behaviors and urban dynamics. This includes observing firms' production behaviors and TFP (Panel A), identifying local versus non-local investments through equity networks(Liu et al., 2022) (Panel B), and examining urban changes and infrastructure developments such as high-speed rail (Panel C)[7]. Additionally, we investigate international trade behaviors (Panel D), patent activities and quality(Hsu et al., 2023) (Panel E), judicial documents to gauge the legal environment (Panel F)[8], site selection activities (Panel G), government land leasing and industrial policies (Panel H)[9], and patent transfers between firms (Panel I)[10] (More details at Appendix B).

At last, we undertook a collection of information related to UIP from various sources, including government websites and news reports. Specifically, we analyzed 15 representative instances of urban integration occurring between the years 2000 and 2013. The cases were drawn from the following areas: Changzhutan, Guangfo, Xixian, Zhengbian, Shenfu, Wuchang, Taijin, Hehuai, Lanbai, Changji, Ningzhenyang, Xiazhangquan, Shantou Chaojie, GUI'an, and Wu'e (More details at Appendix A).

In Appendix C, Table C.1 presents a summary of statistics that delineate the principal characteristics of Chinese firms and cities, categorizing them into treatment and control groups. It is distinctly evident that the mean TFP of the firms in the treatment group exceeds that of the control group.

[6] It is noteworthy that the industrial enterprises referred to herein specifically denote above-scale manufacturing firms. The criterion for 'above-scale' varies across different years. For instance, during 2005-2006, the classification encompassed all state-owned enterprises and those with main business revenues exceeding 5 million RMB. In the period 2007-2009, it included enterprises with main business revenues over 5 million RMB, and during 2011-2013, the threshold was raised to enterprises with revenues exceeding 20 million RMB. To validate that our design is unaffected by this change in survey scope, we have employed different specifications of data structure for robustness checks.

[7] Additionally, to identify the spillover effect of UIP, we collected geographic coordinate information of the center of mass for both firms and cities.

[8] We organized textual materials and calculated the total number of legal cases in each city, including cases with keywords *patent* and *ownership*, to depict a city's legal environment related to intellectual property protection and assess UIP's influence.

[9] We utilized comprehensive data on land transactions from local government from the China Land Market website, https://landchina.com/#. Concurrently, to contemplate the influence of China's industrial strategy on corporate behavior, we employed text analysis on provincial governments' work reports to discern industry codes earmarked for preferential support.

[10] Using patent legal status change information from the National Intellectual Property Administration, we extracted over two million cases of patent rights transfers, resulting in a total of 138,941 observations. By cleaning data related to the timing and entities involved in patent rights transfer, we captured the geographical trajectory of patent movements.

This implies that the UIP may exert a positive influence on the firm's TFP. Subsequent sections will provide a robust causal relationship between the two entities.

4 UIP, Local Protectionism, and Regional Trade

In this section, our primary objective is to clarify the nature and economic implications of the UIP. Align with the model, two critical questions guide our analysis. First, as a cornerstone for dismantling regional trade barriers, has the UIP effectively accelerated the decline of local protectionism? Second, has the weakening of local protectionism genuinely facilitated the expansion of regional trade markets, and to what extent has it contributed to such an expansion?

4.1 Disorganization of Local Protectionism

Significant local protectionism exists across different regions in China, which we partly attribute to competition among local governments. We argue that the sources of iceberg costs in the model are multifaceted, driven by systemic institutional frictions. These frictions include industrial policies aimed at protecting and supporting local firms, the level of transportation infrastructure, and barriers to market entry. Such institutional frictions may exacerbate difficulties in interactions among firms or hinder the exchange of knowledge. Consequently, even when natural proximity exists between regions (e.g., cultural similarities), these interaction difficulties can constrain regional trade, thereby impeding productivity growth.

Government Behaviors: We document the key policy shifts undertaken by the government to dismantle local protectionism from three perspectives.

Reducing the Intensity of Industrial Policies: Based on Panel A of Table 1, we find that the government reduced adverse economic distortions by scaling back fiscal interventions. According to Columns 1-2, the implementation of the UIP led to a significant reduction of approximately 16% in the average subsidies allocated to firms compared to the control group, while the average number of zombie firms decreased significantly by 0.5%. On the one hand, this may indicate a policy shift under the central government's guidance from protectionist measures based on industrial policies to a collaborative model rooted in regional policies. On the other hand, from the perspective of firms, this may reflect an increase in the cost of independent innovation, thereby incentivizing them to engage in more efficient imitation. As shown in Columns 3-4, whether we consider the key industries explicitly designated in central policy documents (Column 3) or industries identified as actively encouraged based on semantic analysis (Column 4), we find that the UIP has promoted productivity improvements among firms not categorized under industrial policies, while suppressing the productivity of firms benefiting from such policies. This pattern signifies substantial efficiency gains.

Significant Development of Infrastructure: As shown in Panel B of Table 1, government investment in the public sector surged by 4.5%, indicating substantial progress in infrastructure development. To verify this, we utilize a manually collected dataset on high-speed railway construction to examine the causal relationship between the UIP and infrastructure advancement, as shown in Columns 3-4. Specifically, under the influence of the UIP, both the speed and track length of high-speed railways in treated cities increased significantly. Notably, these increases were almost entirely driven by railway lines containing UIP clusters, with speed increasing by 43 km per hour and track length extending by 448 km. Moreover, as shown in Column 2, this infrastructure improvement also led to a significant 10.7% enhancement in personnel mobility, which serves as a carrier for knowledge diffusion, fostering the emergence of knowledge spillovers within UIP clusters.

Land Market Transparency: As per Figure E.2, following the implementation of UIP, affiliated treated cities spearheaded the growth in the average area of newly-sold land plots. However, this

shift was accompanied by a significant rise in average land prices (Panel A). More specifically, the growth in building area and land prices is predominantly driven by industrial land, echoing our focus on industrial firms (Panel B). To elucidate this price surge, we discern that the price increment is chiefly steered by land contracts sold through public market auctions (Panel C), while the prices of lands more likely transacted internally by governments did not change significantly (Panel D). This indicates that the peripheral city governments are promoting transparency in the land market, hinting that these cities aspire to attract investments and industries from core cities.

Economic Outcomes: Based on the aforementioned shifts in government decisions, we identify corresponding changes in economic outcomes that confirm the decline in local protectionism.

Interregional Investment Flows: Drawing from Table 1, Columns 1-2 of Panel C, UIP significantly increased the proportion of investments received by treated cities from other cities within the same province, with an average increase of approximately 11,550 yuan per firm (or roughly 0.3% in proportional terms). We argue that this result is primarily driven by the decline in protectionism among cities within UIP clusters, rather than among control group cities or between treated and control group cities. On the one hand, we present strong descriptive evidence that, since the introduction of UIP in 2002, external investments in treated cities have exceeded those in other cities, and this gap has continued to widen over time (see Appendix F, Figure F.1). On the other hand, referring to Columns 3-4 of Panel C, we find that investments received by treated cities from cities outside their province remain unchanged, indicating that cross-provincial protectionism has persisted.

In summary, our findings provide a comprehensive picture of how the UIP has mitigated local protectionism. Specifically, with the implementation of UIP, government decision-making underwent a significant shift from focusing on industrial policies to prioritizing regional coordinated development. This, in turn, led to the dismantling of local protectionism, substantially alleviating economic distortions and enhancing interregional knowledge flows. More specifically, on the one hand, the weakening of industrial policy intensity facilitated rapid growth in TFP among firms that did not rely on industrial policies. On the other hand, investors, particularly affluent entrepreneurs from core cities, were more inclined to invest in collaborative cities, exploring new ventures. Simultaneously, interregional labor mobility surged, enabling knowledge to flow more effectively across regions.

4.2 Regional Trade Expansion

Subsequently, we empirically demonstrate that the dissolution of local protectionism has led to a significant expansion of regional trade markets. Specifically, we argue that the expansion of trade markets exhibits several fundamental characteristics: (1) *Production behavior*: Firms increase production and sales in response to surging demand, thereby achieving higher profits. (2) *Sources of production growth*: Firms more likely to participate in regional trade experience more pronounced production growth. (3) *Costs*: Participation in regional trade leads to increased selling expenses (including transportation costs), while unit production costs may remain unchanged. However, to attract consumers, unit product advertising costs increase. (4) *Trade activities*: Intensified competition reduces firms' markups, while the expansion of regional trade decreases import demand.

Expansion of Production Activities: As shown in Table 2, Panel A, UIP led to an increase of over 15% in production output and sales among enterprises, with average profits rising by more than 3 million RMB. This indicates that UIP facilitated the integration of demand across cities within clusters, enabling firms to significantly expand their supply to meet the demands of consumers in collaborative cities.

Sources of Production Growth: As evidenced by Table 2, Panel B, we find that the growth in production is primarily driven by firms that are located far from ports, do not engage in exports, and are not situated along coastlines. These firms are more likely to participate in regional trade rather

than the international trade market. This finding rules out a competing hypothesis that changes in treated cities are driven by exposure to international trade.

Dynamics of Firm Costs: The results in Table 2, Panel C, while unit production costs remained unchanged, firms' selling expenses increased significantly by 17.4%, and unit product advertising expenses rose by 5.4%. This aligns with the narrative of regional trade expansion, as firms increased expenditures to sell their products in partner cities and utilized advertising to attract consumers in these collaborative markets.

Firms' Trade Activities: According to Table 2, Panel D, compared to the control group, UIP significantly suppresses firms' import activities by 33.3%. However, the key counterfactual suggests that this has not greatly changed their export volumes (only a 9.2% increase in export activities), continuing to suggest the expansion of the regional trade market[11]. Accordingly, we observe that UIP significantly suppresses firms' markup by about 3%, consistent with the hypothesis of increased competition in treated cities.

Broadly speaking, these changes echo to the narrative of the regional trade markets expansion, and to the sharp predictions of trade model (Melitz, 2003; Bernard, Redding and Schott, 2007; Melitz and Ottaviano, 2008; Melitz and Redding, 2014). In the first place, the demand from the export market remains unaffected by the implementation of UIP. However, there is an observed increase in demand from partner cities, which enhances production, especially those firms capable of conducting regional trade. Consequently, these firms have increased their expenditures on transportation and advertising to fulfill consumers from partner cities. Simultaneously, this competitively priced supply from firms in cooperative cities competes with foreign supply, thereby curbing firms' import demands.

5 TFP Growth Under UIP

5.1 Baseline Results

Having established that the essence of UIP lies in dismantling local protectionism to facilitate regional trade expansion, we will now demonstrate the primary implication of the model: the strong positive correlation between UIP implementation and firm-level TFP growth.

To show this, we estimated the equation (8), wherein the implementation of UIP is regressed on TFP, serving as the dependent variable, for the period from 2000 to 2013. Table 3 presents the OLS estimates for equation (8). Across all three columns of Table 3, a positive causal relationship between UIP and TFP is evident, with all estimates demonstrating both statistical significance and observability. In comparison to the control firms, UIP leads to an approximate 7.8% increase in intra-firm TFP, while for the treatment group cities, an augmentation of 8.1% in TFP is observed. This suggests that UIP predominantly influences aggregate TFP changes through the channel of intra-firm TFP growth (intensive margin). In contrast, the variation in TFP determined solely by the entry and exit of firms accounts for a mere 0.3% at the city level (extensive margin). According to our model, this indicates that although UIP precipitates a rightward shift in the firm exit cutoff, it does not govern the most critical effect in TFP growth. Instead, innovation appears to be the most salient factor, which shaping the focal point of our subsequent empirical investigation.[12]

[11] Descriptive facts provided in Appendix F (see Figure F.1) more forcefully demonstrate this point. Before 2003, when UIP was first introduced, treated group firms had significantly higher average imports than their exports compared to control group firms. However, following this introduction, a reversal trend is observed, where the import activities of treated group firms are notably restricted, while the export activities of both treated and control group firms continue to trend similarly.

[12] Notably, when using specification 3, which controls for firm, year, and city fixed effects, it manages to control for variations in the firm's geographical location. However, its estimated results remain consistent with column 2, indicating that the inter-regional transfer (Between treatment and control group) of firms is limited and insufficient to compromise

Figure 2A shows the full set of estimated δ coefficients in equation (9), for d = -5, -4, ..., -1, 0, ..., 7, where we normalize δ_0 for comparison. The time patterns in firms' TFP are statistically parallel between the treatment and control groups; however, after the UIP is implemented, there is a significant and sizeable increment in a firm's TFP in the treated cities relative to the control group. Specifically, in the first year, the positive effect is close to 15%. After 7 years, the positive effect strongly increases, exceeding 15%. Figure 2A implies two significant implications: First, the parallel trend assumption that we have estimated is valid. Second, the UIP can foster long-term enhancement of TFP.[13]

According to our model, knowledge diffusion driven by regional trade prompts firms to make trade-offs between imitation and innovation. We argue that the surge in imitation, rather than independent innovation, is the more plausible narrative to explain this TFP growth. Three pieces of evidence support this conclusion:

Growth dynamics across TFP levels: As shown in Figure 2B, we find that the productivity growth is entirely driven by firms with productivity levels below the 95th percentile in 2002. Firms above this percentile contribute little to productivity growth.

Growth dynamics based on firms' innovation history: Evidence from Figure 2C shows that productivity growth is primarily driven by firms that have never held patents. These firms are more likely to gain market share through costless imitation rather than by independently innovating and patenting their results.

TFP distribution: As illustrated in Figure 2D, regression analyses of firms' TFP distribution at the city-year level reveal evidence consistent with theoretical predictions. Specifically, UIP has a positive impact on TFP only for firms ranked above the 50th percentile, suggesting that the regional trade threshold lies near this percentile. However, for firms ranked above the 80th percentile, the positive effect of UIP on TFP diminishes, indicating that the innovation threshold is close to the 80th percentile. Firms between these two percentiles experience rapid TFP growth through imitative innovation.

In conclusion, all this evidence consistently highlights the essence and dominant role of knowledge diffusion under regional trade conditions. We will provide more detailed evidence in the following sections.

5.2 Two Margins of TFP Growth

We now further identify the core mechanisms driving productivity growth under UIP and their relative importance. As demonstrated by the model, within heterogeneous innovation channels, imitation has substituted independent innovation and led to improvements in TFP. When comparing heterogeneous innovation with firm dynamics, the former emerges as the dominant channel for productivity advancement.

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the regression results. Therefore, we will employ specifications from columns 1 and 2 in the subsequent text as necessary to elucidate the inherent mechanism through which UIP promotes TFP.

[13] Regarding the speed and trajectory of dynamic productivity growth, we find that firms' productivity increased by 10% in the first year following the implementation of UIP, which we interpret as the effect of imitation. This interpretation aligns with the macroeconomic definition of imitation, which considers productivity growth as imitation as long as it does not expand the knowledge pool and contribute to future innovation. The rapid productivity response observed here likely suggests that firms improved their production technology and efficiency by adopting more advanced input structures through imitation. As shown in Figure D.1, firms' sales and production increased by more than 5% in the first year, implying that firms may have learned more advanced production techniques from their counterparts in partner cities.

5.2.1 Intensive Margin: Innovation and Imitation Trade-off

In the previous section, we demonstrated that UIP enabled the government to dismantle local protectionism, shifting policy focus from industrial policies to regional cooperation, thereby facilitating regional trade expansion. The following will show that productivity growth under regional trade conditions is achieved through imitation replacing independent innovation. Specifically, due to reduced subsidies and the availability of imitation, independent innovation—particularly subsidy-driven innovation—has declined. At the same time, low-productivity firms learn from high-productivity firms primarily through two channels: *Formal learning*: This occurs via patent transfers and formal knowledge reference from trade partners. *Informal imitation*: Firms directly adopt the production techniques of high-productivity firms.

Firms' Independent Innovation Activities: According to Table 4, Panel A, Columns 1-2, the average number of patent applications per firm decreased by 0.335, primarily driven by low-productivity firms. This finding aligns with the narrative of independent innovation being substituted and is consistent with the hypothesis that low-productivity firms turn to imitation, while high-productivity firms rely solely on independent innovation.[14]

Importantly, we argue that this shift does not imply a lack of attention to innovation but rather a decrease in strategic innovation activities associated with moral hazard (Argente et al., 2020; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020), accompanied by an increase in imitation, thereby alleviating economic distortions. Specifically, in China, government subsidies are often tied to the number of patents held by firms. As the intensity of industrial policies decreases, the returns from patenting diminish. Consistent with this, using the method recommended by Chen et al. (2021)—which measures subsidy-seeking behavior by using the ratio of administrative expenses to selling expenses as a proxy for reclassifying expenditures as R&D expenses—we find that such reclassification activities decreased significantly, by at least 6.2% (Column 3).

Furthermore, patents are often declarations that disclose innovative activities and their underlying details to protect future innovation outputs. With the rise of regional trade, competitors may deconstruct each other's traded products and combine this with patent disclosures to imitate their products. This reduces the incentive for high-productivity firms to disclose patents. Supporting evidence shows that R&D investments by treated firms increased by 6.4% (Column 4), consistent with a strategy where lagging firms allocate resources to imitation, while leading firms invest in R&D without disclosure.

The Rise of Formal Learning: Based on evidence from Table 4, Panel B, Columns 1-2, we find that with the implementation of UIP, the probability of patent transfers from treated cities to other cities within the same province increased relative to the control group, while the probability of patent transfers to cities outside the province significantly decreased. Concurrently, considering patent citations, as evidenced by Columns 3-4, the number of citations received by patents from firms in core cities increased, and this increase was entirely driven by high-productivity firms. This suggests that low-productivity firms in peripheral cities imitated high-productivity firms in core cities through formal patent activities, thereby achieving productivity growth.

Dynamics of Informal Imitation: In addition to formal imitation (e.g., through official technology transaction markets or patent citations), we argue that informal imitation (e.g., business stealing) may also support this TFP growth pattern. Specifically, low-productivity firms may directly adopt the technologies of high-productivity firms to catch up (Arqué-Castells and Spulber, 2022). To examine this mechanism, we adopt a cost-benefit perspective. Specifically, if imitation is easier or less costly

[14]The results remain robust when considering other types of patent activities. As shown in Appendix E, Table E.3, the decline in patent applications is primarily attributed to reductions in invention patents and utility model patents related to inventions. There is no significant change in design patent activity, as it is less associated with innovative inventions.

for certain firms, we would expect these firms to experience faster productivity growth and exhibit stronger substitution effects on independent innovation.

The ease of imitation: As shown in Panel A, Columns 1-3 of Table 5, we find that under the influence of UIP, industries with higher knowledge diffusion intensity (evidenced by a large number of patent disclosures) experienced productivity growth of 10.8%. In contrast, industries with higher imitation thresholds (characterized by high patent quality) saw slower productivity growth of 7%. More importantly, industries with both high potential knowledge diffusion intensity and low imitation thresholds exhibited the fastest productivity growth, at 12.7%.

More directly, we apply the method proposed by Dechezleprêtre et al. (2023) to calculate the technological similarity between each peripheral city and its corresponding core city at the industry level. This allows us to formally identify industries that benefit more from knowledge diffusion due to higher technological consistency. As shown in Columns 4-5, under the influence of UIP, industries with greater technological consistency with core cities exhibited stronger substitution effects of imitation for innovation, with a reduction of 0.44 patents, while achieving TFP growth of 12.8%.

The penalty of imitation: Referencing Table 5, Panel B, on the one hand, as shown in Columns 1-2, the results indicate that under the influence of UIP, firms located in cities with higher patent infringement risks experienced productivity growth of 15.3%, while the number of patent applications significantly decreased by 1.084. This suggests that lower imitation costs make high-productivity firms less inclined to disclose patents, whereas low-productivity firms can achieve rapid productivity growth through imitation.

At the same time, as shown in Columns 3-5, we find that this pattern does not stem from a deterioration in the institutional environment for intellectual property protection under UIP, which would otherwise facilitate imitation. In fact, the number of cases related to intellectual property infringement decreased, albeit insignificantly.

In summary, the evidence depicts intensive margin growth in firm TFP. As the UIP leads to a governmental shift from industrial to regional policies, the rise of regional trade and the reduction in government subsidies have suppressed strategic patent activities. The productivity growth of firms is now driven by imitation innovations from low-productivity firms. In the next section, we will explain how this mechanism leads to heterogeneous changes in productivity between core and peripheral cities, and how heterogeneous innovation activities support long-term productivity growth.

5.2.2 Extensive Margin: Firms Composition

In our model predictions, regional trade expansion leads to a rightward shift in the firm exit threshold, i.e., the extensive margin effects on TFP growth under UIP[15]. Previous results indicate that UIP brings about a broad flow of investment between cooperating cities and increased transparency in the land markets of peripheral cities. Based on this, the expectation related to the extensive margin is that companies unsuitable for continuing operations locally may be attracted to participating peripheral cities that favor their organizational production. Notably, this process is also related to the intensive margin, as Akcigit and Ates (2023) points out, knowledge diffusion is an essential factor in firm dynamics. As knowledge diffusion channels operate among UIP cooperative entities, investment flows promote beneficial changes in firm composition.

In Table 6, we use firm administrative data and matched data between industrial firms and administrative records to capture the dynamics of firm activities. The former covers all firms in China, while the latter identifies dynamic activities of surveyed firms above a certain size, providing richer internal performance information to determine their specific characteristics. Using firm administrative

[15]This refers to the entry of high-productivity firms and the exit of low-productivity firms due to competition effects.

data, Panel A shows that under the influence of UIP, compared to the control group, the probability of firm entry within counties in treated cities increased by 0.192%, the probability of exit decreased by 1.5%, and relocation probability remained unaffected. Based on the matched data, evidence from Panel B indicates that for larger firms, the entry rate significantly decreased, the exit rate remained unchanged, but the likelihood of relocation increased. These findings suggest that UIP tends to promote the development of small, emerging firms, while some large, existing firms are more likely to relocate to regions more conducive to their operations, namely collaborative cities. At the same time, the magnitude of these results is modest, consistent with baseline regressions, where the intensive margin dominates.

Meanwhile, Panel C of Table 6 further shows that firms with higher productivity have a higher probability of entry and a lower probability of exit. This aligns with the model's prediction that extensive margin effects help shift firm composition toward more productive firms. Additionally, we find that firms in industries aligned with local comparative advantages exhibit more active entry and exit activities but are less likely to relocate. This suggests economic implications related to comparative advantage, which we will discuss later.

In sum, our empirical evidence substantiates the picture that under the UIP, the entry-exit threshold for firms shifts rightward, transitioning the firm composition of treated cities towards a structure with higher TFP. Specifically, with the attenuation of local protectionism and the consequent trade expansion, local firms-particularly those operating below optimal productivity levels-either exit the market or relocate to more conducive cooperative cities for organizing production, thereby engaging in regional trade with one another. In subsequent analyses, we will document how this pattern of firm composition varies between treated core and peripheral cities, illustrating how it forms the microfoundation for the macroeconomic explanation of productivity gains, particularly through improved resource allocation efficiency.

6 Robustness Check and Discussion of Mechanisms

6.1 Robustness Check

Assumption of DID: Common Trend

We conducted parallel trend tests for the key variables, which can be found in Appendix D. These tests confirm that there were no pre-existing trend differences between the treatment and control groups. Additionally, the magnitude and direction of the observed changes align closely with the results presented in the tables, reinforcing the robustness of our estimates.

Assumption of DID: SUTVA

The potential spillover effect pose a risk to our baseline estimates (See Appendix D, Table D.3). To address this, we provide formal evidence indicating that the boundary of the UIP spillover effect is 80 km. (See Appendix D, Figure D.3). Accordingly, we can test the SUTVA by excluding firms in the control group located in areas less than 80 km from the treated cities. Table D.4 presents the estimates and reveals that the positive effect of UIP on a firm's TFP is slightly larger than in our baseline specification. It is reasonable to infer that UIP may exert a potentially positive impact on some firms near the treated cities, subsequently decreasing the estimates of UIP in the treatment group. However, these underestimates of the function of UIP do not alter our belief in UIP's significance, as the bias is only slight and downward. This slight bias may even further reinforce the predictions in our model, as our estimates are more conservative than the actual one. More importantly, in Table 3, the estimates in column 2 are nearly identical to those in column 3, suggesting that the boundary of the spillover effect at 80 km is precise.

Others Threats to Our Specification

In Appendix D, we further addressed several threats to the robustness of our baseline estimations. We confirmed the robustness of the UIP's impact on firm TFP against alternative accounting methods for TFP (Appendix D, Table D.1), controls for several time-invariant or time-varying variables or fixed effects at different levels (Appendix D, Table D.2), flexible panel construction methods (Appendix D, Table D.8), and a placebo test involving random sampling of pilot cities to demonstrate the uniqueness of the treatment group allocation (Appendix D, Figure D.9). Considering several competitive assumptions (Appendix D.10), we also prove the impact of UIP is not driven by contemporaneous other policies related to TFP (Appendix D, Tables D.8). Finally, in Appendix D's Tables D.5 to D.7 and Figure D.4, we demonstrate that the UIP's influence on TFP is not contaminated by heterogeneous treatment effects.

6.2 Discussion of Mechanism

In this section, we employ instrumental variable strategy to capture the selection process of UIP. On one hand, this strategy enables us to address the endogeneity challenge posed by non-random allocation. On the other hand, we leverage the properties of instruments to investigate the underlying logic behind the mechanisms discussed previously.

Wang and Yang (2021) highlights that China's institutional design encompasses potential non-random selection patterns, determined even by key parallel economic factors, which could contaminate estimates of policy effects. In our design, the implementation timing of UIP is determined randomly[16]. However, the adoption of UIP might be threatened by selection bias. This bias becomes particularly concerning when such selectivity is determined by key economic factors such as industrial structure, or even level of development, as it affects the causal interpretation of the estimation results. Actually, as we demonstrate in Figure F.3, the adoption of UIP is less likely to have originated from economic factors and more likely to have stemmed from culturally determined historical development. However, to more rigorously confirm this and investigate the relative importance of the mechanisms, we propose three shift-share style instrumental variables.

First, we examine a city's intrinsic cultural traits. Within the context of local protectionism, cultural factors primarily determine the extent of government influence on local protectionism. Specifically, cities with cultural similarities face fewer obstacles when the government commits to addressing local protectionism. For this purpose, we use whether a city's dialect before the year 2000 matches that of its provincial capital or sub-provincial city (which we refer to as core cities) as an instrumental variable for the city's inclusion in the UIP. The second is the pre-determined level of peripheral city infrastructure. The third is the historical trade accessibility of core cities. According to our theory and empirical results, the reduction in iceberg costs is a key channel for knowledge diffusion. Therefore, we use whether a peripheral city had a railway connection with a core city in 1933 as an instrumental variable and whether a core city had a postal station during the Ming dynasty as another instrumental variable. For those peripheral cities that had railway connections by 1933, their infrastructure tends to be better, which might make the knowledge diffusion channels of the UIP less effective. Similarly, for core cities that had postal station during the Ming dynasty, their trade connections with other cities are often stronger, and because they are core cities, their own productivity tends to be higher, making it more challenging to benefit from imitation. In designing the shift component, we exploit a major exogenous shock: since the start of the 21st century, China's central government has expanded its emphasis on regional coordinated development to foster common prosperity. Consequently, we incorporate a time trend beginning in the 21st century as the measure of this shift, reflecting the mounting

[16]Under the guidance of the "Tenth Five-Year Plan," local leaders innovatively proposed the UIP approach, but the specific year of rollout was random.

pressure on local governments to align with central directives—thereby increasing the likelihood of implementing UIP over time.

Regarding exogeneity in the design of these three shares, there is reason to believe that past characteristics such as dialects, railways, and postal stations are unlikely to change among cities due to anticipated future decisions to UIP. The exclusion restriction, which implies they would not affect firms' TFP except through the implementation of UIP, is plausible (especially considering our control for firm characteristics and numerous fixed effects). This assumption is strongly supported by empirical observations. On one hand, before the introduction of the UIP in 2003, dialect had no significant impact on firms' TFP; the positive impact only materialized after 2003. On the other hand, the productivity development patterns of peripheral cities with railways by 1933 and core cities with postal stations reversed after the introduction of UIP in 2003, consistent with the mechanism that UIP enhances the productivity of treated peripheral cities by lowering iceberg costs and facilitating channels for imitation (see Appendix D, Table D.13). Finally, it's reasonable to assume that the adoption of UIP is closely related to the instrumental variables, as Figure D.10 shows, where all three instrumental variables demonstrate potential geographical correlations with the actual distribution of UIP.

As shown in Table D.12, the instruments are significantly correlated with the adoption of UIP, with sufficiently high first-stage F-statistics. Additionally, Table 7 provides the second-stage results of our IV specifications, with Wald test p-values close to zero, except in Columns 8-9. We observe that all instruments point to the same conclusion: if UIP makes imitation easier, TFP growth is primarily driven by knowledge diffusion channels, while changes in firm composition play a secondary role. On the one hand, as shown in Columns 1-3, using dialect similarity as an instrument, UIP promotes productivity growth through both the extensive and intensive margins, but the impact of knowledge diffusion is much stronger. This suggests that, prior to UIP, institutional frictions were a core component of iceberg costs. Despite high cultural similarity and geographic proximity between cities, iceberg costs remained high, and UIP removed these institutional frictions, substantially reducing iceberg costs to facilitate imitation. On the other hand, Columns 4-9 show that if pre-UIP trade conditions (or a composition of firms with higher productivity) were already favorable, improvements in imitation conditions under UIP were limited, making knowledge diffusion channels less effective at the intensive margin (as seen in Columns 5-6 and 8-9). However, through favorable changes in firm composition, TFP growth was still significantly enhanced (as shown in Columns 4 and 7). In summary, this evidence profoundly illustrates the relative importance and sources of firm composition and knowledge diffusion channels for productivity growth under varying regional trade conditions.

7 Further Analysis

In this section, we aim to demonstrate how our findings contribute to addressing unresolved issues in trade models, as highlighted by Akcigit and Melitz (2022); Melitz and Redding (2023); Bai, Jin and Lu (2019). These include questions such as: Who benefits more from regional trade—the lagging parties? Does comparative advantage influence these dynamics? Are there alternative explanations linked to TFP growth?

7.1 Who Benefits More From Regional Trade?

Within the domain of trade theory, one question challenging to assess within a causal framework is how trade impacts the parties engaged in it? Under what conditions do the latecomers benefit more (Bai, Jin and Lu, 2019)? The empirical design of the UIP offers an excellent opportunity to address this

question. This is attributable to a distinct characteristic of the UIP-they are collaborations between provincial or sub-provincial metropolises (termed core cities) and one or two additional cities (termed peripheral cities). Hence, it becomes feasible to evaluate the heterogeneous effects of trade produced by UIP on the advanced and the latecomers.

Within the UIP cluster, the core cities represent the capital of each province, possessing higher ex-anti productivity composition. Consequently, the significant distinction between core and peripheral cities lies in their development stages; core cities are more advanced a priori, while peripheral cities are relatively less developed. Based on the operating mechanism of UIP, the following proposition arises: *The momentum of TFP growth is likely driven primarily by latecomer cities (peripheral cities).* This is because, on the intensive margin, firms in peripheral cities are more likely to benefit from knowledge spillover effects associated with higher productivity firms located in core cities. Meanwhile, the extensive margin implies that the average productivity of firms in both locales would increase, as the variations of firm composition.

These assertions are empirically validated through our research, which further offers some novel insights. Firstly, empirical observations from Figures 3A and 3B demonstrate that the enhancement of TFP due to the UIP is primarily driven by firms in peripheral cities. Meanwhile, production activities in core cities are more vibrant, implying that a greater volume of products is sold to peripheral cities, potentially increasing the likelihood of imitation in these peripheral cities.

Secondly, with respect to the extensive margin: empirical features of industrial structure reveal that core cities are predominantly oriented towards the tertiary sector, while peripheral cities exhibit a proclivity for the secondary sector, thereby echoing core-periphery theory (see Appendix F, Figure F.1). Distinctively, under the influence of UIP, the efficacy of this pattern's realization is augmented. Specifically, we observe that the relocation behavior of large enterprises occurs only in treated core cities, while the entry and exit of small enterprises are more active in treated peripheral cities (see Appendix E, Table E.1), leading to a macro-level decline in industrial diversity (or in crease in industrial specialization) in core cities and a corresponding ascent in industrial diversity and concentration in peripheral cities (see Figure 3C). This implies a transference of secondary industries from core to peripheral cities[17]. Collectively, these features proffer an empirical insight to the theory: if the costs of regional trade/entry are excessively high, the structural transformation aligned with the industrial development trajectory will be inhibited.

Synthesizing the evidence, we can address which entities benefit more from regional trade expansion. On one hand, firms in regions with lower average productivity can experience overall productivity gains through imitation-driven innovation, particularly when intensive marginal effects of knowledge diffusion are present. On the other hand, under the extensive marginal effects of regional trade, firms may shift operations from more advanced regions to latecomer regions, attracted by favorable production conditions in the latter. This relocation process phases out lower-productivity firms, thereby contributing to an overall increase in aggregate productivity.

7.2 Does Comparative Advantage Operate in Regional Trade, and If So, How?

The role of comparative advantage in economic welfare remains a debated topic. Economic models offer conflicting predictions: regional specialization based on comparative advantage could result in static welfare losses (Lucas, 1988), yield static welfare gains at the expense of dynamic welfare (Young, 1991), or potentially enhance dynamic welfare (Lucas, 1993). This section aims to address this issue. As Melitz and Redding (2023) highlights, if comparative advantage affects productivity through endogenous innovation—specifically via learning effects from knowledge spillovers—trade could drive

[17]This stems directly from the development of transportation infrastructure between core and peripheral cities, as well as the increased transparency in the land markets of peripheral cities.

rapid growth.

Based on the empirical evidence collected, it appears that UIP has catalyzed long-term TFP growth, stemming from knowledge spillovers facilitated by regional trade expansion and the shifting composition of firms. This section elaborates on several key characteristics that underpin the sustained economic dynamic welfare gains through these mechanisms, which are tied to the notion of comparative advantage.

The most direct empirical observation suggests that UIP primarily promotes TFP growth in local industries with revealed comparative advantage (RCA industries, as shown in Figure 3D) while significantly suppressing patent disclosure activities in these industries.

We argue that this pattern aligns with the two margins that sustain long-term productivity growth, as documented earlier. On the intensive margin, RCA industries can more effectively leverage local endowment structures, consistent with location-based competitive advantages. In this sense, these industries experience greater demand expansion, prompting more firms to shift from less efficient independent innovation to imitation, thereby achieving faster productivity growth. On the extensive margin, as shown in Panel D of Table 6, RCA firms are less likely to relocate to other markets but are more likely to enter and exit markets compared to NRCA firms. This indicates that regional trade plays a crucial role in shaping the development of industries toward RCA sectors. In this process, intense competition within RCA industries drives low-productivity firms to exit, thereby sustaining the long-term trend of TFP growth.

In conclusion, our analysis highlights the critical role of comparative advantage in generating the dynamic welfare gains of regional trade. Through the spillover effects of knowledge diffusion induced by regional trade, industries aligned with local comparative advantages often experience greater demand, incentivizing them to shift further toward imitation to enhance productivity. Meanwhile, industry adjustments under competitive pressure drive sectoral structures closer to comparative advantages, sustaining the long-term trajectory of productivity growth.

7.3 Alternative Explanations and Discussions

Besides the issues previously discussed, on one hand, trade theory accentuates the role of market size in shaping the dynamics of welfare growth through innovation, yet the effect remain controversial. On the other hand, the classical theory of resource misallocation has proven that much of China's growth is largely due to enhancements in the efficiency of resource allocation. We will demonstrate that the mechanisms we argue for and the dynamics of TFP validate the roles of these assumptions.

Intensive Margin - Market Size: The reduction in patent activity we have documented readily prompts skepticism regarding its benefit for the long-term growth of TFP, as imitation predominantly enables mid-tier TFP firms to ascend to the upper tier. Once they all reach the upper tier, imitation becomes challenging. We will show that assumptions about market size under regional trade help illuminate the heterogeneous long-term growth of TFP. As demonstrated by Melitz and Redding (2023); Akcigit and Melitz (2022), the expansion of market size allows firms to more broadly distribute the fixed costs of innovation, thereby encouraging innovation incentives. Below, we will explain how the dynamics of TFP respond to this assumption.

As previously demonstrated, treated peripheral cities lead in terms of TFP growth. Under the assumption of market size, this could be due to these cities experiencing more significant marginal improvements in infrastructure, thereby enjoying greater market scale expansion in regional trade. Empirical evidence provided in Appendix E (Table E.2 and Figure E.1) suggests that TFP growth driven by UIP is propelled by cities with lower average wages and a lower level of infrastructure development, indicating that more favorable production conditions attract businesses to relocate there. Moreover, in terms of innovation mechanisms, consistent with the outcome that imitative innovation

boosts TFP, we indeed find that UIP has a significant dampening effect on patent activities in both peripheral and core cities (Appendix E, Table E.3). However, in peripheral cities, the dampening effect is noticeably weaker, resonating with the hypothesis that cities with larger market scale expansion benefit more from the diffusion of fixed costs of innovation, thereby engaging in more innovative activities. Thus, this provides a theoretical underpinning for the sustained growth of TFP in peripheral cities, indicating that a decrease in patent activities in peripheral cities does not severely impact TFP growth; on the contrary, they may benefit more from a significant reduction in strategic patent activities and more favorable production conditions.

Extensive Margin - Resources Relocation: Within the framework of classic resource misallocation theory (Hsieh and Klenow, 2009; Song, Storesletten and Zilibotti, 2011; Tombe and Zhu, 2019), an important macroeconomic prediction is that the key endogenous force driving the improvement of China's TFP should originate from enhanced efficiency in resource allocation. We demonstrate that the directional changes in firm composition at the extensive margin under regional trade expansion, specifically the exit of low productivity firms, and the alignment with local comparative advantages at the city level, are the roots of the improvement in allocative efficiency.

Figure 3E - 3H demonstrates that under the influence of UIP, firms with higher TFP levels are able to attract more labor and capital, and the same holds for firms with comparative advantages. Additionally, non-subsidized, non-zombie firms mainly benefit from resource reallocation, receiving increased labor and capital inputs. This implies that UIP has improved the efficiency of resource allocation, which is driven by the variations of firm composition.[18]

7.4 Economic Consequences

Finally, we return to the pivotal question: To what extent has UIP stimulated the improvement of TFP and fundamentally influenced long-term growth?

Based on our reduced form regression results, several important insights emerge: (1) The growth in aggregate productivity, under the influence of UIP and the expansion of regional trade, is partly attributed to improved efficiency in factor allocation[19]. This arises from a directional shift in firm composition, indicating a transition of the industrial structure towards a stable growth path characterized by specialization. (2) The growth is mainly driven by improvements in firm-level TFP due to the imitation innovation model under the effect of knowledge diffusion.

To formally quantify the contribution of UIP to the growth of China's aggregate productivity, we adopt two complementary strategies based on the aforementioned insights: First, we adopt the quasi-natural experiment estimation method for TFP growth under capital misallocation, as proposed by Sraer and Thesmar (2023). This method quantifies policy effects on aggregate TFP growth by alleviating resource misallocation, while accounting for general equilibrium effects. Second, leveraging our rich firm-level data, we implement a back-of-the-envelope calculation of aggregate TFP growth, using the coefficients from the reduced-form regression. Although this approach involves stronger assumptions regarding general equilibrium effects and does not fully account for changes in the market environment, it allows us to capture the growth in firm-level TFP under the imitation-innovation mechanism at the intensive margin.

Scale up under general equilibrium effects

[18] Hsieh and Klenow (2009) found that by eliminating distortions, China's total factor productivity increased by 2% annually. Our empirical evidence resonates with this finding and provides causal support for this projection. However, our subsequent work elaborately demonstrates that this progress in total factor productivity primarily stems from knowledge diffusion, complemented by improvements in capital allocation efficiency due to changes in firm composition.

[19] Specifically, considering that a substantial impact of UIP is the reduction in government subsidies to firms, the improvement in the efficiency of capital allocation plays a dominant role in this process.

According to Sraer and Thesmar (2023), variations in TFP associated with capital reallocation can be determined by examining the distribution of Log-MRPK, the logarithmic ratio of industry value-added to the capital stock. A detailed explanation of this method can be found in Appendix G.

$$\Delta \log(a) \approx \underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1,c=1}^{S,C} Cap\%_{s,c}\Delta\widehat{\Delta\sigma^2(s,c)}}_{-5.64\%}$$
$$\underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1,c=1}^{S,C}(Sale\%_{s,c}-Cap\%_{s,c})\left(\widehat{\Delta\Delta\mu(s,c)}+\widehat{\Delta\Delta\varsigma_{logMRPK,logValueAdd}}(s,c)+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\Delta\widehat{\Delta\sigma^2(s,c)}\right)}_{7.64\%}$$
$$\approx 2\% \tag{10}$$

The results, as demonstrated in Equation 10, reveal that the overall TFP, influenced by the UIP, has surged by 2% primarily due to the improvements in capital allocation efficiency. This growth is predominantly driven by cross-industry capital reallocation, contributing 7.64% and aligning with the fact of industry structure development towards comparative advantage. In contrast, within-industry capital reallocation has had a counter-effect, reducing TFP by 5.64%.

Scale up based on in-sample inference

We conduct a back-of-the-envelope calculation to directly estimate the contribution of UIP to TFP growth. In this calculation, we assume that the treatment and control groups are strictly isolated, disregarding any potential general equilibrium effects from interactions between them. Given that both the treatment and control group had equivalent productivity levels in 2003[20], we leverage the characteristics inherent in the database to infer the aggregate impacts of UIP, addressing the previous methodology's lack of focus on the intensive margin effects of UIP. The growth rate of TFP for the treatment group exceeded the baseline rate by 7.8%, while the control group's annual TFP growth rate was predicated on the average TFP growth rate from 2000 to 2003, is 1.87%.

The results can be found in Figure G.2 and Table G.2 of Appendix G, elucidating the entire simulation process and specific details. Under this rudimentary estimate, in the post-reform window, UIP increases China's TFP reaches a notable 11.90%.

Discussion

Reflecting on our analysis of the UIP mechanism and its cross-sectional assessment, we observe several key insights. Initially, the UIP played a crucial role in dismantling local protectionism, paving the way for extensive investment flows between cooperative cities. While the reduction in subsidies generally curtailed capital accumulation among firms, the competitive pressures brought about by trade facilitated the continued development of industries in both core and peripheral cities according to their comparative advantages. This process resulted in the cross-sectoral reallocation of capital resources, directing resources preferentially to firms with long-term productivity growth potential[21]. The impact of this resource reallocation is magnified by general equilibrium effects, suggesting that cross-sectoral capital reallocation is a significant driver of productivity enhancement.

Furthermore, when considering both intensive and extensive margin effects—based on reduced-form coefficients and within-sample structural characteristics—we find that the overall magnitude of

[20]This assumption, based on our analysis, is deemed tenable. We utilized a dataset encompassing all major manufacturing firms, which account for over 70% of China's production activities (Brandt, Van Biesebroeck and Zhang, 2012). Our covariate balance tests indicate that, prior to 2003, there were no significant differences in TFP between the treatment and control groups.

[21]This includes non-zombie firms, which can thrive without subsidies, and those with strong imitation innovation capabilities, such as industries closely aligned with the technological strengths of core cities.

productivity growth reaches 11.9%. This underscores the substantial economic implications of the UIP for China's productivity. Importantly, the capital reallocation observed in our analysis, which fosters total productivity growth, aligns with the predictions of Hsieh and Klenow (2009). This leads to two important conclusions: 1) The method proposed by Sraer and Thesmar (2023) provides a highly accurate way to assess the impact of resource reallocation on productivity, and 2) The increase in productivity is not primarily driven by changes in firm composition on the extensive margin but is instead largely attributed to intensive margin effects driven by knowledge diffusion.

8 Concluding Remarks

It is widely acknowledged that trade contributes to enhancing economic welfare, yet there remains a considerable gap in our comprehensive understanding of its underlying mechanisms and the extent of its impact, particularly in how it functions through endogenous innovation. By analyzing a seemingly paradoxical pattern of productivity improvement - productivity growth accompanied by a decrease in patent activity - we provide evidence supporting the viewpoint that local protectionism could detrimentally affect economic welfare in the long term. This pattern is likely to be prevalent under a trade framework, as efficiency gains are often subject to a substitution relationship between imitation and indigenous innovation. If local protectionism prevails, restricted trade inhibits the full dissemination of knowledge across different regions and the utilization of local comparative advantages for specialized division of labor, leading to long-term efficiency losses.

This paper's efforts yield implications in two dimensions. Practically, our insights into the trade-off between regional development and innovation incentives offer valuable guidance for nations pursuing long-term growth policies. Our core argument suggests that when technological disparities between regions are significant, promoting imitation may be more effective than fostering independent innovation. This stems from a crucial economic trade-off: the policy instruments used to promote independent innovation, whether direct subsidies or tax incentives, are significantly prone to moral hazard issues, such as firms mislabeling R&D expenditures. In contrast, promoting imitative innovation inherently leverages market mechanisms to reallocate resources and generates endogenous innovation incentives. Therefore, in the early stages of development, transitioning from industry policies that encourage independent innovation to policies that promote internal integration offers greater value. Fostering knowledge dissemination through inter-regional connectivity not only better encourages rapid growth among lagging firms but also facilitates efficiency improvements through specialized division of labor. We note that from the 4 trillion RMB infrastructure investment initiative launched in 2008 to the unified large market concept proposed in 2022, China has been continuously advancing its commitment to unify all markets, aiming for "E Pluribus Unum." Thus, the conclusions of us provide a potential explanation for the long-standing mystery of China's economic growth.

Theoretically, our research on the causal relationship between trade and productivity provides representative evidence for many sharp predictions in trade and innovation models. Simultaneously, by integrating these aspects into a unified analytical framework, our findings underscore the necessity for further refinement of trade models and quantitative frameworks. This involves carefully considering the interaction between knowledge diffusion and endogenous firm dynamics within a heterogeneous firm framework and requires customized knowledge diffusion functions to systematically explain the geography of development.

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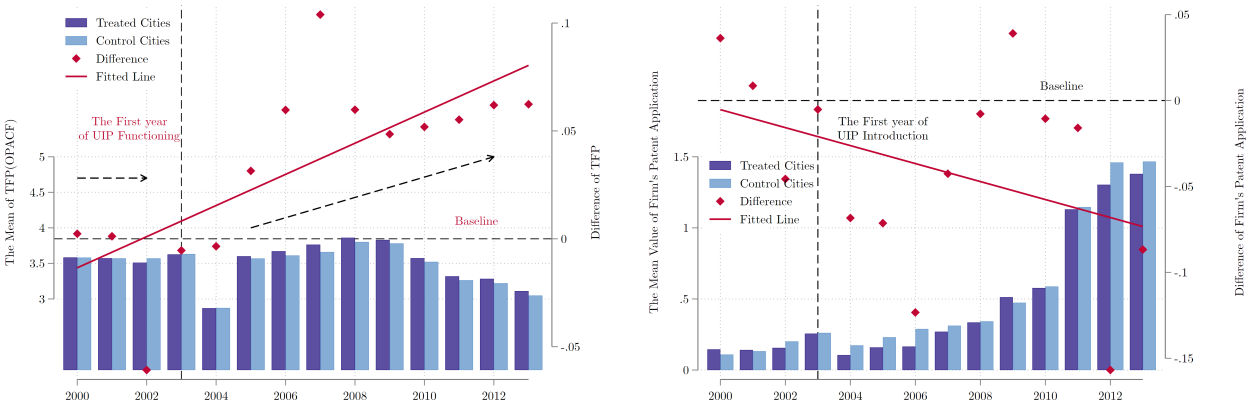
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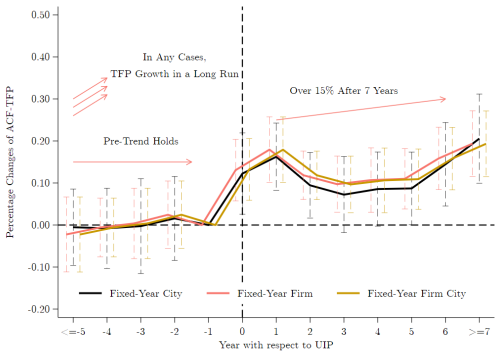
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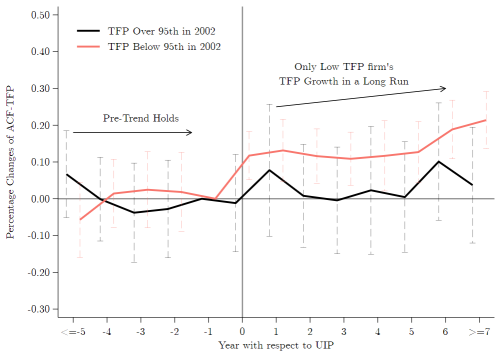
A. TFP B. Patent Activities

Figure 1: Stylized Facts Under UIP: Motivation

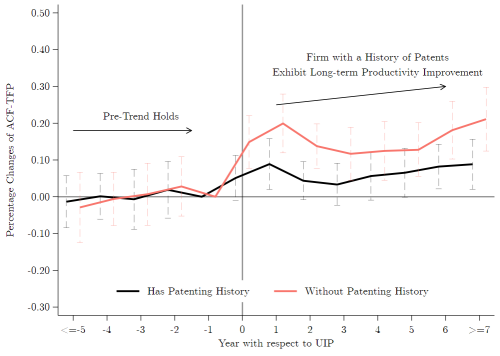
Notes: We described the yearly changes in the average TFP and patents for firms in the treatment and control groups. The left axis represents their absolute levels, while the right axis shows the differences between the two groups. The red line represents the linear fit of the difference levels.



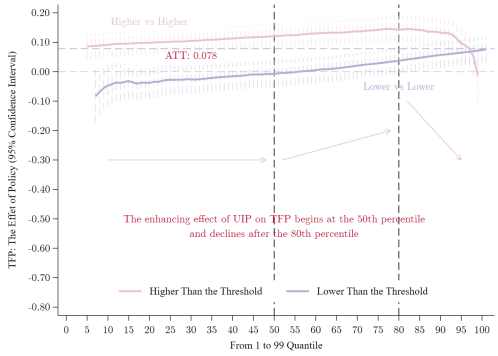
A. Pre-Trend Parallel and Dynamic



B. TFP Dynamic: Grouped by TFP Level



C. TFP Dynamic: Patenting History



D. TFP: Grouped by TFP Quantile

Figure 2: TFP Dynamic Growth and Quantile

Notes: For Panel A, the event-study analysis examines the relationship between UIP and firm TFP, corresponding to Columns (1)-(3) in Table 3. The dependent variable is a panel data measure of TFP, estimated using the ACF method under three specifications with varying combinations of year, firm, and city fixed effects. For Panels B and C, the same strategy as Panel A is applied. Panel B groups firms based on whether their 2002 productivity levels exceed the 95th percentile, while Panel C groups firms based on whether they have a history of patenting. For Panel D, the figure illustrates the regression results using UIP as the independent variable and TFP as the dependent variable. The TFP data are segmented by year-city level percentiles, selecting each percentile from 1 to 99. The blue line represents comparisons below the percentile threshold, while the red line represents comparisons above the threshold.

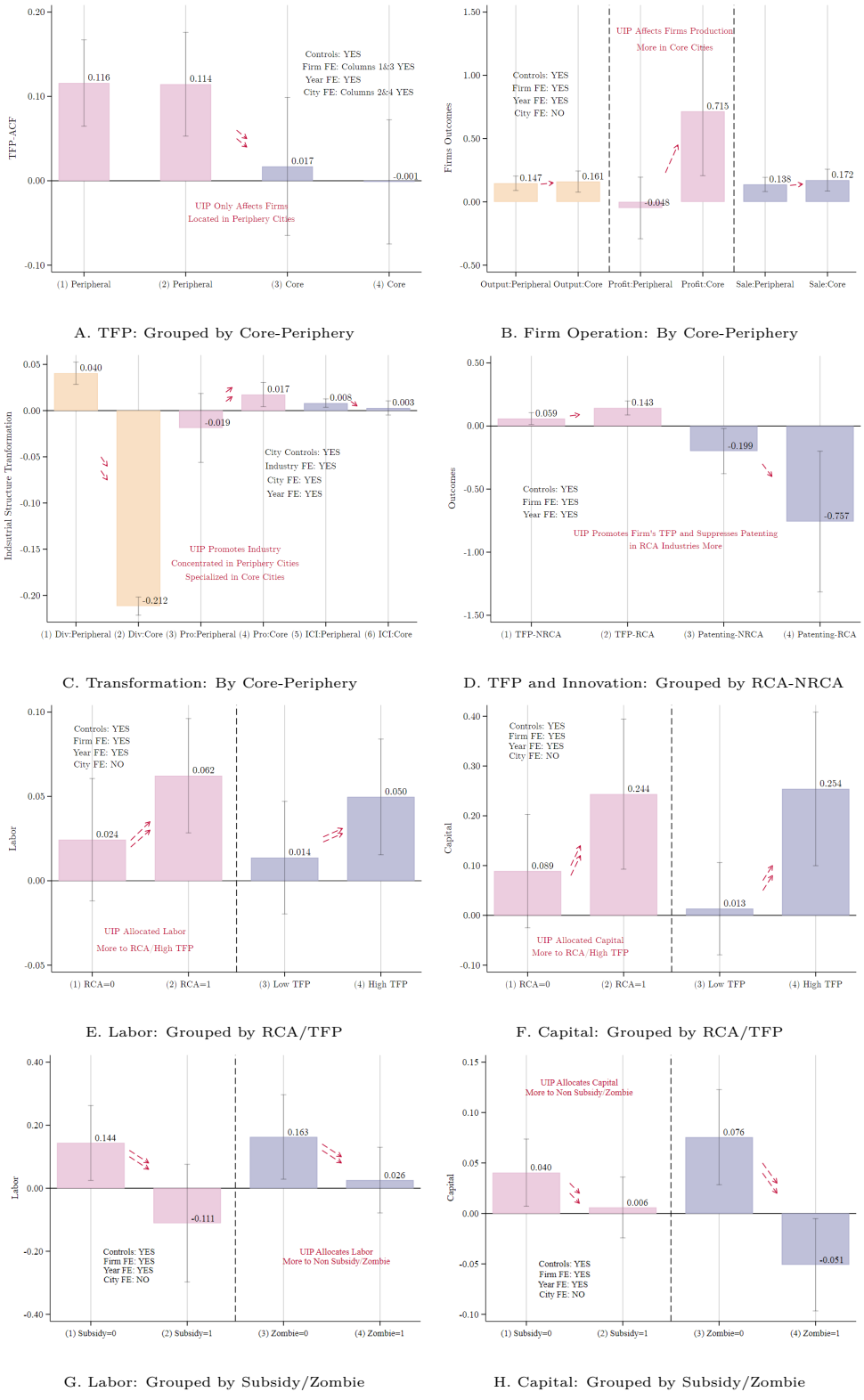


Figure 3: Further Analysis Results

Notes: The table provides a detailed analysis of firms' TFP, operational metrics, production factors, and industrial structure, categorized by Core-Periphery status, RCA-NRCA industries, whether the firms are subsidized or classified as zombie firms, and whether they are High-TFP or Low-TFP firms.

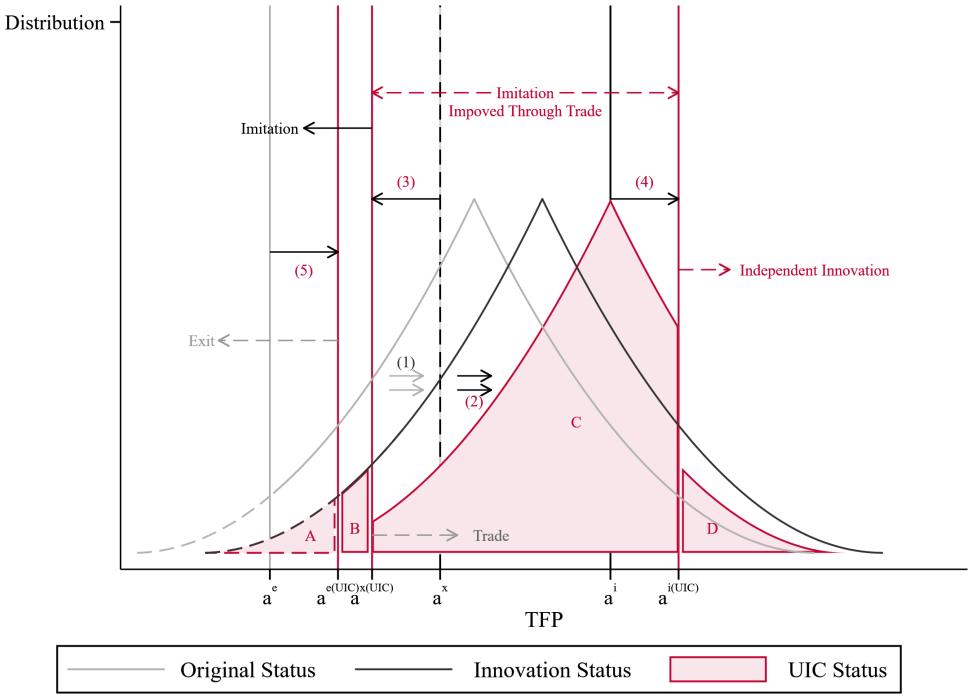


Figure 4: Model Implications

Notes: Comparative statics for explaining the implications and variations in our theoretical model. There are five annotations:

1. Relative to the baseline equilibrium, the innovation equilibrium enables firms to advance in productivity at a velocity v, engendering a rightward shift in the balanced distribution.
2. Compared to the innovation equilibrium, the UIP equilibrium induces heterogeneous productivity growth rates among firms at varying productivity levels. Specifically, firms with productivity levels below the regional trade cutoff point maintain their original velocity of productivity improvement. For those above the regional trade cutoff but below the independent innovation cutoff, a faster velocity of productivity enhancement is realized, attributable to the elevated success rate of imitative innovation facilitated by trade. Firms exceeding the independent innovation cutoff experience a deceleration in productivity growth relative to the innovation equilibrium, attributable to the inhibitory effect of diminishing subsidies on independent innovation efficiency.
3. Under the UIP equilibrium, the attenuation of iceberg costs allows firms with lower productivity to partake in regional trade, causing a leftward shift in the trade cutoff point.
4. As subsidies wane, the cost of independent innovation escalates, making imitative innovation comparatively more advantageous, leading to a rightward shift in the independent innovation cutoff.
5. The decline in iceberg costs elevates the ZCP curve, engendering a rightward shift in the firm exit cutoff point.

Table 1: UIP on Local Protectionism

Panel A: Removing Industrial Policy	(1) Subsidy	(2) Zombie	(3) TFP	(4)
UIP	-0.160***	-0.005**	0.041	0.042
	(0.059)	(0.002)	(0.035)	(0.037)
UIP ×If Industrial Policy			-0.091***	-0.087***
			(0.032)	(0.032)
Observations	2055003	2640726	1543626	1543626
Data	A	A	A	A
Panel B: Investing in Infrastructure	Public Investment	Personal Mobility	Speed of High-speed Rail	Legnth of Railway
UIP	0.045***	0.107***	-1.811	13.513
	(0.014)	(0.033)	(4.806)	(26.864)
UIP×Co-Line			45.712***	435.841**
			(11.415)	(170.234)
Observations	2917	3595	3606	3606
Data	C	C	C	C
Panel C: Investment Flow Across Cities	Outside City and Within Province	Outside City and Within Province (%)	Outside Province	Outside Province (%)
UIP	1.155***	0.003***	0.388	0.000
	(0.364)	(0.001)	(0.569)	(0.002)
Observations	11144252	11137582	11144252	11137582
Year FE	X	X	X	X
Data	B	B	B	B
City FE	X	X	X	X
Control	X	X	X	X

Notes: Panel A examines the reduction in the intensity of industrial policies. Columns 1-2 use dependent variables measuring firms' subsidy income and the probability of becoming zombie firms (defined as firms with negative profits for three consecutive years). Columns 3-4 explore the heterogeneity of UIP's impact on TFP based on whether firms receive provincial-level industrial policy support. Since policy data are only available after 2006, we use the 2006-2013 waves and restrict the sample to treated cities that adopted UIP after 2006. Column 3 focuses on key industrial policies, while Column 4 considers industries explicitly highlighted as requiring support in government work reports. Panel B investigates infrastructure development. Columns 1-4 use dependent variables including government public investment, urban mobility, the speed of high-speed railways, and the length of high-speed railway tracks. The "Co-line" variable indicates that the railway passes through at least one city within the UIP cluster. Panel C studies the cross-city mobility of investment. The dependent variables in Columns 1-4 are the investment from outside the city but within the province (OCIP) and its proportion (OCIP%), as well as the investment from outside the province (OP) and its proportion (OP%). Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 2: UIP on Regional Trade

Panel A: Expansion of Production Activities	(1) Sale	(2) Profit	(3) Output
UIP	0.160***	0.300**	0.156***
	(0.025)	(0.135)	(0.024)
Observations	2387430	2484241	2387459
Data	A	A	A
Panel B: Sources of Production Expansion	Output	Output	Output
UIP	-0.539***	0.214***	0.170***
	(0.165)	(0.027)	(0.027)
UIP×Distance of Port	0.061***		
	(0.015)		
UIP×If Exporter		-0.214***	
		(0.025)	
UIP×If Located at Coastline			-0.091**
			(0.038)
Observations	2382943	2387459	2386875
Data	A	A	A
Panel C: Dynamics of Firm Costs	Selling Cost	Unit Cost	Unit ad
UIP	0.174***	0.006	0.054*
	(0.027)	(0.028)	(0.028)
Observations	2485113	995387	114346
Data	A	A	A
Panel D: Firms' Trade Activities	Markup	Export	Import
UIP	-0.030**	0.092*	-0.333***
	(0.013)	(0.053)	(0.053)
Observations	2427134	728036	728036
Year FE	X	X	X
Data	A	D	D
Firm FE	X	X	X
Control	X	X	X

Notes: Panel A examines the expansion of firms' production activities, where the dependent variables in Columns 1-3 are firms' sales, profits, and output, respectively. Panel B investigates the sources of firms' production expansion. The dependent variable is firm output, and the UIP interacting with conditions such as the distance to the nearest port, whether the firm is an exporter, and whether the firm is located on the coastline. All component terms of the interaction are controlled. Panel C studies the dynamics of firms' production costs. The dependent variables in Columns 1-3 are cost of sales, unit production cost, and unit advertising cost, respectively. For unit costs, the data allow observations only from 2000 to 2006. Regarding advertising expenditures, the available data cover only a subset of the sample from 2004 to 2007, and we exclude treated groups treated prior to 2004. Thus, we interpret these findings as suggestive evidence. Panel D analyzes firms' trade activities. Column 1 examines firms' markups, measured following the method proposed by Gandhi, Navarro and Rivers (2020). The dependent variables in Columns 2-3 are firms' exports and imports, respectively. Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 3: Estimates of the Impact of UIP on a Firm's TFP

Dependent Variable	(1)	(2) TFP	(3)
UIP	0.081***	0.078***	0.078***
	(0.024)	(0.022)	(0.022)
Observations	2640726	2485219	2485219
Data	A	A	A
Year FE	X	X	X
City FE	X		X
Firm FE		X	X
Control	X	X	X

Notes: The table presents OLS estimates of the relationship between UIP and a firm's TFP by adopting the model (8). The dependent variable is the firm's TFP employed using the ACF method. Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 4: UIP on Innovation and Formal Learning

Panel A: Firm Innovation Behaviors	(1)	(2) Patent	(3) Relabeling	(4) R&D
UIP	-0.335**	-2.191***	-0.062**	0.064**
	(-2.83)	(-8.32)	(-3.12)	(2.65)
UIP×TFP		0.517***		
		(6.46)		
Observations	2485219	2485219	2371520	711412
Firm FE	X	X	X	X
Data	E	E	E	E
Panel B: Evidence on Formal Learning	Non Local - Inside	Non Local - Outside	Cited Number	
UIP	0.017***	-0.027***	-0.029***	-0.169***
	(0.004)	(0.007)	(0.008)	(0.016)
UIP×Core City			0.033**	
			(0.016)	
UIP×TFP				0.043***
				(0.004)
Observations	98474	98474	2485219	2485219
Year FE	X	X	X	X
Data	J	J	E	E
City FE	X	X		
Firm FE			X	X
Receiver City FE	X	X		
Control	X	X	X	X

Notes: Panel A examines firms' innovation activities. In Columns 1-2, the dependent variable is the number of patent applications filed by firms. In Column 3, following Chen et al. (2021), we use the ratio of administrative expenses to selling expenses as a proxy for firms' efforts to reclassify expenditures as R&D investments. In Column 4, we provide suggestive evidence by using observable firm-level R&D investments from 2005 to 2007 as the dependent variable, excluding treated groups that received treatment prior to 2005. Panel B provides evidence related to formal learning. Columns 1-2 use intra-provincial non-local patent transfers and inter-provincial patent transfers as the dependent variables, respectively. Columns 3-4 examine the number of citations received by firms' patents as the dependent variable, incorporating interaction terms between UIP and firms' productivity, as well as whether firms are located in core cities. All corresponding component terms are controlled. Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 5: UIP on Imitative Innovation

Panel A: The Ease of Imitation	(1)	(2)	(3) TFP	(4)	(5) Patent
UIP	0.060**	0.083***	0.066***	0.049*	-0.182*
	(0.024)	(0.024)	(0.023)	(0.027)	(0.100)
UIP×High Patent	0.048***				
	(0.018)				
UIP×High Quality		-0.013			
		(0.012)			
UIP×High Patent But Low Quality			0.061***		
			(0.017)		
UIP×High Spillover				0.079**	-0.262**
				(0.032)	(0.120)
Observations	2485219	2485219	2485219	2485219	3348418
Data	E	E	E	E	E
Firm FE	X	X	X	X	X
Panel B: The Penalty of Imitation	TFP	Patent	Total Lawsuit	Patent Lawsuit	Right Lawsuit
UIP	0.066***	-0.176**	-569.756	-1.725	-28.293
	(0.024)	(0.069)	(528.389)	(1.721)	(25.312)
UIP×Patent Right Risk	0.087*	-0.908***			
	(0.047)	(0.248)			
Observations	2485219	3348418	1774	1774	1774
Year FE	X	X	X	X	X
Data	E	E	F	F	F
Firm FE	X	X			
City FE			X	X	X
Control	X	X	X	X	X

Notes: Panel A examines the impact of the ease of imitation on productivity growth and innovation. In Columns 1-2, we include interaction terms to assess whether a firm operates in an industry where the number of invention patent applications or patent quality (measured by the knowledge breadth of patents) exceeds the 80th percentile within the city in a given year. In Column 3, we incorporate whether the firm operates in an industry more prone to imitation, defined as industries with patent application volumes above the average but patent quality below the average. In Column 4, we assess whether a firm belongs to an industry more likely to benefit from innovation spillovers generated by its core city, measured by the technological similarity between subsidiary and core city industries. Panel B investigates the implications of imitation penalties. In Columns 1-2, we add interaction terms to evaluate whether a city is more susceptible to infringement risks, with cities having patent-related litigation volumes above the average coded as 1, and those below the average coded as 0. Columns 3-5 regress the total number of lawsuits, patent-related lawsuits, and ownership-related lawsuits at the city level on UIP. Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 6: UIP on Firm's Location

Panel A: Firm Dynamic - Universe	(1) Enter Rate	(2) Exit Rate	(3) Transfer Rate
UIP	0.192*	-1.502***	-0.003
	(0.115)	(0.349)	(0.005)
Observations	3292934	3292934	3292934
Data	B	B	B
Panel B: Firm Dynamic - Industrial Firms	Enter	Exit	Transfer
UIP	-0.007***	0.005	0.002*
	(0.002)	(0.004)	(0.001)
Observations	2640726	2229559	2229844
Data	G	G	G
Panel C: Firm Dynamic - Across TFP	Enter	Exit	Transfer
UIP	-0.029***	0.006**	0.009
	(0.006)	(0.002)	(0.007)
UIP×TFP	0.008***	-0.001**	-0.002
	(0.001)	(0.001)	(0.002)
Observations	2485219	2102425	2102533
Data	G	G	G
Firm FE	X	X	X
Panel D: Across Comparative Advantage	Enter	Exit	Transfer
UIP	-0.009***	0.001	0.003*
	(0.002)	(0.005)	(0.001)
UIP×RCA	0.007***	0.014**	-0.002**
	(0.002)	(0.006)	(0.001)
Observations	2640726	2229559	2229844
Year FE	X	X	X
Data	G	G	G
Firm FE			
City FE	X	X	X
Control	X	X	X

Notes: The dependent variables in Columns 1-3 are firm entry rate, exit rate, and the probability of relocating to another city, respectively. In Panel A, the dependent variables are measured at the county level, focusing on all registered firms in China. Panel B uses firm-level measurements, concentrating on industrial firms. Panel C examines the heterogeneity of firm dynamics based on productivity by including a series of interaction terms related to firm TFP. Panel D explores the heterogeneity of firm dynamics driven by regional comparative advantage, incorporating a series of interaction terms related to RCA. Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 7: IV-2SLS Estimation - Second Stage

Dependent Variable	TFP								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instrumental Variable	Dialect			Railway in 1933			Postal Station in Ming		
UIP	0.774***	1.291***	1.293***	1.052**	0.901	0.908	0.588***	0.281	0.285
	(0.252)	(0.351)	(0.351)	(0.513)	(0.611)	(0.612)	(0.181)	(0.189)	(0.197)
Observations	2631689	2476702	2476702	2640726	2485219	2485219	2640726	2485219	2485219
Year FE	X	X	X	X	X	X	X	X	X
City FE	X		X	X		X	X		X
Firm FE		X	X		X	X		X	X
Control	X	X	X	X	X	X	X	X	X
Anderson-Rubin Wald test p-value	0.002	0	0	0.012	0.086	0.083	0	0.134	0.145

Notes: The table presents IV estimates of the relationship between UIP and a firm's TFP. We report the p-value of the Anderson Rubin test for the coefficient on UIP being zero. Standard errors are clustered at the city-year level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Online Appendix - Not For Publication

E Pluribus Unum: Growing TFP From Regional Trade

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A Appendix A: The Information Related to UIP

A.1 Example of UIP - Guangzhou and Foshan

In this section, we use the "Guangzhou-Foshan urban integration plan 2009-2020," a policy issued by the governments of Guangzhou and Foshan in Guangdong province to implement the UIP, as an example to illustrate the specific details of a UIP. Based on our textual review, our theoretical model reflects nearly all the goals of this policy.

Firstly, the policy aims to strengthen cooperation between the two cities to help disorganize local protectionism. The guiding ideology of the policy points out that "we should comprehensively build a new pattern of urban development featuring overall coordination of urban planning, joint construction, and sharing of infrastructure, win-win cooperation in industrial development, and cooperative management of public affairs." This shift in the relationship between the two governments, from competition to cooperation, contributes to disorganizing local protectionism.

Secondly, the policy requires strengthening infrastructure construction, which helps to promote the flow of factors. The policy calls for an integrated transportation system, including the construction of the Asia-pacific comprehensive aviation center (such as Guangdong Baiyun International Airport expansion and Foshan Shadi Airport), international shipping centers (Nansha Port, Guangzhou Port), rail transit (improvement in rail construction between cities, such as Guizhou and Guangzhou, Nanjing and Guangzhou, Guangzhou and Foshan, and Zhaoqing), and highways (GuangFo network, PingNan highway). Moreover, it also promotes the construction of municipal public facilities and information infrastructure. These measures facilitate the efficient flow of factors within the integrated city.

Thirdly, the policy emphasizes a high-end development strategy and adheres to the objective law of dynamic change of comparative advantage, which helps lift the restrictions on transferring traditional industries. To be more specific, the policy calls for promoting industrial integration and optimizing layout, encouraging the development of modern service industries, advanced manufacturing, and high-tech industries, and upgrading traditional industries. This implies that the government's protection of traditional industries will be weakened after the implementation of UIP, potentially leading to changes in the composition of firms under the effect of competition, making the industries more suited to the local comparative advantage.

A.2 Policy Details Related to UIP

In Table A.1, we provide a detailed description of the adoption of UIP in various cities across China. This includes an implementation timetable, the provinces and cities involved (including core and affiliated), recognition of legal authority, and strategic objectives. These data were manually compiled from specific contracts or online resources.

It can be observed that UIP was first introduced in 2002 and by 2013, a total of 18 cooperative entities had proposed UIP. Some representative characteristics are as follows:

1. All collaborations were led by a provincial capital or sub-provincial (core) city, driving one to two follower (periphery) cities.

2. These contracts were endorsed by at least the government of the city in question, and even by provincial authorities, implying strong legal validity.

3. The objectives of these contracts included infrastructure construction and industrial division of labor, indicating these two goals as policy focuses. Some contracts also mentioned objectives like factor mobility, energy and environment, and public services. However, since this paper discusses the TFP of enterprises, these aspects do not have a very direct connection. Therefore, to save space, we have not further analyzed these points.

A potential criticism might be a subtle bias in our data collection (e.g., adoption time). However, as shown in Figure D.9, our robustness tests suggest that this potential bias is unlikely to significantly undermine the robustness of our results. This is evident since in almost all other random samplings, there is little evidence to suggest that alternative adoption times could elucidate the observed TFP growth.

Table A.1: The Details Related to UIP

Contract	Time	Cities	Province	Legitimacy Endorsing Authority	Strategic Target
Tai-yu Urban Integration	2002	Taiyuan(Core) and Jinzhong	Shanxi	Shanxi Provincial Political Consultative Conference	1. Infrastructure 2. Industrial Division 3. Factor Mobility
Xi-xian Urban Integration	2002	Xian(Core) and Xianyang	Shaanxi	The Government of Xian and Xianyan	1. Infrastructure 2. Industrial Division 3. Ecological Environment
Xia-Zhang-Quan Urban Integration	2003	Xiamen(Core), Zhangzhou and Quanzhou	Fujian	The Government of Fujian Province	1. Infrastructure 2. Industrial Division 3. Resource Complementarity
Wu-Chang Urban Integration	2004	Urumchi(Core) and Changji Prefecture	Xinjiang	Party Committee and People's Government of Xinjiang Autonomous Region	1. Infrastructure 2. Fiscal Unity 3. Integrated Market 4. Industrial Division
Zheng-bian Urban Integration	2005	Zhengzhou(Core) and Kaifeng	Henan	Henan Development and Reform Commission, Provincial Government, Provincial Party Committee	1. Infrastructure 2. Industrial Division 3. Resource Complementarity 4. Financial Linkage
Ning-Zhen-Yang Urban Integration	2006	Nanjing(Core), Zhenjiang and Yangzhou	Jiangsu	The 11th Party Congress of Jiangsu Province, Provincial Government	1. Infrastructure 2. Ecological Environment 3. Industrial Division 4. Public Service
Chang-Zhu-Tan Urban Integration	2007	Changsha(Core), Xiangtan and Zhuzhou	Hunan	National Development Commission	1. Infrastructure 2. Ecological Environment 3. Industrial Division 4. Financial Center
Sheng-Fu Urban Integration	2007	Shengyang(Core) and Fushun	Liaoning	Provincial Party Committee and Provincial Government	1. Infrastructure 2. Industrial Division 3. Ecological Environment 4. Resource Complementarity
Wu-E Urban Integration	2007	Wuhan(Core) and Ezhou	Hubei	The Government of Hubei Province	1. Infrastructure 2. Industrial Division 3. Public Service 4. Ecological Environment
He-Huai Urban Integration	2008	Hefei(Core) and Huainan	Anhui	The Government of Huainan and Hefei	1. Infrastructure 2. Industrial Division 3. Ecological Environment 4. Urban and rural functions
Guang-Fo Urban Integration	2009	Guangzhou(Core) and Foshan	Guangdong	The Government of Guangzhou and Foshan	1. Infrastructure 2. Industrial Division 3. Ecological Environment 4. Public Service
Lan-Bai Urban Integration	2010	Lanzhou(Core) and Baiyin	Gansu	Provincial Government	1. Infrastructure

Table A.1 Continued from previous page

Contract	Time	Cities	Province	Legitimacy Endorsing Authority	Strategic Target
					2. Urban and rural functions 3. Industrial Division 4. Ecological Environment 5. Public Service
Chang-Ji Urban Integration	2010	Changchun(Core) and Jilin	Jilin	Provincial Party Committee and Provincial Government	1. Infrastructure 2. Industrial Division 3. Ecological Environment 4. Public Service
Shan-Chao-Jie Urban Integration	2011	Shantou(Core), Chaozhou and Jieyang	Guangdong	Provincial Government	1. Infrastructure 2. Industrial Division 3. Ecological Environment 4. Public Service
Gui-An Urban Integration	2011	Guiyang(Core) and Anshun	Guizhou	Provincial Government	1. Infrastructure 2. Industrial Division 3. Public Service
Chang-Jiu Urban Integration	2013	Nanchang(Core) and Jiujiang	Jiangxi	Provincial Government	1. Infrastructure 2. Industrial Division 3. Public Service 4. Resource Complementarity
Cheng-De Urban Integration	2013	Chengdu(Core) and Deyang	Sichuan	The Government of Chengdu and Deyang	1. Infrastructure 2. Industrial Division 3. Ecological Environment 4. Public Service
Ji-Lai Urban Integration	2013	Jinan(Core) and Laiwu	Shandong	Provincial Government	1. Infrastructure 2. Industrial Division 3. Public Service 4. Resource Complementarity

Notes: The table presents the policy details of UIP, including the time of adoption, treated cities, treated province, legitimacy endorsing authority and the aim/focus of the policy.

B Appendix B: Supplement of Dataset and Variable Construction

As a supplement to the data introduction provided in the main text, we first detail the various panels we have used, followed by an explanation of the construction methods for several key panels.

Panel A Universe of Industrial Firm

Following the coding and cleaning procedures by Brandt, Van Biesebroeck and Zhang (2012), this is used to identify the impact of UIP on firm productivity.

Panel B Universe of Business Registrations

Referencing the work of Liu et al. (2022), we cleaned the business registration data, and through constructing equity network data at the city level, we calculated the firm investment amount related to "local" vs "non-local" investments to identify the impact of UIP on city and provincial levels of localism.

Panel C City Panel

We further compiled a macro-level database using different Chinese statistical yearbooks, including the China Statistical Yearbook, China Financial Statistical Yearbook, China City Statistical Yearbook, etc., to obtain control variables and test the mechanism of UIP's impact on TFP[22]. Further, we also manually collected the construction details of high-speed railway in China [23], to create a city level panel for identifying the variations of infrastructure construction under UIP.

Panel D Custom Panel

By acquiring detailed Chinese import and export data from China's General Administration of Customs, we aggregated products at the firm level and matched them with Panel A to build a panel, identifying UIP's impact on firm international trade behavior, thus inferring changes in regional trade.

Panel E Universe of Industrial Firm & Chinese Patent

From the National Intellectual Property Administration, we obtained detailed Chinese patent application data, and using the patent-level information, we computed knowledge breadth to reflect patent quality (Hsu et al., 2023), then matched this with Panel A to identify UIP's impact on firm innovation.

Panel F Universe of Judicial Document

Following Liu et al. (2022), we obtained the universe of judicial document from 1985-2021. By organizing textual materials, we calculated the total number of legal cases in each city and cases containing the keywords *patent* and *ownership*, allowing us to depict a city's legal environment related to intellectual property protection and assess UIP's influence on the legal environment.

Panel G Universe of Industrial Firm & Business Registrations

Based on the organization of Panel B, we further matched commercial business registration data with Panel A using location, name, year, industry code, etc., to identify changes in firm entry, exit, and transfer activities. A significant advantage of this approach is its ability to mitigate the endogeneity problems caused by changes in the sampling objects of the industrial enterprise database and firms' discretion.

Panel H Universe of Land Leasing and Industry Policy

[22] Additionally, in an effort to identify the spillover effect of UIP, we gathered the geographic coordinate information pertaining to the center of mass for both firms and cities. This process entailed extracting the geographical locations and names of individual firms from our database. Subsequently, using Stata, we interfaced with AMAP to obtain the precise longitude and latitude details of each firm's geographical location.

Simultaneously, in order to ascertain the coordinates for each city's center of mass, we employed R to compute the geographic coordinates. This computation was based on the vector data of Chinese cities, allowing us to accurately assess the spatial dynamics involved in urban integration.

[23] In China, the development of high-speed railways serves as a significant practice in the construction of transportation infrastructure. This has substantially reduced the commuting costs between cities, emblematically reflecting the level of inter-city cross-regional transportation infrastructure development.

To illuminate the substantive ramifications of UIP on government decision-making processes, we harnessed comprehensive data on land transactions of local government from the China Land Market website [24] by means of web scraping, encompassing all records since 2000. The dataset, enriched with pivotal attributes such as land area, transaction values, land classifications, and crucial information pertaining to land users, furnishes a robust foundation for our examination of land market transparency. Concurrently, with an aim to contemplate the influence of China's industrial strategy on corporate behavior, we discerned industry codes earmarked for preferential support or encouragement by employing text analysis techniques on the work reports of provincial governments.

Panel I Universe of Patent Transfer

Using the patent legal status change information provided by the National Intellectual Property Administration, we extracted over two million cases of patent rights transfers. During the study period of this paper, there were a total of 138,941 observations. By cleaning the data related to the timing and entities involved in the transfer of patent rights, we captured the geographical trajectory of patent movements. This approach enables us directly identify the formal knowledge diffusion effects induced by UIP.

B.1 Universe of Industrial Firm

Since Brandt, Van Biesebroeck and Zhang (2012) altruistic sharing of the cleansing process for the Chinese Industrial Enterprises Database (ASIEC), this database, led by the NBS, has become the standard resource for researching Chinese firms. As a confidential data set, it meticulously records the production details of all Chinese industrial enterprises from 1998 to 2013, serving as the core material for computing and studying firm TFP. Notably, while it facilitates direct observation of various internal changes in firms, it lacks additional information concerning imports and exports, entry-exit decisions, and patent applications. By integrating it with the Chinese Customs Database, Patent Database, and Business Registration Database, we further obtained these details, enabling us to observe the full picture of firm dynamics from 2000 to 2013.

Prior to the matching process, we undertake two steps to organize the full panel of the CIED:

Step 1: We adopt a hybrid approach to organize the raw data into a panel while ensuring the accuracy of matches. This approach involves combining the precise matching of a firm's name with the fuzzy matching of specific firm details (Brandt, Van Biesebroeck and Zhang, 2012).

Step 2: To reduce measurement errors within the data, we proceed with the following steps: we remove erroneous samples in which the establishment date of the firm predates 1900. We fill the missing values of industrial intermediate input and added value in certain years, adhering to the database's accounting principles and relevant information. We discard samples that fail to meet specific criteria - for instance, where the annual average balance of the net value of fixed assets surpasses total assets, where total assets are less than the total current assets, where accumulated depreciation is below the current depreciation, where the industrial sales value falls below 500,000, where the number of employees is less than 8, and where the paid-in capital is non-existent.

We referred to the matching methods of previous related works, such as the matching with the Customs Database (Dai, Maitra and Yu, 2016), and the Patent Database (Hsu et al., 2023). However, what distinguishes our work is that (1) we alleviated the measurement errors in the entry-exit of firms caused by self-reporting and random sampling through matching business registration data; (2) we incorporated these data into a unified analytical framework to observe the full dynamics of firms; (3) we parsed the latitude and longitude information of firm locations through the Gaode geographic API, thereby detailedly observe the specific location of firm, and also largely improve the matching accuracy.

[24] https://landchina.com/#/.

B.2 Universe of Business Registration with Stock Network

In our mechanism analysis, there are two important aspects: firstly, documenting the changes in local protectionism at the micro level, and secondly, investigating the changes in the dynamics of enterprise entry and exit. To achieve these objectives, we have incorporated corporate administrative data used in recent studies on Chinese companies (Shi et al., 2021; Liu et al., 2022), specifically the commercial registration and detailed equity structure data stored by the State Administration for Industry and Commerce (SAIC).

In measuring local protectionism, following the method used by Liu et al. (2022) in assessing corporate equity structures, we identified the geographical locations of investors. We consider the locations of institutional investors and the locations of the companies where individual investors hold the most shares as their respective locations, thus calculating the amount of local and non-local investment each company receives. Given the focus on investment amounts, we adopted two descriptive methods: investment amount and the number of investments.

Our method differs from Liu et al. (2022) in that, based on the uniqueness of UIP, we further distinguish the specific attributes of non-local investments. This includes investments from outside the company's city, from outside the province but within the city, from outside the province, and from core cities corresponding to surrounding cities.

Through this more detailed depiction, we can clearly reflect two different forms of protectionism, inter-city and inter-provincial protectionism. Therefore, with UIP as an institutional arrangement for inter-city cooperation, we can test the hypothesis that treated-city protectionism is alleviated while inter-provincial protectionism remains unchanged.

In identifying the dynamics of enterprise entry and exit, the ASIEC data we use, as mentioned in our main text, only includes all above-scale industrial enterprises. For this data, we may not know the exact timing of a company's entry and exit because if their main business income does not meet the survey standards, they will not appear in the database. To address this, we use administrative data as a supplement. On the one hand, by matching the two datasets through company names, locations, etc., we directly define the precise entry and exit times of companies, thus mitigating potential measurement errors. On the other hand, we directly use administrative data to calculate the entry, exit, and transfer rates of enterprises at the county-level, industry-year level, thus complementing the empirical work of the former. Through these two methods, we are able to accurately identify the causal impact of UIP on enterprise entry-exit behavior.

B.3 Universe of Judicial Document

A critical challenge in studies investigating the impact of the institutional environment on corporate innovation lies in differentiating the level of property rights protection from the overall legal environment. The key distinction between the two lies in the fact that the former is comprehensive, encompassing aspects such as the adjudication of criminal cases, family internal disputes, and administrative affairs, among others. The latter, however, specifically focuses on the adjudication of property rights protection cases. Common measurements of regional legal environment often struggle to segregate these two aspects[25].

Recently, a study by Liu et al. (2022) employed judicial document data, providing valuable insight into this distinction. Drawing from their methodology, we made substantial efforts to gather all judicial documents from 1985 to 2021 from the China Judgment Online (CJO, allowing us to examine the entire spectrum of judicial rulings in China.

Leveraging this data, we calculated the legal cases in several dimensions for each city, including all legal cases, those related to patents, and those related to property rights. This approach enables a direct definition of the shifts in the legal environment related to intellectual property at the city level, and further capture the cross-city variations. Consequently, it allows us to test the hypothesis that the improvement in total factor productivity through imitation innovation in corporations is driven by the inadequate establishment of intellectual property systems in China at the beginning of the 21st century.

[25] In many scenarios, higher legal environment are not necessary related to a decent system of property rights protection.

B.4 Variables Construction

We constructed a series of indicators based on relevant theories to test the research hypotheses. The methods for constructing these indicators are described below.

Total Factor Productivity

Our approach to measuring firm-level TFP follows the classical strategy of Ackerberg, Caves and Frazer (2015). First, we consider the Cobb-Douglas production technology for firm i at time t:

$$v_{it} = \Phi_{it}(p_{it}, \boldsymbol{x}_{it}, \boldsymbol{w}_{it}, l_{it}) + \varepsilon_{it}$$

where

$$\Phi_{it}(p_{it}, \boldsymbol{x}_{it}, \boldsymbol{w}_{it}, l_{it}) = \boldsymbol{x}_{it}\gamma + \boldsymbol{w}_{it}\beta + \mu l_{it} + h(p_{it}, \boldsymbol{x}_{it}, \boldsymbol{w}_{it}, l_{it}),$$

$$m_{it} = m(\mathrm{TFP}_{it}, \boldsymbol{x}_{it}), \quad l_{it} = l(\mathrm{TFP}_{it}, \boldsymbol{x}_{it}),$$

$$l_{it} = l\left\{h(m_{it}, \boldsymbol{x}_{it}), \boldsymbol{x}_{it}\right\}.$$

v_{it} represents the value-added output, w_{it} is a $1 \times J$ vector of logged freely variable inputs, and x_{it} is a $1 \times K$ vector of logged state variables. m_{it} is intermediate inputs, l_{it} denotes labor, and $p_{it} = f(\boldsymbol{x}_{it}, l_{it}, \mathrm{TFP}_{it})$ is the proxy variable policy function, invertible in TFP_{it}. $\mathrm{TFP}_{it} = h(p_{it}, \boldsymbol{x}_{it}, \boldsymbol{w}_{it}, l_{it})$ denotes productivity, and ε_{it} is the white noise capturing idiosyncratic output shocks.

Under the assumptions of Ackerberg, Caves and Frazer (2015), once $\widehat{\Phi}_{it}$ is recovered, for any candidate vector $[\gamma^*, \beta^*, \mu^*]$, it is possible to obtain the residuals:

$$\widehat{TFP}_{it} = \widehat{\Phi}_{it} - \boldsymbol{x}_{it}\gamma - \boldsymbol{w}_{it}\beta - \mu l_{it}$$

and, exploiting the Markov chain assumption $\mathrm{TFP}_{it} = E(\mathrm{TFP}_{it}|\mathrm{TFP}_{it-1}) + \xi_{it} = g(\mathrm{TFP}_{it-1}) + \xi_{it}$, obtain the residuals ξ_{it}. These, combined with the set of moment conditions $E(\xi_{it} z_{it}^k) = 0$, $\forall k$, where k is the index of the instrument vector $\boldsymbol{z} = [\boldsymbol{x}_{it}, m_{it-1}, l_{it-1}]$, lead to the GMM criterion function (second stage):

$$\begin{bmatrix} \gamma^* \\ \beta^* \\ \delta^* \end{bmatrix} = \arg\max \left\{ -\sum_k \left(\sum_i \sum_t \xi_{it} z_{it}^k \right)^2 \right\}.$$

Based on this method, we can obtain firm-level productivity measures that change annually, reflecting variations in firms' internal production technology or production efficiency over time. Notably, in our robustness checks, we employ the methods proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Gandhi, Navarro and Rivers (2020), which are similar but differ slightly in assumptions and specific implementations. We omit a detailed discussion of these methods for brevity.

Comparative Advantage

To determine whether an industry conforms to local comparative advantage, we refer to the ideas of dominant comparative advantage from Balassa (1965), and use the entropy index to measure it (Hanson, Lind and Muendler, 2016):

$$\begin{aligned} LQ_{dct} &= \frac{\text{output}_{\text{dct}} \,/\, \text{output}_{ct}}{\text{output}_{dt} / \,\text{output}_{t}} \\ RCA_{\text{idct}} &= I\left(LQ_{dct} >= mean(LQ_{dct})\right) \end{aligned} \tag{11}$$

Here, LQ_{dct} denotes the entropy index of industry d in year t of city c, and *output* represents the total industrial output value. The former implies that the share of industry d's output in its city is a proportion of the share of the industry in the country, while the latter generates a dummy variable

for RCA. That is, if an industry has LQ larger than the mean value, we can define that the industry has a comparative advantage in the region.

ICI

To judge the degree and direction of industrial structural change, we refer to Lu et al. (2013), using the industrial concentration index (ICI) to estimate the variation of industrial structure and whether the industry is tending to centralize:

$$ICI_{dct} = \frac{insh_{dct}}{insh_{dpt}} \tag{12}$$

Here, $insh$ represents industry d as the share of total manufacturing in year t of the city, and p denotes the province. ICI represents the degree of industrial concentration, which means the share of a city's industry in its province.

Pro and Div

To determine whether the industrial structural change points to specialization, we refer to Glaeser et al. (1992) and Henderson, Kuncoro and Turner (1995), measuring the industrial specialization index (Pro) and industrial diversification index (Div) using the entropy index and the inverse of HHI, respectively.

$$pro_{dct} = \frac{\frac{lab_{dct}}{lab_{ct}}}{\frac{lab_{dt}}{lab_{t}}} \tag{13}$$

$$\text{div}_{dct} = \frac{1/\sum_{d^1 \neq d}\left(\frac{lab_{d^1ct}}{lab_{ct}-lab_{dct}}\right)^2}{1/\sum_{d^1 \neq d}\left(\frac{lab_{d^1t}}{lab_{t}-lab_{dt}}\right)^2} \tag{14}$$

Here, lab denotes the number of laborers in industry d, and hence, equation (5) means that the share of industry d's labor in its city is a proportion of the share of the industry in the country. It is a standard measurement of the inverse of HHI to represent the diversification of industry d.

Measuring Technical Consistency

To formally determine the component of TFP growth under UIP that stems from the intensive margin effects of imitative innovation, we adopt the methodology proposed by Dechezleprêtre et al. (2023), which relies on the measure of technological similarity introduced by Jaffe (1986). In our design, our focus is on identifying which industries in peripheral cities are more likely to imitate the innovations of core city industries through trade.

To achieve this, we use patent granularity data, aggregating at the two-digit industry code-city-patent main class level to construct technology vectors. Then, we calculate the technological similarity between each peripheral city's industry and its corresponding core city industry based on this technology vector. Based on the statistical characteristics of this technological similarity, we can determine which industry is technologically most similar to its counterpart industry in the core city. For example, industries with a technological similarity exceeding the average (90th percentile, etc.) are designated as 1, indicating a greater tendency to benefit from innovation spillovers.[26]

[26] An inherent limitation of this measurement approach is that it inevitably overlooks the intensity of innovation spillovers from core cities, as it is challenging to determine a corresponding city for core cities. Theoretically, core cities tend to be at a more advanced industrial development stage and are more likely to be sources of technological spillover effects rather than imitators. Therefore, we uniformly set their innovation spillover intensity index to 0.

C Appendix C: Summary Statistic and Covariate Balance

In the subsequent subsections, we report the descriptive statistics for all variables utilized, as illustrated in Tables C.1 and C.2, with all descriptions separately delineating the treatment and control groups. In Tables C.3 and C.4, we present the balance tests for covariates in the pre-treatment window. We find that, across both the firm and city dimensions, the given key covariates exhibit no significant differences between the treatment and control groups in the pre-treatment window. This suggests that the treatment is largely random, which also resonates with our analysis in the instrumental variable section.

C.1 Summary Statistic

Table C.1: Summary Statistics

	Treatment Group			Control Group		
Variables	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
The variables at firm level (Panel A, E, and G)						
Total factor productivity (LP)	6.435	1.205	507459	6.360	1.173	2255955
Total factor productivity (ACF)	3.467	1.056	507459	3.424	1.026	2255955
Total factor productivity (OP)	5.725	1.155	507459	5.658	1.123	2255955
Total factor productivity (Gandhi)	10.149	0.825	487337	10.126	0.819	2154170
Enterprise age	2.064	0.778	683494	2.001	0.787	3089585
History of the patent (YES=1)	0.112	0.315	683962	0.094	0.292	3091077
Export (YES=1)	0.182	0.386	683962	0.197	0.397	3091077
Markup	0.915	0.688	504802	0.952	0.712	2233083
Exit	0.179	0.383	576223	0.178	0.383	2583018
Transfer	0.004	0.061	576282	0.005	0.071	2583515
Entry	0.033	0.179	579046	0.039	0.194	2598453
Design patent	0.141	3.902	683962	0.163	4.255	3091077
Innovation patent	0.158	2.743	683962	0.184	12.528	3091077
Utility patent	0.273	3.735	683962	0.237	6.267	3091077
Total patent	0.572	7.809	683962	0.584	17.359	3091077
Patent quality	0.036	0.167	683962	0.031	0.155	3091077
Traffic infrastructure	2.452	0.377	632008	2.599	0.488	2811789
Subsidy	0.655	1.966	411335	0.825	2.134	1773155
Zombie	0.028	0.164	683962	0.027	0.162	3091077
City sized (Pre*T)	52.913	22.859	675915	53.750	22.846	3004504
City GPD per capita (Pre*T)	4.242	5.809	675915	1.743	7.210	2991894
City Secondary Industry (Pre*T)	4.095	1.927	680800	3.811	1.809	2949971
The variables at Panel C						
Industry Concentration (ICI)	0.158	0.254	57031	0.227	0.272	291988
Industry Specialization (Pro)	0.233	0.801	95732	0.472	8.083	443850
Industry Diversification (Div)	3.804	1.318	95732	3.598	1.279	443850
Public Investment	0.129	0.172	432	0.052	0.140	2801
Passenger Volume	8.872	0.96	546	8.514	0.932	3407
Secondary Industry	0.496	0.070	558	0.456	0.132	4083
Tertiary Industry	0.405	0.081	558	0.356	0.085	4083

Notes: The table presents summary statistics for the variables used in our cross-firm or cross-city analysis. For each variable, we report the standard deviation and mean. The data are presented separately for the treatment and control groups. All time-varying variables are in log values.

C.2 Others Summary Statistic

Table C.2: Summary Statistic

	Treatment Group			Control Group		
Variables	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
The Variables at Panel B						
OCIP	0.234	0.948	2520086	0.180	0.840	9433008
OCIP(%)	0.037	0.175	2519144	0.028	0.161	9427174
OC(%)	0.134	0.287	2519144	0.127	0.286	9427174
OP(%)	0.098	0.25	2519144	0.100	0.257	9427174
OCIP Number	0.055	0.21	2520086	0.045	0.201	9433006
OCIP Number(%)	0.036	0.148	2520086	0.028	0.131	9433044
OC Number(%)	0.140	0.278	2520086	0.133	0.279	9433044
OP Number(%)	0.104	0.244	2520086	0.105	0.252	9433044
The Variables at Panel D						
Export Volume	12.056	5.166	135066	12.517	4.843	673068
Import Volume	7.930	6.601	135066	8.190	6.615	673068
The Variables at Panel F						
Total Lawsuit	11839.322	10661.074	280566	10451.598	10213.637	1206651
Patent Lawsuit	37.962	32.170	280566	32.949	32.150	1206651
Right Lawsuit	529.66	461.432	280566	486.815	484.566	1206651
The Variables at Panel I						
Area of Structure	2.247	5.975	212629	1.699	4.826	1206331
Land Price	1540.506	5306.958	212629	951.680	3795.853	1206331
The Variables at Panel J						
Non Local Transfer - Within Province	0.048	0.211	39751	0.028	0.166	99190
Non Local Transfer - Outside Province	0.178	0.382	39751	0.226	0.418	99190

Notes: The table presents summary statistics for the variables used in our cross-firm or cross-city analysis. For each variable, we report the standard deviation and mean. The data are presented separately for the treatment and control groups. All time-varying variables are in log values.

C.3 Covariate Balance Between Treatment and Control Firms

Table C.3: Covariate Balance Between Treatment and Control Firms

	Treatment (1)	**Control (2)**	**T vs C (3)**
Years less than 2003			
Year of Opening	1989	1989	-0.871
	(13.119)	(13.07)	(1.067)
Soe (1=Yes, 0=Others)	0.158	0.169	-0.005
	(0.365)	(0.375)	(0.032)
History (1=Yes, 0=Others)	0.041	0.030	-0.022
	(0.198)	(0.17)	(0.018)
Export (1=Yes, 0=Others)	0.270	0.285	-0.033
	(0.444)	(0.451)	(0.032)
Lp (log)	6.620	6.594	-0.092
	(1.170)	(1.068)	(0.159)
Op (log)	5.925	5.902	-0.093
	(1.119)	(1.011)	(0.171)
ACF (log)	3.554	3.575	-0.094
	(1.051)	(0.94)	(0.185)
Gandhi (log)	10.052	10.049	-0.108
	(0.732)	(0.744)	(0.074)
Markup (log)	0.862	0.901	-0.017
	(0.669)	(0.691)	(0.053)
Profit (Million yuan)	2.563	3.336	-5.885
	(43.151)	(166.517)	(6.892)
Value added (log)	8.404	8.350	-0.091
	(1.355)	(1.263)	(0.147)
Employee (log)	5.102	5.056	0.004
	(1.148)	(1.131)	(0.102)
Capital stock (log)	9.888	9.821	-0.07
	(1.490)	(1.452)	(0.062)
Subsidy (log)	0.528	0.707	-0.142
	(1.767)	(1.992)	(0.208)

Notes: The table presents summary statistics for the variables used in our cross-firm or cross-city analysis. For each variable, we report the standard deviation and mean. The data are presented separately for the treatment and control groups. All time-varying variables are in log values. The difference coefficients are estimated by conducting an OLS regression of firm characteristics on city-level adoption of the UIP dummy, with firm-level fixed effects. Standard errors, clustered at the industry level, are indicated in parentheses.

C.4 Covariate Balance Between Treatment and Control Cities

Table C.4: Covariate Balance Between Treatment and Control Cities

	Treatment (1)	Control (2)	T vs C (3)
The distances to port (km, log)			
	12.452	12.797	-0.110
	(1.344)	(1.244)	(0.098)
The distances to coastline (km, log)			
	5.656	5.840	0.063
	(1.337)	(1.355)	(0.104)
Per capita road area (log)			
	1.930	1.931	0.027
	(0.294)	(0.544)	(0.061)
No. of post offices (log)			
	5.544	5.377	0.175
	(0.76)	(0.761)	(0.117)
Road passenger traffic (log)			
	8.329	8.124	0.149
	(0.883)	(0.888)	(0.120)
Total population (log)			
	5.887	5.561	0.174
	(0.755)	(0.946)	(0.107)
Urbanization level			
(The ratio of non-agricultural population to total population, log)	0.748	0.310	0.428
	(3.215)	(0.708)	(0.327)
Percentage of secondary industry			
(Share of secondary industry employment in total employment, log)	0.406	0.424	-0.000
	(0.244)	(0.286)	(0.034)

Notes: The table presents the balance test for treatment and control cities prior to 2003. Columns 1-2 report the mean and standard deviations of city characteristics, while column 3 illustrates the covariate balance between the treatment and control cities. The difference coefficients are estimated by conducting an OLS regression of city characteristics on a city-level adoption of the UIP dummy, with province-level fixed effects. Standard errors, clustered at the province level, are indicated in parentheses.

D Appendix D: Robustness Check

D.1 Adopt Different Measurements in TFP

We employed various methods for measuring TFP, denoted by the approaches of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Gandhi, Navarro and Rivers (2020), represented respectively as OP, LP, and Gandhi. The results in Table D.1 indicate that all outcomes presented in our main text do not depend on the chosen method for measuring TFP. In more instances, the estimation coefficients using the ACF method, as utilized in our main text, are marginally smaller, implying relatively conservative outcomes.

Table D.1: Regression Results: Alternative TFP Measurements

	Panel A: Universe of Industrial Firm								
	(1) LP	(2) OP	(3) Gandhi	(4) LP	(5) OP	(6) Gandhi	(7) LP	(8) OP	(9) Gandhi
UIP	0.080***	0.069***	0.137***	0.096***	0.087***	0.137***	0.096***	0.087***	0.138***
	(0.025)	(0.024)	(0.021)	(0.023)	(0.023)	(0.019)	(0.023)	(0.023)	(0.019)
Observations	2640726	2640726	2523716	2485219	2485219	2386119	2485219	2485219	2386119
Year FE	X	X	X	X	X	X	X	X	X
City FE	X	X	X				X	X	X
Firm FE				X	X	X	X	X	X
Control	X	X	X	X	X	X	X	X	X

Notes: This table provides a robustness check for changing the measurement method of the company's total factor productivity. In columns 1-3, the dependent variables are the company's TFP using LP, OP, and GNR methods, respectively; columns 4-9 correspond to these, and three are grouped together with different fixed effects. All time-varying variables are represented in log values. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level.

D.2 Control Latent Omitted Variables

We attempted to further control for fixed effects and control variables across different dimensions to examine whether our results are vulnerable to potential omitted variable bias. As illustrated in Table D.2, results from columns 1-2 suggest that time-varying characteristics at the province-year level are unlikely to threaten our estimation results. Columns 3-4 demonstrate that incorporating the time-varying geographic characteristics of cities and interacting them with time trends, such as distance from ports, distance from the coastline, elevation, and slope, does not affect the estimation results. Columns 5-6 indicate that further including some time-varying characteristics at the city level, such as city population size, per capita GDP, and the proportion of secondary industry, significantly underestimates the treatment intensity. This underestimation occurs because these characteristics have already been influenced by UIP, making them so-called "bad" control variables. Nonetheless, the results remain significant, stemming from the robust intensive margin channel.

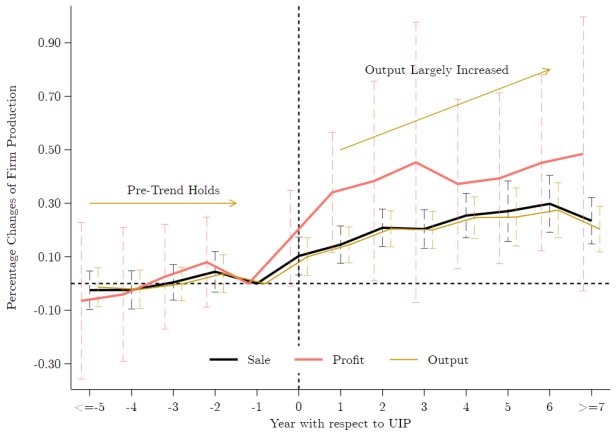
Table D.2: Regression Results: Alternative Control Variables and FE

	Panel A: Universe of Industrial Firm					
	(1)	(2)	(3)	(4)	(5)	(6)
	TFP					
UIP	0.058**	0.054**	0.084***	0.095***	0.058**	0.074***
	(0.023)	(0.025)	(0.023)	(0.023)	(0.026)	(0.024)
Observations	2485219	2640726	2480516	2635653	2472206	2622169
Year FE	X	X	X	X	X	X
City FE		X		X		X
Province-Year FE	X	X				
Firm FE	X		X		X	
Control	City-Firm	City-Firm	City-Firm	City-Firm	Firm	Firm
Pre-determined City Features			X	X	X	X
City-level Time-varying Features					X	X

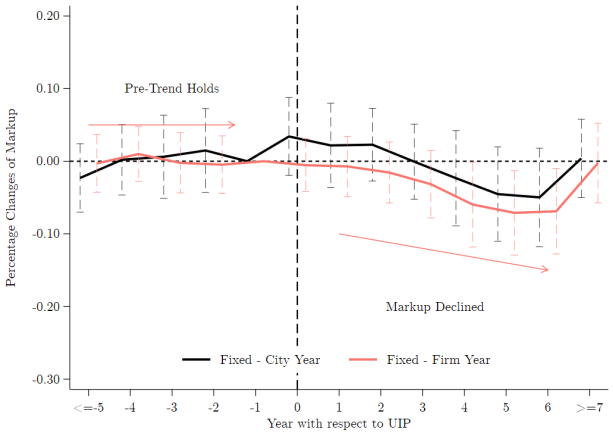
Notes: This table demonstrates a robustness check for regression using different specifications with the ACF method as the TFP measure. For columns 1-2, we attempt to include province-time dimension fixed effects; for columns 3-4, we attempt to include other pre-determined control variables at the city level and multiply by time trends (port, coastline, elevation, and slope); for columns 5-6, we further include city-level time-varying control variables. All time-varying variables are represented in log values. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level.

D.3 Pre-Trend Results

In order to ensure that all the estimated outcome variables, along with all the groups used for comparison, satisfy the assumption of parallel trends, thereby deriving results with causal interpretations, we conducted thorough examinations of parallel trends and dynamic effects across all regressions in the main text. This includes the analysis of mechanisms, cross-sectional analysis, and the various aspects of economic implications, all utilizing specifications consistent with the main text's ESA. Overall, we demonstrate that all results can be interpreted as the average treatment effects under UIP influence, exhibiting causal properties. Furthermore, the magnitude and direction of these effects are consistent with the findings in the main text. We report the parallel trends test for the main results below, while the tests for all other variables are available upon request.



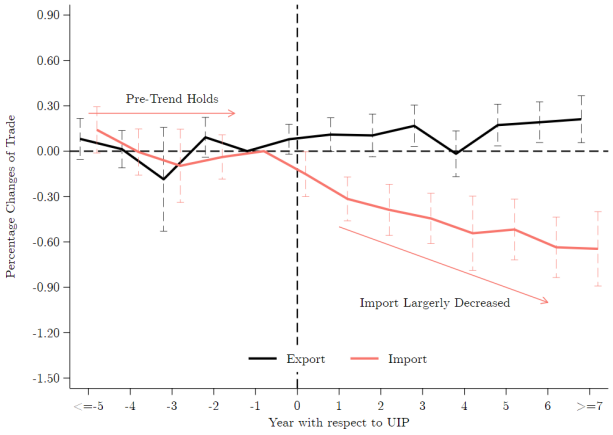
A. Firm Operation



B. Markup



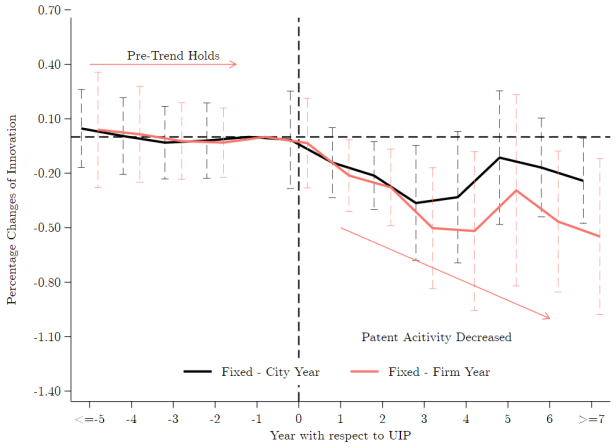
C. Selling Cost



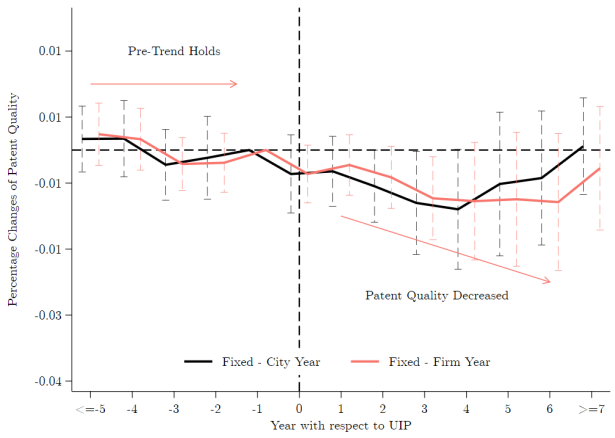
D. Export and Import

Figure D.1: Results on Market Expansion: Dynamic Effects

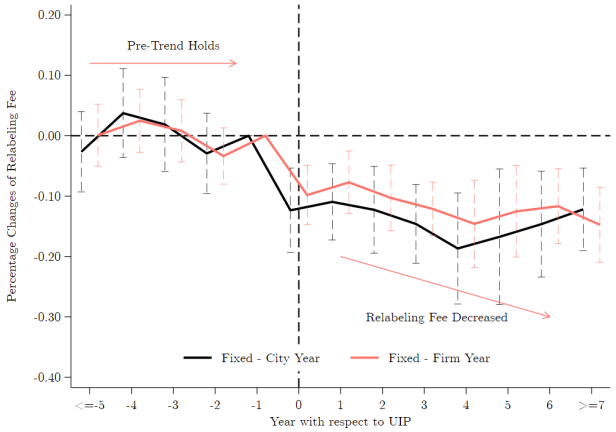
Notes: In this figure, we depict the dynamic effect results of the variables employed in the main text, utilizing regression equations analogous to those employed in the main text's Event Study Analysis (ESA). These outcomes correspond to Table 2 in the main text.



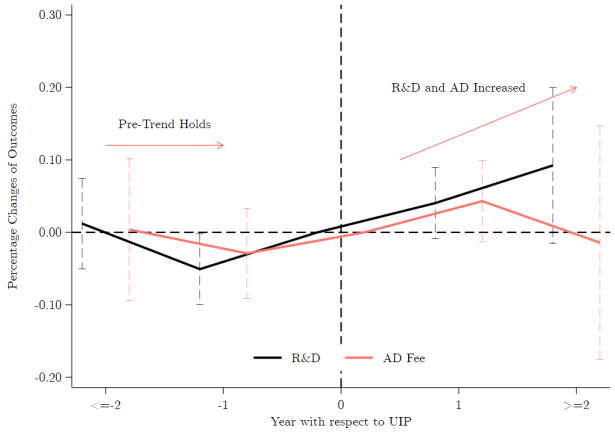
A. Patent



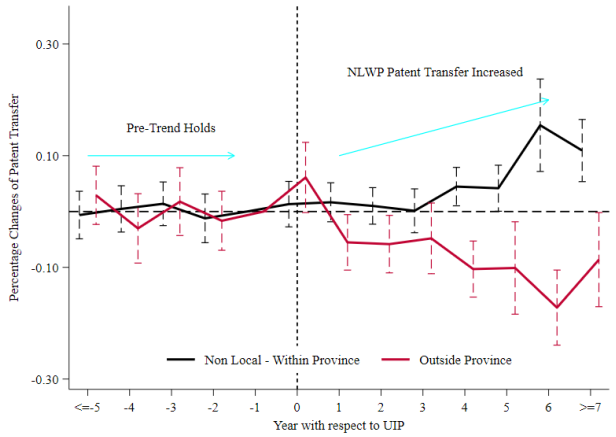
B. Quality



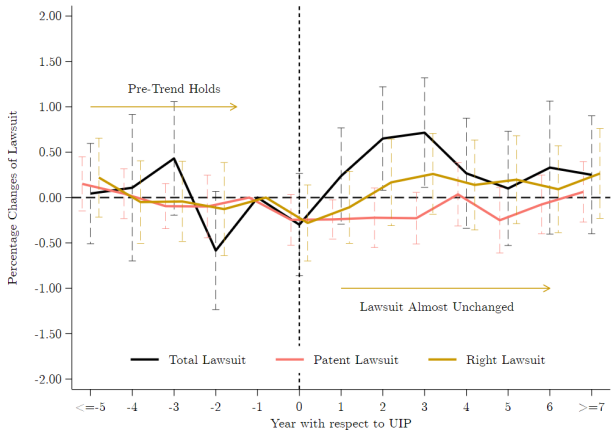
C. Relabeling Fee



D. R&D and AD Cost



E. Patent Transfer



F. Lawsuit

Figure D.2: Results on Innovation and Lawsuit: Dynamic Effects

Notes: In this figure, we depict the dynamic effect results of the variables employed in the main text, utilizing regression equations analogous to those employed in the main text's Event Study Analysis (ESA). These outcomes correspond to Table 4 and 5 in the main text.

D.4 Check the SUTVA of Our Baseline Specification

In this section, we formally discuss the Stable Unit Treatment Value Assumption (SUTVA). The key is to understand whether the effects generated by UIP have contaminated those control groups that are geographically proximate to the treatment group. We employ three designs to test this.

The first design aims to formally capture the geographic boundaries of the potential spillover effects of UIP. To achieve this, we utilize a design based on geographic latitude. Specifically, we modify the dummy variable for UIP to another approach, setting it to 1 for provinces that have implemented UIP (instead of cities), and then we multiply this variable by a dummy variable that changes with the geographic window (for example, firms within 20-30km of the nearest treated city are set to 1, and further firms are set to 0, and so on, with 10km intervals extending outward). This product is then multiplied by another dummy variable that defines the treatment time window. Given that the spillover effects of treatment often decay with distance, this design allows us to identify at what distance further firms no longer differ from closer firms in terms of policy impact, thereby determining the boundaries of spillover effects. The estimated results, as shown in Figure D.3, indicate that beyond 80km, the treatment hardly causes any geographical differences in firm TFP, suggesting that the boundary of spillover effects is around this distance.

The second design complements the first by using a Difference-in-Differences-in-Differences (DDD) approach to identify the boundaries of spillover effects, instead of a geographical design. We define a dummy variable indicating whether a province is treated, then interact it with another dummy variable defining the treatment window. This interaction is further combined with the variable distance, representing the firm's distance from the nearest treated city, to identify how spillover effects diminish with distance. The results, as shown in Table D.3, indicate that the treatment leads to an average increase of 7.6% in TFP for treated provinces. However, the promotional effect disappears when firms are located more than 76km away from the nearest treated city, consistent with our geographical design.

The third design explores how this potential spillover effect influences estimation results. We use the baseline design but exclude firms that are not located in treated cities yet are within 80km of such cities. As identified, these firms are more likely to be affected by spillover effects. The results, presented in Table D.4, show that excluding these firms even increases the promotional effect of UIP on firm TFP to 8.2%, which is 0.3% higher than the baseline results. This implies that spillover effects do not lead to an overestimation of our results; rather, it suggests that our current estimates are more conservative.

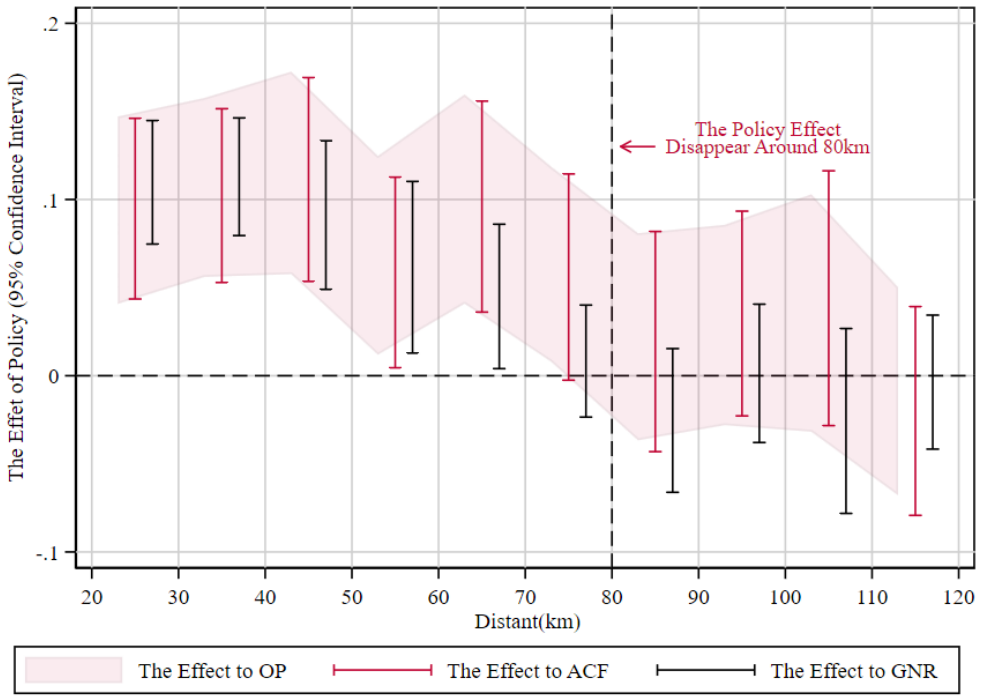


Figure D.3: The Geography Boundary of UIP Function

Notes: This figure presents estimations of the geographical boundary effects of UIP intervention. We maintain the model's other specifications consistent with the baseline regression and modify the variable Dum (Difined treated cities) to dis*DumPro (where dis is a dummy variable measuring the distance group between firms and the nearest core city) For instance, within the 20-30 distance group, we assign a value of 1 to firms located 20-30 kilometers from the nearest core city, and 0 to those exceeding 30 kilometers, and so forth for other distance groups. Additionally, when focusing on the treatment group within the 20-30 kilometers range, we exclude firms located within 20 kilometers. DumPro characterizes whether a province is subject to UIP intervention.

Table D.3: Use the Shortest Distance to Identify Spillover Effects

	Panel A: Universe of Industrial Firm	
	(1)	(2)
Dependent Variable	TFP	
UIP - Province	0.056***	0.076***
	(0.020)	(0.020)
UIP - Province×Distance	-0.001***	-0.001***
	(0.000)	(0.000)
Observations	2640726	2485219
Year FE	X	X
City FE	X	
Firm FE		X
Control	X	X

Notes: This table provides alternative estimations to test the SUTVA. In contrast to the approach utilized in Figure D.3, where distance-based dummy variables were employed to construct the DID specification, we incorporate distance as an interaction term, following a Difference-in-Differences-in-Differences (DDD) strategy for identification. The variable UIP - Province indicates whether a province has implemented the UIP policy, with a value of 1 assigned after the policy's implementation year. All time-varying variables are presented in logarithmic form, and we further control for any relevant interaction terms. Statistical significance levels are denoted by ***, **, and *, corresponding to 0.01, 0.05, and 0.1 significance levels, respectively. Standard errors are clustered at the city - year level.

Table D.4: Exclude Control Group Firms Located Within the Nearest 80km of the Treatment Group

	Panel A: Universe of Industrial Firm		
	(1)	(2)	(3)
Dependent Variable		TFP	
UIP	0.089***	0.082***	0.082***
	(0.024)	(0.023)	(0.023)
Observations	2318335	2181280	2181280
Year FE	X	X	X
City FE	X		X
Firm FE		X	X
Control	X	X	X

Notes: The table presents OLS estimates of the relationship between UIP and a firm's TFP by adopting the model (8). The dependent variable is the firm's TFP employed using the ACF method. We excluded the firms located 0-80 kilometers from the nearest core city. All time-varying variables are presented in log values. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city - year level.

D.5 Heterogeneity Treatment Effect

Recent literature on DID specification suggests that in stagger DID designs, like ours, heterogeneity in treatment effects over time or across groups may lead to considerable bias in conventional DID estimates (Liyang and Abraham, 2021; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). For example, in our design, the estimates may be biased downward when the already treated cities is treated as controls by the newly treated cities. We address these concerns by introducing tests as follows:

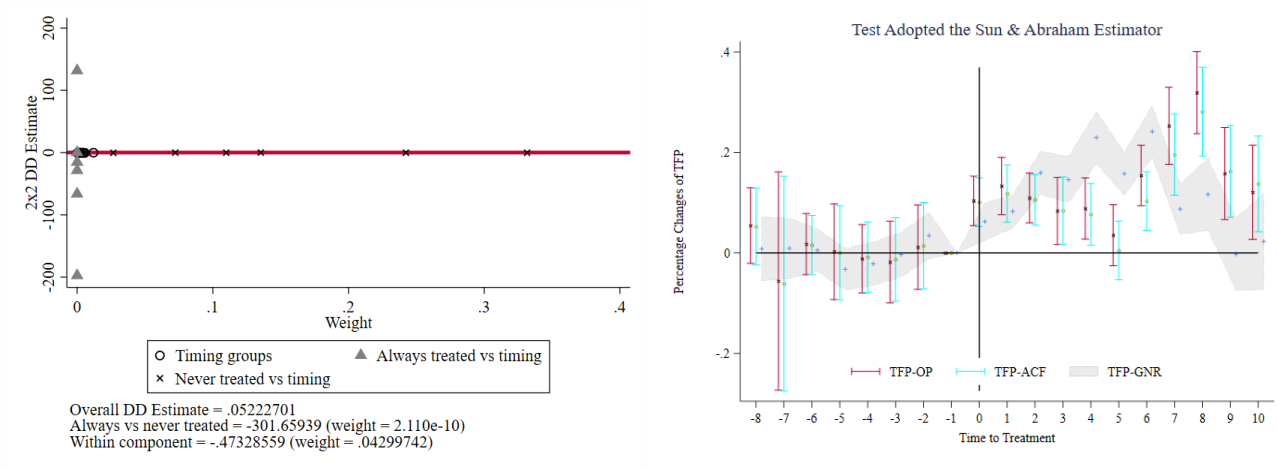
We run the same regression as our baseline specification to check whether the estimates are contaminated by the incorrect comparison of already treated units as controls. To do so, we first divide the data into two windows, 2000-2005 and 2008-2013, and consider the effect of UIP on TFP in 2002 and 2011, respectively (which means that we exclude cities that adopted UIP in other years, hence only never treated units are used as controls). Table D.5 presents the estimates. In columns 1-3, the positive effect of UIP is slightly larger than the baseline estimates, but in columns 4-6, the positive impact of UIP is more sizeable, over 20%. Even though the data windows may cause a difference in estimates, they may also result from the potential heterogeneity in treatment effects over time. Therefore, we further run some new tests to confirm that the heterogeneity in treatment effects does not pollute our estimates.

To directly examine whether the heterogeneity of treatment effects contaminated our baseline estimates, we apply the method of (Goodman-Bacon, 2021) to decompose the treatment effects exactly. The results are shown in Table D.7 and Figure D.4. We find that the estimated coefficient for the comparison between the untreated group and the treatment group is 0.078, accounting for more than 91%, while the coefficient for the comparison between the treatment groups is 0.009, accounting for only 4%. Namely, the heterogeneity of treatments' effects does not significantly contaminate our baseline estimates. At the same time, it can also be found in Figure D.4A that the ATT of UIP is mainly reflected in the comparison between the treatment group and the control group. In addition, to ensure the robustness of common trends and baseline estimates, we further apply some newest method (Liyang and Abraham, 2021; Borusyak, Jaravel and Spiess, 2023; Gardner, 2022) to test it, see Figure D.4B and Table D.6, and the results are consistent with our baseline results.

Table D.5: Check the Heterogeneous Treatment Effect

	2000-2005: Treated 2002		2008-2013: Treated 2011	
	(1) TFP	(2) TFP	(3) TFP	(4) TFP
UIP	0.102**	0.077*	0.214***	0.215***
	(0.048)	(0.046)	(0.056)	(0.046)
Observations	609528	468547	887679	841849
Year FE	X	X	X	X
City FE	X		X	
Firm FE		X		X
Control	X	X	X	X

Notes: The table presents a robustness test of the relationship between UIP and a firm's TFP. For all regressions, the dependent variable is a firm's TFP employing the ACF method. In columns (1)-(3), we use the cross-firm waves from 2000 to 2005 and retain the cities that implemented UIP in 2002 as the treatment groups. In columns (4)-(6), we use the cross-firm waves from 2008 to 2013 and retain the cities that implemented UIP in 2011 as the treatment groups. All time-varying variables are presented in log values. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level.



A. Bacon Decomposition

B. Sun & Abraham Estimator

Figure D.4: Bacon Decomposition and Alternative Estimator

Notes: The figure shows bacon decomposition in detail. We report different comparisons in 2*2 DD estimates.

Table D.6: Alternative Estimator For Heterogeneity Treatment Effect

	BJS Estimator		Gardner Estimator	
	(1) TFP	(2) TFP	(3) TFP	(4) TFP
UIP	0.084***	0.110***	0.079***	0.067***
	(0.020)	(0.019)	(0.025)	(0.018)
Controls	X	X	X	X
Firm FE		X		X
Year FE	X	X	X	X
City FE	X		X	
Observations	2,640,726	2,516,171	2,635,653	2,532,308

Notes: In this table, we adopted the recommended model by Gardner (2022) and Borusyak, Jaravel and Spiess (2023), to check if our baseline estimations are polluted by the heterogeneity treatment effect.

Table D.7: Bacon Decomposition

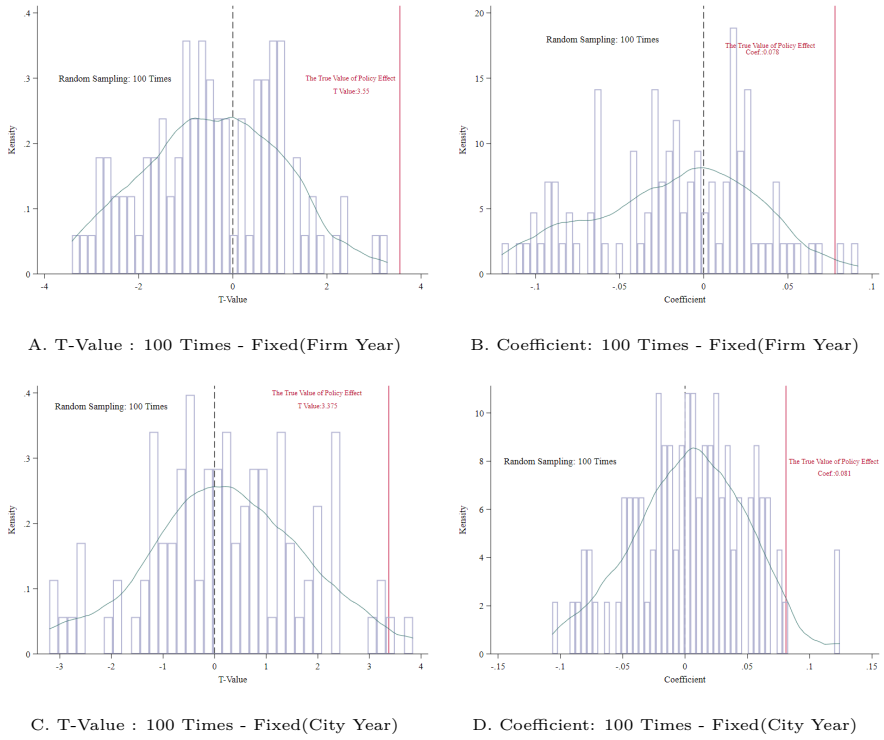
	TFP	
	Beta	Total weight
Timing group comparisons	0.009	0.040
Always group Vs Timing groups	0.185	0.000
Never group Vs Timing groups	0.078	0.917
Always group Vs Never group	-301.659	0.000
Within	-0.473	0.043

Notes: The table presents the Bacon decomposition for the heterogeneous treatment effect. We used the balanced panel from 2000 to 2008 to comply with the requirements of this method and displayed the beta and total weight resulting from the comparison of different groups.

D.6 Placebo Test: Random Sampling

To ascertain the accuracy of our definitions regarding the timing and target entities for the implementation of the UIP policy, we conducted a placebo test. The methodology employed is as follows: Initially, based on the structural features of UIP, which involve collaboration between a core city and one or two peripheral cities, we randomly sampled 15 core cities across China, excluding Beijing, Shanghai, Chongqing, and Shenzhen, as they do not have corresponding affiliated cities. Subsequently, we extracted one to two peripheral cities from the provinces where these sampled core cities are located. Finally, we randomly assigned the policy implementation timing for each group.

After conducting 100 simulations of this process, we obtained the results depicted in Figure D.9. The findings reveal that the mean distribution of the sampling results is proximate to zero, and instances where the estimated coefficients are larger than the actual situation are rare, in comparison to the formal scenario (indicated by the red line). This implies that our delineation of the UIP, with respect to the cities of implementation and the target entities, is consistent with the actual circumstances.



A. T-Value : 100 Times - Fixed(Firm Year)

B. Coefficient: 100 Times - Fixed(Firm Year)

C. T-Value : 100 Times - Fixed(City Year)

D. Coefficient: 100 Times - Fixed(City Year)

Figure D.9: Random Sampling 100 Times

Notes: These figures report the placebo test for our baseline design, for randomizing the adoption time and adoption entities 100 times.

D.7 Panel Construction

A potential threat to using ASIEC data is that its survey methods might have changed. To demonstrate that our panel construction approach does not affect our conclusions, we conducted two sensitivity analyses.

On one hand, as pointed out by Brandt, Van Biesebroeck and Zhang (2012), prior to 2007, the survey sampled all non-state-owned enterprises with sales over 5 million RMB and all state-owned enterprises. Thereafter, the survey criteria were slightly modified, for instance, to survey all enterprises with sales exceeding 20 million RMB. We demonstrate that if we consistently apply the most stringent standards, namely those enterprises with sales exceeding 20 million, or focus solely on non-state-owned enterprises, the results do not change significantly. As shown in columns 1-3 of Table D.8, when using only samples with sales exceeding 20 million nominal RMB, we find slightly smaller estimation results, but still close to 6%, due to the UIP significantly altering firm composition, such as incentivizing smaller scale but higher productivity firms to enter the market. Columns 4-6 indicate that focusing solely on non-state-owned enterprises, the UIP's promotion effect on productivity is greater, nearing 9%, consistent with the fact that inefficient state-owned enterprises exited the market during this phase.

On the other hand, we regressed using a balanced panel, as indicated in Table D.9, utilizing samples of firms that existed for at least 10 to at least 14 years. We found that the treatment effect is even larger, reaching at least a 9% promotional effect. This underscores that our findings are robust and further emphasizes our conclusion that the intensive margin effects of imitative innovation are a leading mechanism for TFP growth. The larger magnitude is because this construction method only

uses a subset of the full sample.

Table D.8: Investigate the Selection Bias in Industrial Surveys

	Use Only Sales Exceeding 20 million			Use Only Non-state-owned Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	TFP					
UIP	0.058**	0.074***	0.074***	0.088***	0.098***	0.098***
	(0.025)	(0.022)	(0.023)	(0.028)	(0.027)	(0.027)
Observations	1919147	1769451	1769451	1603996	1475494	1475494
Year FE	X	X	X	X	X	X
City FE	X		X	X		X
Firm FE		X	X		X	X
Control	X	X	X	X	X	X

Notes: The table presents OLS estimates of the relationship between UIP and a firm's TFP by adopting the model (8) adopting different sample. The dependent variable is the firm's TFP employed using the ACF method. All time-varying variables are presented in log values. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level.

Table D.9: Adopt Balance Panel

Life Span	=10	=11	=12	=13	=14
	(1)	(2)	(3)	(4)	(5)
Dependent Variable	TFP				
UIP	0.091***	0.104***	0.109***	0.104***	0.121***
	(0.022)	(0.021)	(0.021)	(0.020)	(0.021)
Observations	913191	590885	502882	403934	254519
Year FE	X	X	X	X	X
City FE					
Firm FE	X	X	X	X	X
Control	X	X	X	X	X

Notes: The table presents OLS estimates of the relationship between UIP and a firm's TFP by adopting the model (8). The dependent variable is the firm's TFP employed using the ACF method. From column 1 to column 5, we keep the sample that firms existed over 10 to over 14 years for regression. All time-varying variables are presented in log values. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level.

D.8 Concurrent Policy Related to a Firm's TFP

As a transitioning economy, the Chinese government has continuously implemented a series of policies aimed at enhancing the TFP of firms. Simultaneously, beyond UIP, numerous studies have emphasized the influence of other factors on enterprise TFP, including intellectual property protection, urban stratification and urbanization (Bo and Cheng, 2021), environmental regulations (He et al., 2020), and industrial policy (Chen et al., 2021). Therefore, our baseline estimates may be threatened by the inability to control for these policy impacts.

To isolate the contemporaneous policy effects related to these aspects on enterprise TFP, we will attempt to control for them. Specifically, we have considered a range of representative policies connected to Chinese enterprise TFP at both the urban and industry levels. These are:

1.National Intellectual Property Rights Model Cities, which influence enterprise TFP by enhancing the level of intellectual property protection.

2.National Central Cities, which may alter enterprise TFP due to political power heterogeneity.

3.Administrative region adjustments (known as the "county-district ADD"), an urbanization policy undertaken at the county level within cities, which might also relate to enterprise TFP promotion.

4.Low-Carbon Cities (LCC), an environmental regulation policy aimed at reducing corporate pollution emissions, which could potentially lead to a reduction in enterprise TFP.

5.Industrial policy (Five-Year Plan), designed to support selected industries, thus promoting their development, and consequently altering enterprise TFP.

Further details on all the aforementioned policies are elaborated in Table D.10 In Table D.11, we report estimates by including a series of the above strategies to ascertain the robustness of our baseline estimation, as previously mentioned. After controlling for these policies, the positive effect of UIP continues to increase, gaining statistical significance. Thus, the positive impact on enterprise TFP is not driven by other correlated policies, especially considering the representativeness of the selected policies above.

Table D.10: Policies, Timing, Treatment Groups, and Content Overview

Category	Timing	Details
		Panel A: City Level
National Intellectual Property Demonstration Cities (PRP)	2012	Cities: Wuhan, Guangzhou, Shenzhen, Chengdu, Hangzhou, Jinan, Qingdao, Harbin, Nanjing, Dalian, Xian
	2013	Cities: Changsha, Suzhou, Nantong, Zhenjiang, Zhengzhou, Luoyang, Dongying, Yantai, Fuzhou, Quanzhou, Wenzhou, Wuhu
	Purposes	1. Improve the intellectual property system; 2. Promote the creation and application of intellectual property rights; 3. Strengthen intellectual property management; 4. Foster Intellectual Property Culture
The National Center City (NCC)	2010	Cities: Beijing, Tianjin, Shanghai, Guangzhou, Chongqing
	Purposes	1. Infrastructure development; 2. Urban and rural functions optimization; 3. Strengthening international relationships; 4. Adjusting industrial structure
Adjustment of Administrative Division (ADD)	1992	Baoan county-Shenzhen-Guangdong, Hanyang county-Hubei
	1994	Muping county-Yantai-Shandong
	1995	Wuchang county-Wuhan-Hubei
	1996	Tongan county-Xiamen-Fujian
	1997	Jinshan county-Shanghai, Tong county-Beijing, Lintong county-Xian-Shaanxi
	1998	Songjiang county-Shanghai, Shunyi county-Beijing, Xinzhou county-Wuhan-Hubei, Huangpi county-Wuhan-Hubei
	1999	Changping county-Beijing, Qingpu county-Shanghai
	2009	Hulan county-Haerbin-Heilongjiang, Yancheng county-Luohe-Henan, Yongning county-Nanning-Guangxi, Jiangyuan county-Baishan-Jilin
	2011	Dazu county-Chongqing, Qijiang county-Chongqing, Tanghai county-Tangshan-Hebei, Mingshan county-Yaan-Sichuan, Qingxin county-Qingyuan-Guangdong, Jiedong county-Jieyang-Guangdong
	2013	Lingui county-Guilin-Guangxi, Ledu county-Haidong-Qinghai, Lishui county-Nanjing-Jiangsu, Gaochun-Nanjing-Jiangsu, Da county-Dazhou-Sichuan, Chaoan county-Chaozhou-Guangdong, Shangyu county-Shaoxing-Zhejiang, Mei county-Meizhou-Guangdong
	Purposes	1. Urbanization challenges; 2. Executive power enhancement; 3. Strengthening international relationships; 4. Industrialization strategies

Continued on next page

Table D.10 continued from previous page

Category	Timing	Details
Low Carbon City (LCC)	2010	Provinces: Guangdong, Liaoning, Hubei, Shaanxi, Yunnan Cities: Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, Baoding
	Purposes	1. Cultivating low-carbon economy; 2. Enhancing industrial structure; 3. Promoting energy-efficient buildings; 4. Improving transportation systems
		Panel B: Industry Level
Central Five-Year Plan	2001-2005	Supported Industry codes: C43, C61, C65, C67, C01, C11, C13, C31, C47, C76, C51, C71, C73, C75, C76, C78, E01, E05, C55, C57, C81, C85, G81, G83, G85, G87 Focused Industry codes: C51, C71, C73, C75, C76, C78, G81, G83, G85, G87, C55, C57, C59
	2006-2010	Supported and Focused Industry codes: C51, C55, C57, C59, C78, G81, G83, G85, G87, C75, F09, C43, C47, C61, C67, C85, C71, C73, C76, E01, E05, C14, C49, D01, C65, C31, C01, C03, C05, C81, B03, F05 Focused Industry codes: C51, C55, C57, C59, C78, G81, G83, G85, G87, C85, C71, C73, C75, C76, D01, C01, C03, C05, C81
	2011-2015	Supported and Focused Industry codes: C51, C55, C57, C59, C78, G81, G83, G85, G87, C85, C71, C73, C75, C76, D01, C01, C03, C05, C81 Focused Industry codes: C01, C43, C71, C73, C76, C51, C78, G81, G83, G85, G87, C85, C57, C75, D01, C47, D05, E01, A07, F07
Provincial Five-Year Plan	2006-2013	Building upon the five-year planning reports of individual provinces from 2006 to 2013, we employed text analysis methods involving keyword extraction and sentiment analysis. Similarly, this approach enabled us to delineate the identified industry codes of primary interest to each province, as well as those industry codes for which policies exhibited an encouraging stance.
	Purposes	1. Adjusting industrial structure; 2. Implementing subsidies; 3. Enhancing regulations; 4. Facilitating trade; 5. Promoting innovation

Notes: This comprehensive overview table presents controlled policies with specific implementation timelines, treatment groups, and policy objectives. Notably, these policies primarily cover the years 2000 to 2013, endorsed by China's central authorities.

Table D.11: Control the Concurrent Polices

	City level				Industry level		All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable				TFP			
UIP	0.082***	0.078***	0.076***	0.070***	0.081***	0.081***	0.064**
	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.025)
PRP	-0.022						-0.011
	(0.033)						(0.033)
NCC		0.123***					0.097**
		(0.039)					(0.041)
AAD			0.149***				0.140***
			(0.035)				(0.034)
LCC				0.117*			0.105
				(0.064)			(0.071)
IP-support					0.000		-0.028***
					(0.006)		(0.006)
IP						0.025***	0.041***
						(0.005)	(0.006)
Observations	2640726	2640726	2640726	2640726	2640726	2640726	2640726
Year FE	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X
Firm FE							
Control	X	X	X	X	X	X	X

Notes: The table presents a robustness test for controlling a series of policies related to a firm's TFP. The dependent variables all employed the ACF method. In columns 1-4, we control policies at the city level, PRP is the intellectual property rights protection policy, NCT is the national core cities policy, AAD is the policy related to the adjustment of administration division, LCC is low-carbon city policy. In columns 5-6, we control industrial policy, IP-support is a more comprehensive identification method. We set industry as being supported if the documentations mention the words related to support But for IP, we only define the industry as being supported when the documentation directly mentions preferentially developing them. In column 7, we add all the policies mentioned above. All policy variables are dummy variables, and time-varying variables are in log values. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors clustered at the city-year level.

D.9 The Robustness of IV-2SLS

As shown in Table D.12, we report the first-stage results for our instrumental variables. Consistent with expectations, cities with dialectal affiliations are more likely to be included in the UIP over time, peripheral cities with railway connections to core cities by 1933 are less likely to adopt the UIP, and core cities with postal stations during the Ming dynasty are more likely to promote UIP adoption. These predetermined historical characteristics determine the selection pattern for UIP, independent of concurrent economic factors, thus mitigating the selection bias threat of UIP.

An important test for the validity of the selected instruments is the exclusivity assumption, which posits that the instrumental variables can only affect firms' TFP through the adoption of UIP.

Our empirical analysis of the nature of the instrumental variables provides evidence for this. Specifically, on the one hand, dialect as a cultural feature is more likely to affect TFP development over the long term through channels other than UIP, given its association with the current system of local protectionism. On the other hand, the predetermined transportation infrastructure features are unrelated to current local protectionism and are only associated with current iceberg costs. This allows us to conduct hypothesis tests based on the notion that 2003 is the cutoff point for UIP adoption.

If dialect similarity could change a firm's TFP without promoting the implementation of UIP, then we would consider it to be systematically related to firms' TFP at least before 2003. Meanwhile, an exclusivity analysis of historical traffic conditions is nearly impossible because historical differences in iceberg costs have already led to uneven development of productivity across cities. However, we can infer the operational modes of the two instruments relative to the UIP system by leveraging two facts. Specifically, with the introduction of UIP, what we aim to capture is the role played by the exogenous changes in iceberg costs. Whether for periphery cities more likely not to be included in UIP due to railways or for core cities more likely to promote UIP adoption due to having postal stations, a reversal in productivity progress would occur. This is because, as we find, post-UIP adoption, the productivity of treated peripheral cities significantly increases due to the reduction in iceberg costs.

The results from Table D.13 are consistent with our expectations: dialect similarity had no impact on firms' TFP before 2003, while the positive impact primarily occurred after the introduction of UIP between 2003 and 2013. Thus, we confirm the exclusivity assumption of dialect similarity. Regarding railways, we indeed find that, before 2003, cities with railway connections to core cities had a slower rate of productivity progress, possibly due to historically uneven development strategies that concentrated large industrial enterprises in core cities of China. However, after the introduction of UIP in 2003, we observe that this negative impact disappears. Similarly, the results for postal stations are consistent; core cities with postal stations before 2003 had higher productivity, but this advantage diminished after 2003. This is consistent with the findings that, after 2003, the treated peripheral cities experienced a significant increase in productivity due to UIP.

Table D.12: IV-2SLS Estimation - First Stage

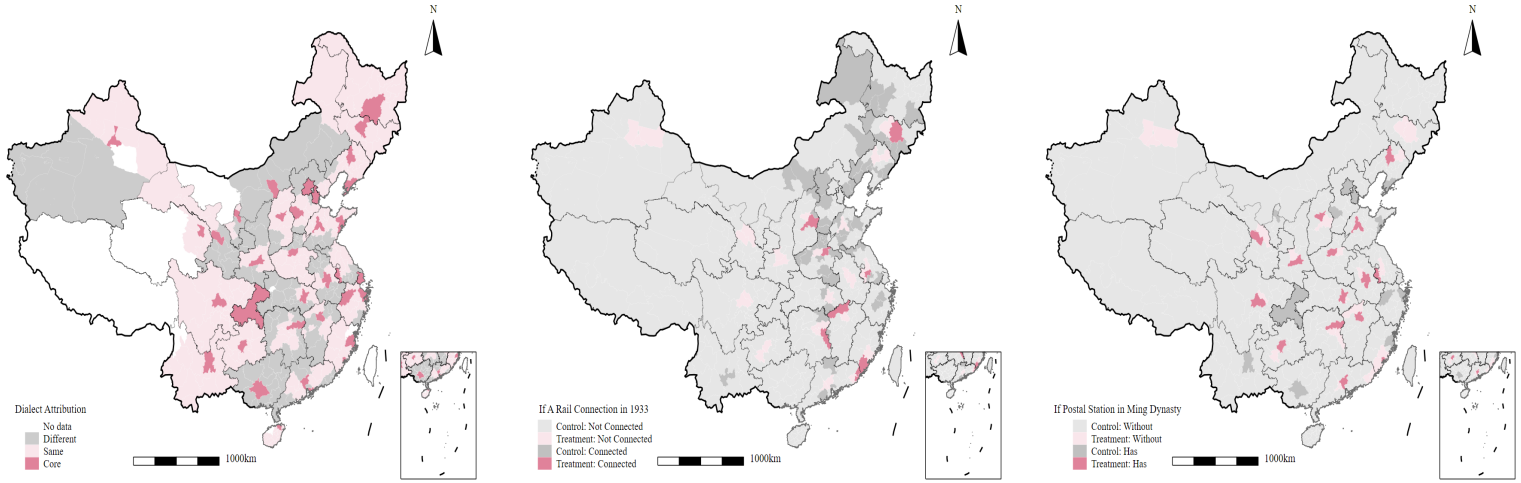
	First Stage: UIP								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instrumental Variable	Dialect			Railway in 1933			Postal Station in Ming		
Dialect	0.013***	0.011***	0.011***						
	(0.002)	(0.003)	(0.003)						
If Railway Between Periphery and Core City In 1933				-0.007***	-0.006**	-0.006**			
				(0.003)	(0.003)	(0.003)			
If Core City Has Post Station In Ming Dynasty							0.023***	0.020***	0.019***
							(0.004)	(0.004)	(0.004)
Observations	2631689	2476702	2476702	2640726	2485219	2485219	2640726	2485219	2485219
Year FE	X	X	X	X	X	X	X	X	X
City FE	X		X	X		X	X		X
Firm FE		X	X		X	X		X	X
Control	X	X	X	X	X	X	X	X	X
First-stage F-stat.	34.151	18.957	18.918	7.421	3.888	3.881	27.307	20.97	19.786

Notes: The table presents IV estimates of the relationship between IV and UIP adoption. We report the first-stage F-statistic under the table. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level.

Table D.13: The Exclusion Restriction

	2000-2003			2003-2013		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	TFP	TFP	TFP	TFP	TFP	TFP
Dialect	0.004	0.012	0.012	0.016***	0.016***	0.016***
	(0.009)	(0.009)	(0.010)	(0.005)	(0.005)	(0.005)
	2000-2003			2003-2013		
If Railway Between Periphery and Core City In 1933	-0.019***	-0.022***	-0.022***	-0.007	-0.002	-0.002
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
	2000-2003			2003-2013		
If Core City Has Post Station In Ming Dynasty	0.024**	0.010	0.010	0.018***	0.009	0.009
	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)
Observations	497953	459515	459515	2142773	2009929	2009929
Year FE	X	X	X	X	X	X
City FE	X		X	X		X
Firm FE		X	X		X	X
Firm Controls	X	X	X	X	X	X
City Controls	X	X	X	X	X	X

Notes: The table presents the OLS estimates of the relationship between IV and a firm's TFP. In columns 1-4, we use the panel from 2000 to 2003, while columns 5-8 is from 2003 to 2013. The other setting is the same as our baseline estimation. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors clustered at the city-year level.



A. Dialect B. Train Road in 1933 C. Postal Station in Ming Dynasty

Figure D.10: IV and UIP Landscape

Notes: The relationship between the implementation of UIP, dialect affiliation, the existence of railway connections in 1933, and the postal station in Ming Dynasty is illustrated in the following figures: Figure (a) is a map of dialect affiliations, where gray represents different dialects, light pink indicates the same dialect, and dark pink denotes core cities. Figure (b) displays the distribution of UIP implementation in relation to railway construction. Here, light gray denotes the control group without railway access, whereas dark gray indicates areas with railway access. Light pink represents the treatment group without railway access, and dark pink signifies areas with railway access. Figure (c) displays the distribution of UIP implementation in relation to postal station. Here, light gray denotes the control group without station, whereas dark gray indicates areas with station. Light pink represents the treatment group without station, and dark pink signifies areas with postal station in Ming Dynasty.

E Appendix E: Others Results For Explanations

E.1 The Heterogeneity of Firm Location

Table E.1: UIP on Firm Location: Heterogeneity on Core-Periphery Cites

	Panel B: Business Registrations			Panel A: Universe of Industrial Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Entry	Exit	Transfer	Entry	Exit	Transfer
UIP	0.374***	0.659*	-0.000	-0.005*	0.001	-0.001
	(0.136)	(0.349)	(0.004)	(0.003)	(0.002)	(0.001)
UIP×Core Cities	-0.363*	-4.303***	-0.007	-0.004	0.002	0.006**
	(0.201)	(0.629)	(0.010)	(0.004)	(0.003)	(0.003)
Observations	3292934	3292934	3292934	2640726	2102425	2229844
Year FE	X	X	X	X	X	X
City FE	X	X	X	X		X
Firm FE					X	
Control	X	X	X	X	X	X

Notes: This table presents the OLS estimation of the relationship between UIP and firm dynamics using the model specified in (8). Columns 1-3 utilize administrative survey data, reflecting the probability of firm entry, exit, and transition for each district and county, while columns 4-6 pertain to the activities of large-scale enterprises. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level. In Appendix B, we introduce the measurement strategies for all variables.

E.2 The Heterogeneity of Cities

Table E.2: The Heterogeneity of infrastructure

	Panel A: Universe of Industrial Firm			
	(1)	(2)	(3)	(4)
Dependent Variable	TFP		Output	
UIP	0.315**	0.374***	0.438***	0.489***
	(0.129)	(0.144)	(0.119)	(0.131)
UIP×Traffic	-0.096*	-0.125**	-0.107**	-0.139***
	(0.052)	(0.059)	(0.049)	(0.053)
Observations	2239921	2393800	2841274	3033510
Year FE	X	X	X	X
City FE				
Firm FE	X	X	X	X
Control	X	X	X	X

Notes: The table presents the heterogeneous effect of infrastructure. In columns 1 - 4, we add the city's transportation infrastructure and a series of interaction terms related to infrastructure. In columns 1 -2, the dependent variables are a firm's TFP employing the ACF method; In columns 3 - 4, the dependent variables are a firms's output. All time-varying variables are in log values, and we also further control any related interaction terms. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors clustered at the city-year level.

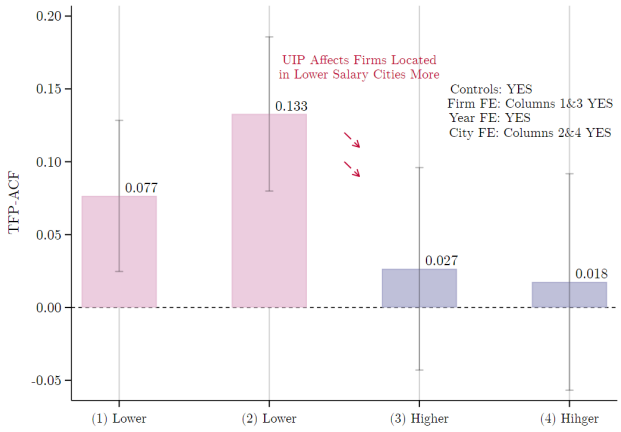


Figure E.1: TFP: Grouped by City's Salary Level

Notes: The figure shows the regression coefficient of the DID terms when we grouped the sample by high and low salary cities. We treated higher salary cities as average salary higher than the average level of the nation in a given year.

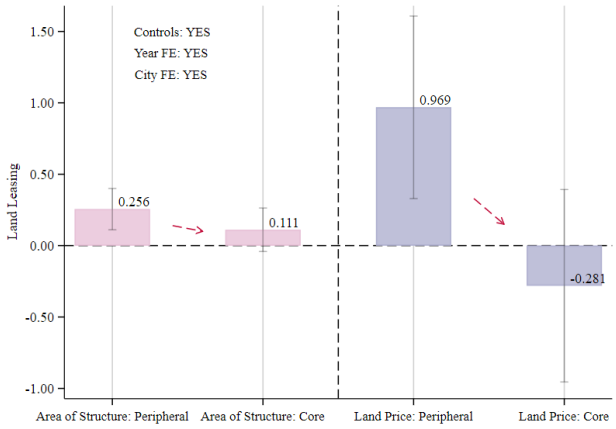
E.3 The Heterogeneity of Innovation

Table E.3: Heterogeneity on Patent Activity

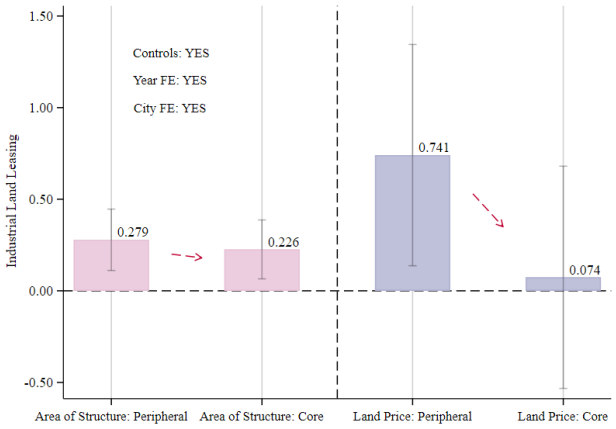
	Core	Periphery	Full Panel			
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Patent		Design	Innovation	Utility	Total
UIP	-0.473**	-0.345***	-0.123***	-0.188***	-0.024	-0.335***
	(0.207)	(0.100)	(0.040)	(0.066)	(0.046)	(0.118)
Observations	793527	1691572	2485219	2485219	2485219	2485219
Year FE	X	X	X	X	X	X
City FE						
Firm FE	X	X	X	X	X	X
Control	X	X	X	X	X	X

Notes: The table presents the heterogeneous effect of UIP on innovation. In columns 1-2, we regressed the outcomes as firm patent application, grouped the sample by core and periphery cities. In columns 3-6, we split the type of patent into different dimensions, such as design, innovation utility and total. All time-varying variables are in log values. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors clustered at the city-year level.

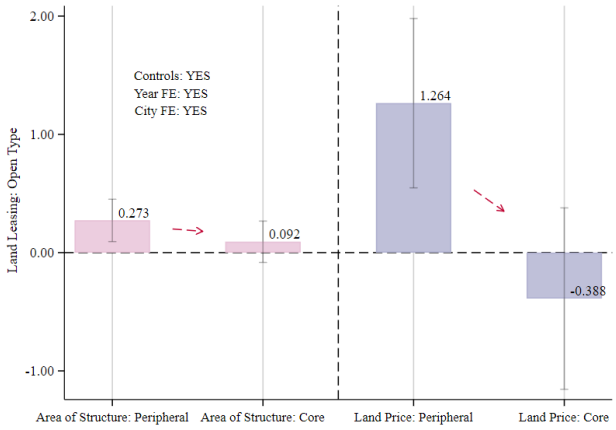
E.4 Land Leasing of Government



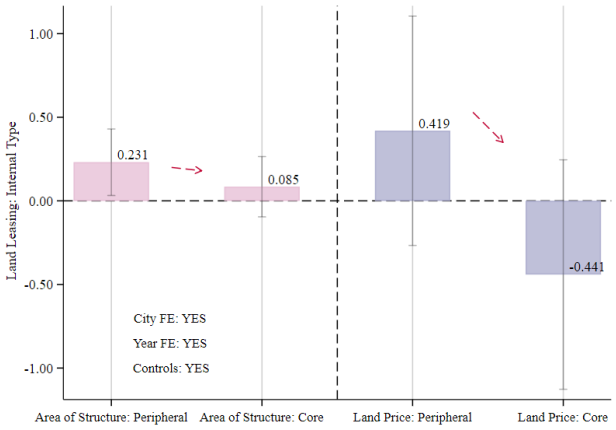
A. Land Leasing: New Land



B. Industrial Land Leasing: New Land



C. Land Leasing: New Land & Open Type



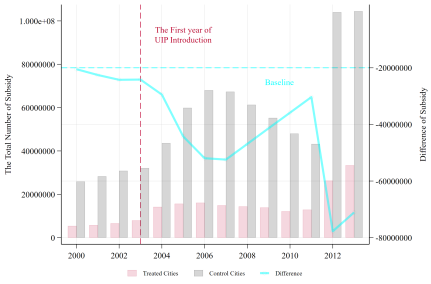
D. Land Leasing: New Land & Internal Type

Figure E.2: Local Protectionism: Land Leasing

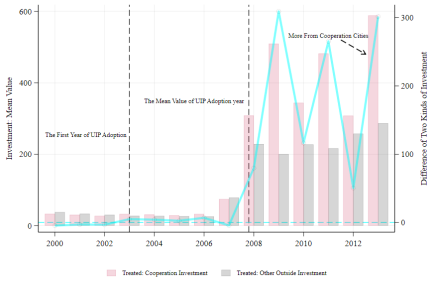
Notes: The table demonstrates the implications of UIP on land leasing. The regression analysis is conducted at the aggregated city-year panel level. The variables of interest that we seek to explain comprise the average are of structure and land price within a specific urban locale. We segment the sample into core and peripheral cities. Standard errors are clustered at the city-year level. Each column within the graph reflects the estimated value of the average treatment effect of the UIP, along with the 95% confidence interval. Controlled variables and fixed effects are detailed in the figure's notes. In Appendix B and Appendix D, we introduce the panel construction of the dataset and dynamic effect for all variables.

F Appendix F: Stylized Facts

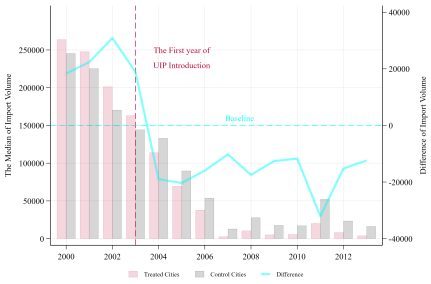
F.1 Main Variations in Mechanism Analysis



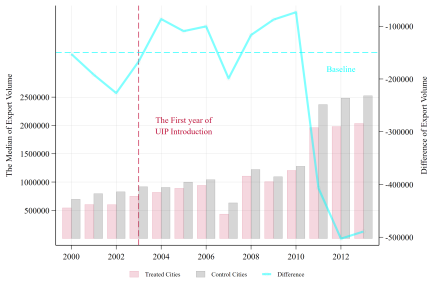
A. Subsidy



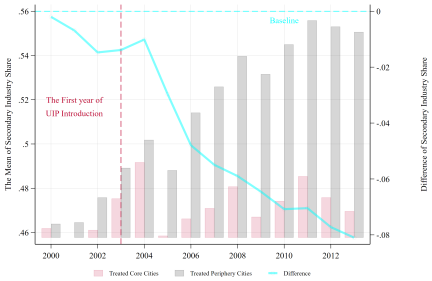
B. Outside Investment



C. Import Volume



D. Export Volume

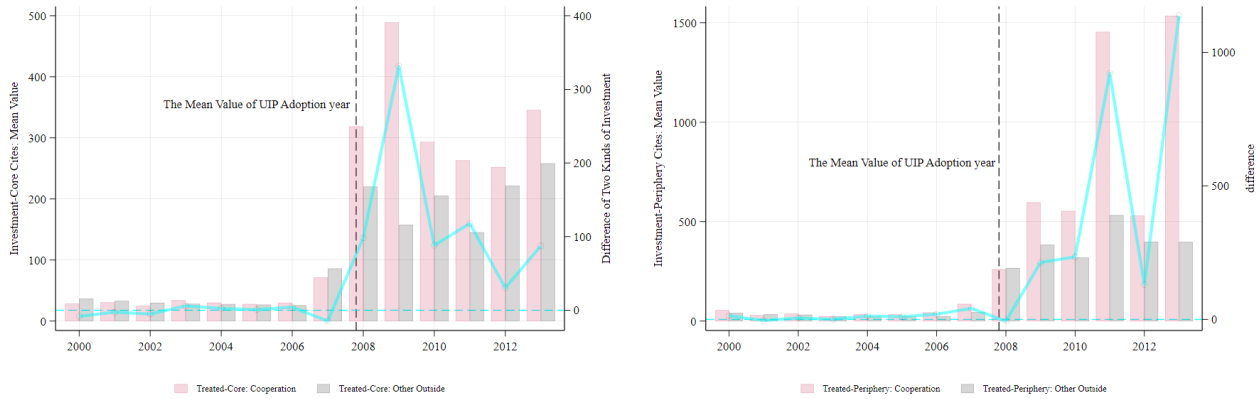


E. The Share of Secondary Industry

Figure F.1: Stylized Facts Under UIP: Explanations

Notes: The aim of these figures is to elucidate several patterns potentially associated with fluctuations in TFP. We further provide the trends in key indicators for both treatment and control cities. Panels A, C, and D offer insights into the changes in the total amount of city subsidies and the median value of total imports and exports by firms in both treatment and control cities. Panels B and E delineate the variations in average external investments within core and peripheral cities in the treatment group (where core cities refer to provincial capitals or sub-provincial cities within the UIP cluster), differentiated between investments from cooperating and non-cooperating cities, as well as changes in the proportion of secondary industries.

F.2 The Investment Flow Between Core-Periphery Cities



A. Treatment: Core Cites

B. Treatment: Periphery Cites

Figure F.2: The Variations of Investment Structure Between Core-Periphery Cites

Notes: The figure shows the stylized facts of investment changes between core and periphery cities. The black bar represents the mean value of investment coming form investor located other than their corresponding cooperation cities each year, while the red bad represents the investment coming from corresponding cooperation cites.

F.3 A Stylized Case Related to the Firm Dynamic Pattern and UIP Adoption

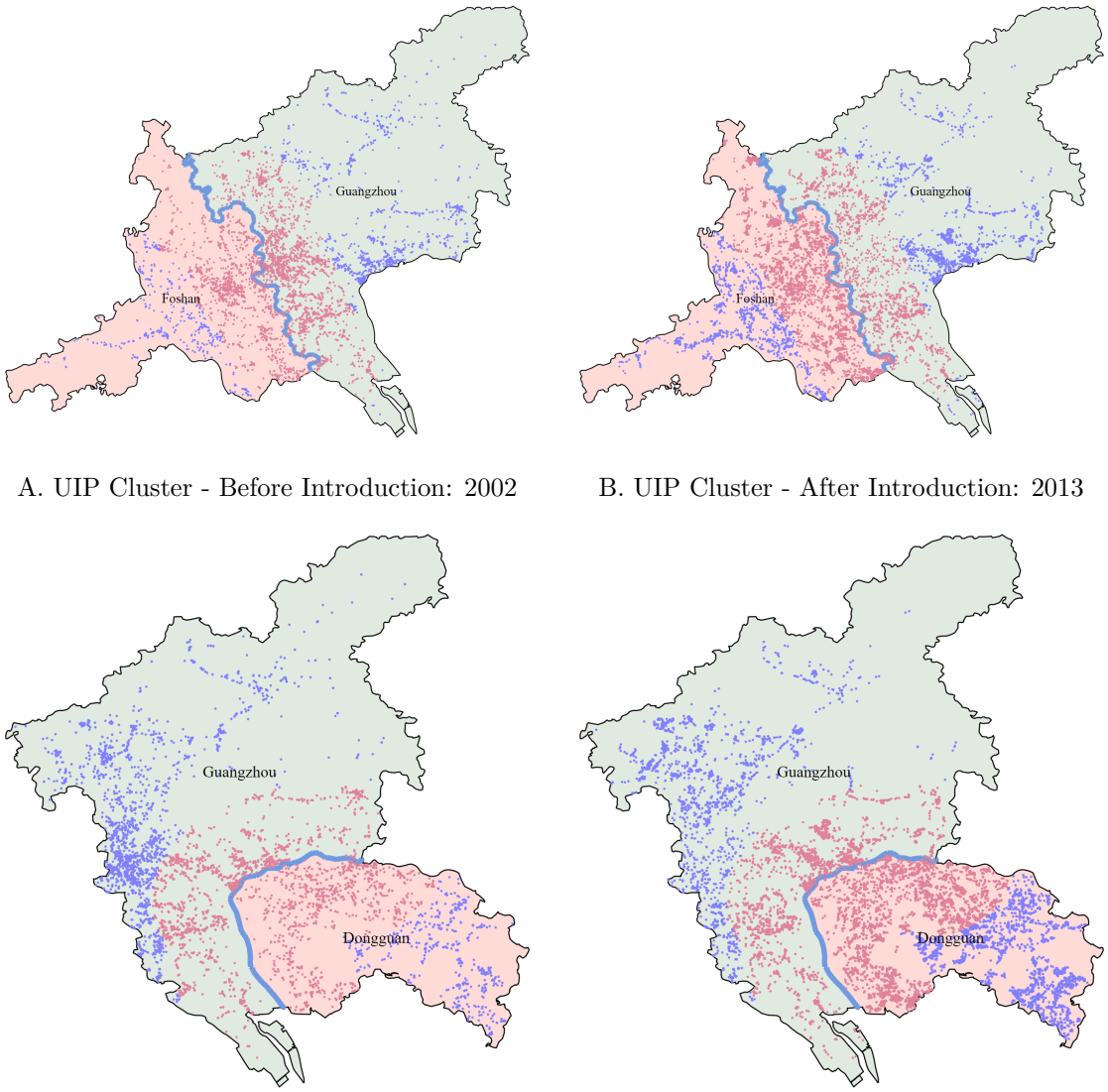
We provide a representative case of a UIP cluster to illustrate two key points:

1. Why we assert that UIP indeed promotes regional trade and firm dynamics.
2. Why we claim that the adoption of UIP was not due to economic factors, but rather culturally determined by historical factors.

The following figure F.3 shows the firm dynamics within the UIP cluster formed by Guangzhou and Foshan, as well as the non-UIP cluster of Guangzhou and Dongguan. This figure conveys two main implications:

First, although we do observe relatively more firms near the city borders of Guangzhou, Dongguan, and Foshan before the implementation of UIP, Guangzhou chose to form a UIP cluster with Foshan because they share the same dialect, unlike Guangzhou and Dongguan. Therefore, this figure vividly demonstrates the rationale behind using dialect similarity as an instrumental variable.

Secondly, we observe that following the formation of UIP clusters between Guangzhou and Foshan, numerous firms emerged within a 20-kilometer radius of the city boundary (indicated by red dots). However, when examining Guangzhou and Dongguan, despite the continuous rise in firm numbers, there is no evident difference in the growth trends of firms within and beyond the 20-kilometer range. This reflects a scenario where regional trade, facilitated by proximity, drives firm agglomeration near areas where local protectionism has been effectively mitigated. Consequently, we capture robust firm dynamics and strong regional trade flows induced by UIP.



A. UIP Cluster - Before Introduction: 2002 B. UIP Cluster - After Introduction: 2013

C. Non UIP Cluster - Before Introduction: 2002 D. Non UIP Cluster - After Introduction: 2013

Figure F.3: A Stlized Case Related to the Firm Dynamic Pattern and UIP Adoption

Notes: This table presents stylized facts about firm dynamics. For Panels A and B, we show firm dynamics within a UIP cluster before and after the implementation of UIP. For Panels C and D, we display firm dynamics within a non-UIP cluster, also before and after the UIP implementation. Essentially, this figure indicates that due to regional trade flows caused by the presence of UIP, more emerging firms arise near the city borders adjacent to UIP cities.

G Appendix G: Economic Significant of UIP on TFP

Scale up under general equilibrium effects

Under our city-industry-year panel structure, changes in aggregating TFP can be estimated using equation 15.

$$\Delta \log(a) \approx \underbrace{-\frac{\alpha^*}{2}\sum_{s=1,c=1}^{S,C} Cap\%_{s,c}\left(1+\frac{\alpha_s\theta_s}{1-\theta_s}\right)\widehat{\Delta\Delta\sigma^2}(s,c)}_{\text{The Change of within-industry reallocation caused by UIP}}$$
$$\underbrace{-\sum_{s=1,c=1}^{S,C}(Sale\%_{s,c}\alpha_s - Cap\%_{s,c}\alpha^*)\left[\widehat{\Delta\Delta\mu}(s,c)+\Delta\Delta\widehat{\varsigma_{logMRPK,logValueAdd}}(s,c)+\frac{1}{2}\frac{\alpha_s\theta_s}{1-\theta_s}\widehat{\Delta\Delta\sigma^2}(s,c)\right]}_{\text{The Change of cross-industry reallocation caused by UIP}} \tag{15}$$

Broadly speaking, the first term of the equation captures the growth of overall TFP due to within-industry capital reallocation under UIP, while the second term reflects the growth from cross-industry effect. As evidenced by the preceding reduced-form evidence, UIP leads to the evolution of the industry structure in the direction of comparative advantage. Therefore, it can be anticipated that the changes in overall TFP are primarily driven by cross-industry factor reallocation.

To assess the contribution of UIP to the aggregate TFP growth, our first step is to use a reduced-form equation to estimate the impact of UIP on the moments of Log-MRPK. This includes the mean, $\widehat{\Delta\Delta\mu}(s,c)$, variance, $\widehat{\Delta\Delta\sigma^2}(s,c)$, and the covariance between Log-MRPK and Log-ValueAdd, $\widehat{\Delta\Delta\varsigma}(s,c)$. We aggregate at the level of four-digit industry codes, year, and city. We then regress the aforementioned moments on the staggered implementation of UIP.

Table G.1 presents the regression results. We observe that the UIP substantially elevates the average Log-MRPK by 7.7%. However, it has an almost negligible effect on the variance of Log-MRPK and the covariance between Log-MRPK and Log-ValueAdd. This observation resonates with our prior empirical findings: the wedge introduced by government subsidies directly bolsters the mean of Log-MRPK[27]. Yet, for the latter two moments, the primary effect of UIP has been the reallocation of capital between RCA and NRCA industries. Concurrently, the relationship between the marginal output of capital and firm value-added remains unaffected by the expansion of regional trade.

Now, based on the estimated DID parameters from columns 1-3 of Table G.1, namely $\widehat{\Delta\Delta\mu}(s,c) = 0.077$, $\widehat{\Delta\Delta\sigma^2}(s,c) = 0.004$, and $\widehat{\Delta\Delta\varsigma}(s,c) = -0.004$, we can formally scale up the TFP growth. Given the presence of several other undetermined parameters in our model, we calibrate by referring to Sraer and Thesmar (2023) and David, Hopenhayn and Venkateswaran (2016), setting the capital share in production, α, to 0.33 and the price elasticity of demand, θ, to 0.85. We then compute the pre-policy total sales share, $Sale\%_{s,c}$, and capital stock share, $Cap\%_{s,c}$, for each city-industry based on the year 2003.

[27] Government subsidies can often be translated into a portion of the capital stock

Table G.1: Estimates of the Impact of UIP on MRPK

	Aggregate Panel A to a Industry-Year-City Panel		
	(1) Mean:Log-MRPK	(2) Var:Log-MRPK	(3) Cov:Log-MRPK Vs Log-ValueAdd
UIP	0.077**	0.004	-0.004
	(0.039)	(0.006)	(0.022)
Observations	45428	45428	45428
Year FE	X	X	X
City FE	X	X	X
Industry FE	X	X	X
Industry-Trend	X	X	X
Control	X	X	X

Notes: The table presents OLS estimates of the relationship between UIC and the moments of Log-MRPK. The dependent variable is the average, variance and the covariance between Log-MRPK and Log-ValueAdd. All time-varying variables are presented in log values. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year level. In Appendix G, we introduce the measurement strategies for all variables.

Scale up based on in-sample inference

Based on our comprehensive examination of Chinese firms within our dataset, we conduct a back-of-the-envelope analysis to assess the impact of the UIP on aggregate TFP growth, leveraging simplified form evidence derived from our findings. As illustrated in Figure G.1, the average growth rate of TFP during the period from 2000 to 2003 was 1.87%. Hence, we assume that the control group maintains this TFP growth trend from 2003 to 2013. Meanwhile, according to the simplified evidence, the productivity growth of the treated group is 7.8% higher than that of the control group, thus growing at a rate of 9.67% between 2003 and 2013. Under this growth scenario, we weight the contributions of the treated and control group firms based on their proportions in the total, with the treated group accounting for 10.91%. It is found that, relative to a scenario where both the treated and control groups maintain a 1.87% growth rate, the aggregate TFP growth under the UIP scenario in 2013 is at least 11.91% higher. A detailed demonstration of this estimation can be found in Figure G.2 and Table G.2.

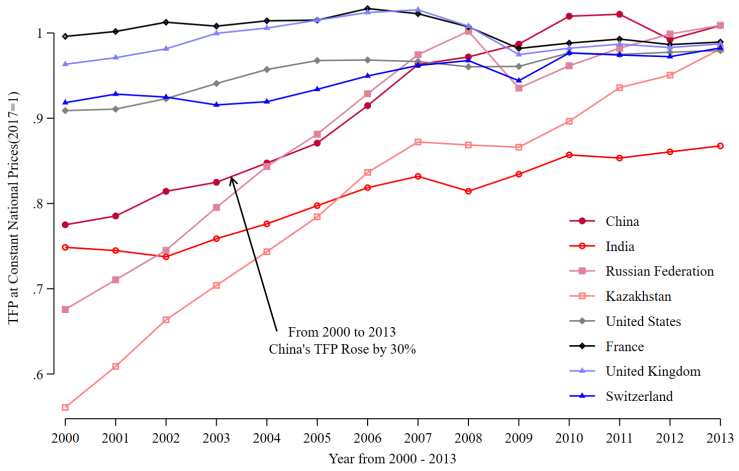


Figure G.1: TFP Variations Across Country

Notes: The variations of TFP at constant national prices (2017=1) across some main countries in the world. Sources: Penn World Table (Feenstra, Inklaar and Timmer (2015)).

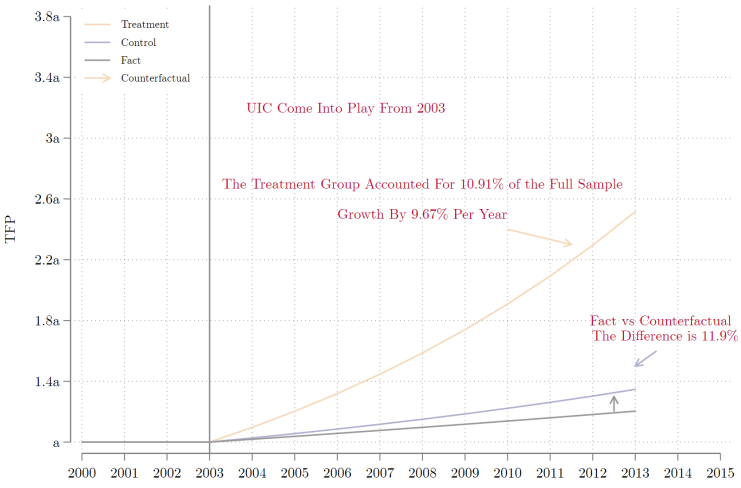


Figure G.2: The Simulation of TFP Variations

Notes: The figure presents a rough estimate of the impact of UIP on firm TFP, based on descriptive results from our universe of firms and the estimated regression parameters in the paper.

Table G.2: Economic significant of UIP on TFP

	Counterfactual		Fact				C vs F
Time	Growth Rate	Full	Growth Rate	Treatment	Control	Full	Different
2003	-	a	-	a	a	a	0
2004	Both: 1.87%	1.0187a	T: 9.67% C: 1.87%	1.0967a	1.0187a	1.0272a	0.0085a
2005	Both: 1.87%	1.0377a	T: 9.67% C: 1.87%	1.2028a	1.0377a	1.0557a	0.0180a
2006	Both: 1.87%	1.0572a	T: 9.67% C: 1.87%	1.3191a	1.0572a	1.0857a	0.0286a
2007	Both: 1.87%	1.0769a	T: 9.67% C: 1.87%	1.4466a	1.0769a	1.1172a	0.0403a
2008	Both: 1.87%	1.0971a	T: 9.67% C: 1.87%	1.5865a	1.0971a	1.1504a	0.0534a
2009	Both: 1.87%	1.1176a	T: 9.67% C: 1.87%	1.7399a	1.1176a	1.1855a	0.0679a
2010	Both: 1.87%	1.1385a	T: 9.67% C: 1.87%	1.9082a	1.1385a	1.2224a	0.0839a
2011	Both: 1.87%	1.1598a	T: 9.67% C: 1.87%	2.0927a	1.1598a	1.2615a	0.1017a
2012	Both: 1.87%	1.1815a	T: 9.67% C: 1.87%	2.2950a	1.1815a	1.3029a	0.1215a
2013	Both: 1.87%	1.2035a	T: 9.67% C: 1.87%	2.5170a	1.2035a	1.3468a	0.1432a
Composition: Treatment Group 10.91%; Control Group 89.09%					Total Growth: 11.90%		

Notes: This table shows the parameter settings and data corresponding to figure G.2. All parameter choices are based on the samples and regression results we used. From 2003 to 2013, the TFP growth of China at constant national prices (2017=1) rose by 22.29%.

H Appendix H: Full Model Overview

In this section, we first address key outcomes omitted from the main text, including profit conditions under optimal economic production and the aggregation of macroeconomic indicators. Subsequently, based on these foundations, we provide proof supporting the assertions made in the main text.

Demand

Consider n types of products, M firms in equilibrium, M_x firms participate in regional trade, and M_t types of products. The product output $q(n)$ is aggregated by a C.E.S utility function, where they can be substituted for one another with $\rho \in (0,1)$, and the elasticity of substitution is $\sigma > 1$.

$$U = [\int_{n\in\Omega} q(n)^{\rho} dn]^{1/\rho}, \quad Y \equiv U, \quad \sigma/(\sigma-1) = 1/\rho \tag{16}$$

Production

In an open economy, similar to Melitz (2003), the equilibrium expressions for the price p, revenue r, and profit π for a representative firm d only engages local market and a representative firm e also engages regional trade can be defined by an equation with heterogeneous productivity a. The key difference between the profit functions of these two kind of firms is that the former face a fixed production cost f, while the latter face a fixed regional trade cost f_x, which includes additional fixed costs for trading investments.

$$p(a) = \begin{cases} p_d(a) = \frac{1}{\rho a} & \text{if Local Market} \\ p_x(a) = \frac{\iota}{\rho a} = \iota p_d(a) & \text{if Regional Trade} \end{cases} \tag{17}$$

$$r(a) = \begin{cases} r_d(a) = R(P\rho a)^{\sigma-1} & \text{if Local Market} \\ r_d(a) + n r_x(a) = (1 + n\iota^{1-\sigma}) r_d(a) & \text{if Regional Trade} \end{cases} \tag{18}$$

$$\pi(a) = \begin{cases} \pi_d(a) = \frac{r_d(a)}{\sigma} - f & \text{if Local Market} \\ \pi_x(a) = \frac{r_x(a)}{\sigma} - f_x & \text{if Reginal Trade} \end{cases} \tag{19}$$

Innovation and Productivity

Building upon the framework established by König et al. (2022), we introduce heterogeneity in firm innovation behavior to characterize the intensive margin growth of productivity within firms. Within a two-period innovation decision framework, a firm can internally experience TFP advancement in the form of $\tilde{g}$, originating from the firm's imitative innovation and independent innovation. These are characterized by $m(\iota)$ and I, respectively, as realization probabilities, where $m'(\iota) = 0 \; if \; a < a^x, m'(\iota) < 0 \; if \; a >= a^x$, where a^x is the regional trade cut-off point will be introduced formally later [28], and I is randomly drawn from an i.i.d.- c.d.f $B : (0, \bar{I}]$, and $\bar{I} \leq 1$. To simplify the analysis, the firm's individual productivity is defined in a step-like discrete ranking form represented by a_r, where both successful imitative innovation and independent innovation can increase a_r by one level, as shown below:

$$\log(a_{i,t+1}) = \log(a_{i,t}) + \tilde{g}, \tilde{g} > 0 \quad \& \quad a_r \equiv \log(a)/\tilde{g}. \tag{20}$$

[28] The economic intuition is straightforward: higher iceberg costs impede regional trade for firms, making it less likely for low-productivity firms to encounter firms with higher productivity levels (as typically only higher-productivity firms can afford to engage in trade).

Thus, if $\mathcal{T}$ is defined as the productivity level for each a_r, the productivity c.d.f. up to a_r can be written as:

$$F_{a_r} = \sum_{j=1}^{a_r} \mathcal{T}_j \tag{21}$$

For firms initially opting for independent innovation, there exists the opportunity to pivot toward imitative innovation in the event of failure, with the probability of realization, $c(\tau)m(\iota)(1 - F_{a_r})$. However, this entails an opportunity cost, $c(\tau)$. If $c(\tau) > 1$, it indicates that engaging in independent innovation is advantageous for better realizing imitative innovation, and vice versa if $c(\tau) < 1$. We have $c'(\tau) > 0$ and $c(\tau) < 1$, implying that subsidies serve to enhance the incentives for firms to undertake independent innovation[29]. Firms will only engage in independent innovation activities if the return of independent innovation exceeds that of imitative innovation. Therefore, the probability of successful innovation realization must satisfy the following condition:

$$I_i > T(a, \tau, \iota; \mathcal{T}) \equiv \frac{m(\iota)(1 - c(\tau))(1 - F_{a_r})}{1 - c(\tau)m(\iota)(1 - F_{a_r})} \tag{22}$$

We set a threshold T such that independent innovation occurs only when the expected probability of innovation exceeds T. This threshold is defined by a firm's own productivity level a, iceberg costs ι, and subsidies τ. Clearly, $\frac{\partial T}{\partial a} < 0$, as defined by König et al. (2022), indicating that higher-productivity firms are more likely to rely on independent innovation. Concurrently, the higher the productivity level, the harder it is to encounter firms with higher productivity levels for realizing imitative innovation, and the lower the subsidy, the more it harms the firm's long-term profits and suppresses independent innovation activities. We then use χ_{im} and χ_{in} to define a firm's innovation decisions, i.e., undertaking imitative innovation and independent innovation, respectively.

$$\chi_{\text{im}}(a, I, \tau, \iota; \mathcal{T}) = 1 - \chi_{\text{in}}(a, I, \tau, \iota; \mathcal{T}) = \begin{cases} 1 & \text{if } I \leq T(a, \tau, \iota; \mathcal{T}) \\ 0 & \text{if } I > T(a, \tau, \iota; \mathcal{T}) \end{cases} \tag{23}$$

Equilibrium Condition: Regional Trade

$$q(n) = Q\left(\frac{p(n)}{P}\right)^{-\sigma} \tag{24}$$

$$r(n) = R\left(\frac{p(n)}{P}\right)^{1-\sigma} \tag{25}$$

Based on the aforementioned conditions, we can present the Free Entry condition (FE) and the Zero Profit Condition (ZCP). The former monotonically increases with productivity, while the latter monotonically decreases, thereby uniquely determining the equilibrium state under trade conditions:

$$\bar{\pi} = \pi_d(\tilde{\varphi}) + x_r n \quad (FE) \tag{26}$$

[29]This hypothesis concerns the economic intuition that independent innovation entails risk of failure. Firms that choose independent innovation in the first phase and fail may face intense competition in the second phase from those that enhanced their productivity through imitation. Consequently, the likelihood of these innovating firms exiting the market significantly increases, leading to a backward induction result: firms avoid independent innovation if the probability of success is low. However, government subsidies for independently innovating firms might boost their innovation incentives. It is crucial to note that subsidies can introduce moral hazards. Firms seeking subsidies might mislabel their R&D spending to fraudulently claim government support (Chen et al., 2021). This point is vital as it relates closely to our later empirical analysis. When interpreting innovative behavior, the observed variables represent a mix of actual innovation activities and mislabeled innovations, which we will differentiate in subsequent analyses.

$$\tilde{\pi} = fk(a^e) + x_r n f_x k(a^x), \quad Where \quad k(a) = \left[\left(\frac{\tilde{a}(a)}{a}\right)^{\sigma-1} - 1\right] \quad (ZCP) \tag{27}$$

Equilibrium Under UIP: Extensive Margin

Firm Entry, Exit and Regional Trade

We now can define the current value function of the firm, $V(a)$, determined by current productivity a and without intertemporal preference. It is expressed by the firm's cumulative profits($\pi(a)$) from survival (with survival probability $(1-\kappa)$) until time t, and it cannot be negative (exiting the market):

$$V(a) = \max\left\{0, \sum_{t=0}^{\infty}(1-\kappa)^t \pi(a)\right\} = \max\left\{0, \frac{1}{\kappa}\pi(a)\right\} \tag{28}$$

From this, we can write the cutoff productivity levels for firms to enter the market and participate in trade as a^e and a^x, respectively. These two satisfy a given relationship that is weighted by product substitution elasticity with iceberg cost ι and regional fixed trade cost f_x [30] over entry cost f:

$$a^e, a^x = \begin{cases} a^e = \inf\{a : V(a) > 0\} & \text{if Successful Entry} \\ a^x = \inf\{a : a > a^e, \quad \pi_x(a) > 0\} & \text{if Regional Trade} \end{cases} \tag{29}$$

$$a^x = a^e \iota \left(\frac{f_x}{f}\right)^{\frac{1}{\sigma-1}} \tag{30}$$

Based on the entry cutoff point for firms, the equilibrium distribution function of productivity can be expressed in terms of the conditional distribution for successful entry. This implies that firms with productivity levels below the entry cutoff point will immediately exit the market due to a negative firm value, whereas the productivity of firms exceeding this entry threshold is a function of a^e:

$$F(a) = \begin{cases} \frac{z(a)}{1-\mathcal{Z}(a^e)} & \text{if } a \geq a^e \\ 0 & \text{otherwise} \end{cases} \tag{31}$$

Where $z(a)$ represents a common distribution from which entrants draw their initial productivity parameter a, while $\mathcal{Z}(.)$ denotes its cumulative distribution over the interval $(0, \infty)$. And we have $e_r = 1 - \mathcal{Z}(a^e)$ and $x_r = \frac{1-\mathcal{Z}(a^x)}{1-\mathcal{Z}(a^e)}$, documenting the ex-ante possibility of successful entry and one of these successful firms will conduct regional trade, respectively.

Aggregation

Average revenue, average profits, the market price index, and total revenue of the firms can also be solved in the following forms:

$$\bar{r} = r_d(\tilde{a}) + x_r n r_x(\tilde{a}(a^x)) \quad \text{and} \quad \bar{\pi} = \pi_d(\tilde{\varphi}) + x_r n \pi_x(\tilde{a}(a^x)) \tag{32}$$

$$P = \left[\int_0^{\infty} p(a)^{(1-\sigma)} MF(a)\, d(a)\right]^{1/(1+\sigma)} \tag{33}$$

$$\tilde{a} = \left[\int_0^{\infty} a^{\sigma-1} F(a) da\right]^{\frac{1}{\sigma-1}} \tag{34}$$

[30] For analysis simplify, we assume f_x is exogenous given without change in our environment.

$$\begin{aligned} P &= M^{\frac{1}{1-\sigma}} p(\tilde{a}), \quad R = PQ = Mr(\tilde{a}), \\ Q &= M^{1/\rho} q(\tilde{a}), \quad \Pi = M\pi(\tilde{a}), \end{aligned} \tag{35}$$

These expressions, with the expected changes occurring due to exogenous variable intervention, will serve as hypotheses to be empirically tested in subsequent sections.

$$\frac{\alpha[q_x(a > a^x)]}{\alpha o} > 0, \frac{\alpha[r_x(a > a^x)]}{\alpha o} > 0, and \ \frac{\alpha[\pi_x(a > a^x)]}{\alpha o} > 0 \tag{36}$$

Next, we present the market aggregation function defined over the equilibrium distribution of productivity $F(a)$, which endogenously determines the final form of firm TFP dynamics. The average productivity of the economy, $\tilde{a}_t$, is given by the following expression, defined as a form of CES aggregation of the productivity of incumbent non-trading firms and trading firms:

$$\tilde{a}_t = \left(\frac{1}{M_t} \left[M\tilde{a}(a^e)^{\sigma-1} + nM_x \left(\tau^{-1}\tilde{a}(a^x) \right)^{\sigma-1} \right] \right)^{\frac{1}{\sigma-1}}, \quad M_t = M + nM_x = M + nx_r M \tag{37}$$

Equilibrium Under UIP: Intensive Margin

Subsequently, we delve into the internal innovation trade-offs within firms that lead to the equilibrium dynamics of TFP at the intensive margin. Analogous to the model proposed by König et al. (2022), we posit the existence of an innovation threshold a^i, such that firms with $a > a^i$ engage in independent innovation, while those with $a \leq a^i$ partake in costless imitative innovation. Intuitively, a decrease in iceberg costs ι—making imitative innovation more accessible—and a decrease in subsidies τ—escalating the cost of independent innovation activities—both contribute to a rightward shift in the equilibrium of independent innovation cut-off point. We define this as a function positively correlated with a threshold T along the TFP equilibrium growth trajectory, $\alpha a^i / \alpha T > 0$[31].

Now, We obtain the equilibrium dynamics for TFP at the intensive margin as follows:

$$\begin{aligned} &\mathfrak{T}_{a_r}(t+1) - \mathfrak{T}_{a_r}(t) \\ &= \int_0^{\bar{I}} \left[\begin{array}{c} \chi^{\text{in}}(a_r - 1, I, \tau, \iota; \mathfrak{T}) \times (I + (1-I)c(\tau)m(\iota)(1 - F_{a_r-1}(t)))\, \mathfrak{T}_{a_r-1}(t) + \\ +\chi^{\text{im}}(a_r - 1, I, \tau, \iota; \mathfrak{T}) \times m(\iota)(1 - F_{a_r-1}(t))\, \mathfrak{T}_{a_r-1}(t) \\ -\chi^{\text{in}}(a_r, I, \tau, \iota; \mathfrak{T}) \times (I + (1-I)c(\tau)m(\iota)(1 - F_{a_r}(t)))\, \mathfrak{T}_{a_r}(t) \\ -\chi^{\text{im}}(a_r, I, \tau, \iota; \mathfrak{T}) \times m(\iota)(1 - F_{a_r}(t))\, \mathfrak{T}_{a_r}(t) \end{array} \right] dB(I), \end{aligned} \tag{38}$$

Equation (8) delineates the dynamical law governing changes in firm productivity arising from imitative and independent innovation. The first two terms characterize how a firm with productivity $a_r - 1$ at time t can elevate its productivity to a_r through innovation. The latter two terms encapsulate how a firm with productivity a at time t progresses to $a_r + 1$ in period $t + 1$.

This transformation allows the productivity distribution $F_{a_r}(t) = f(a - vt)$ to evolve as a traveling wave solution with velocity $v = v(m, c, b(I))$, where $v'(m) > 0, v'(c) = 0 \ if \ a < a^i; < 0, \ otherwise.$

Proof of Proposition 1

[31] The economic intuition behind this assumption is clear: since the probability of achieving independent innovation is randomly drawn from an exogenously given distribution, an increase in T implies that only firms with much higher productivity find it more profitable to pursue independent innovation over imitation, given the probability drawn for successful innovation. Consequently, in the dynamics of the productivity distribution, a^i will shift to the right, indicating that more firms will rely on imitation to enhance productivity.

Motivated by Melitz (2003), we focus on examining how the changes of o affect the cut-off point of entry and regional trade, also the average productivity of the economic.

Given $\frac{\partial a^x}{\partial \tau} = \frac{a^x}{\tau} - \frac{a^x}{a}\frac{\partial a^e}{\partial \tau}$, $j'(a) = -\frac{1}{a}(\sigma-1)[1-\mathcal{Z}][k(a)+1] < 0$, $k(a) = \frac{\bar{r}}{r(a^e)} - 1$, $\bar{r} = R/M$. yields:

$$\frac{\partial a^e}{\partial \tau} = -\frac{a^e}{\tau}\frac{nf_x j'(a^x)a^x}{fa^e j'(a^e) + nf_x a^x j'(a^x)} < 0$$

$$\frac{\partial a^x}{\partial \tau} = -\frac{fj'(a^e)}{nf_x j'(a^x)}\frac{\partial a^e}{\partial \tau} > 0$$

Then we have $\frac{\alpha a^e}{\alpha o} > 0$, and $\frac{\alpha a^x}{\alpha o} < 0$. For the $\tilde{a}_t$, we have the following:

$$\tilde{a}_t = \left(\frac{1}{M_t}\left[M\tilde{a}(a^e)^{\sigma-1} + nM_x\left(\tau^{-1}\tilde{a}(a^x)\right)^{\sigma-1}\right]\right)^{\frac{1}{\sigma-1}}, \quad M_t = M + nM_x = M + nx_r M \tag{39}$$

Where we have

$$\frac{\partial \tilde{a}(a^e)}{\partial o} > 0, \quad \frac{\partial \tilde{a}(a^x)}{\partial o} < 0, \quad \frac{\partial M_x}{\partial o} > 0, \quad \frac{\partial M_t}{\partial o} > 0 \tag{40}$$

When the entry cutoff condition shifts to the right, the average productivity of entering firms is higher. Conversely, when the regional trade cutoff condition shifts to the left, the average productivity of firms participating in regional trade decreases. Simultaneously, the number of firms engaging in regional trade, M_x, increases, and the total varieties of goods consumed by the city (M_t) also rise with the intensification of regional trade activities. Therefore:

$$\frac{\tilde{a}}{\alpha o} > 0 \tag{41}$$

Then we conclude the proof.

Proof of Proposition 2

When take the derivative of $T(a, \tau, \iota; \mathfrak{T})$ with respect to o, we have:

$$\frac{\partial T}{\partial \iota} = \frac{[m'(1-c)B + m'cA]K}{B^2} < 0, \quad \text{Conditional on} \quad a >= a^x \tag{42}$$

$$\frac{\partial T}{\partial \tau} = \frac{[A-B]c'Km}{B^2} < 0, \quad \text{Where} \quad A - B < 0 \tag{43}$$

Where

$$T = \frac{m(\iota)(1-c(\tau))K}{1-c(\tau)m(\iota)K}, \quad K = (1-F_{a_r}), \quad B = 1 - c(\tau)m(\iota)K, \quad A = m(\iota)(1-c(\tau))K \tag{44}$$

Given that $\frac{\partial \tau}{\partial o} < 0$, $\frac{\partial \iota}{\partial o} < 0$, $\frac{\partial c(\tau)}{\partial \tau} > 0$, $m'(\iota) = 0\ if\ a < a^x, m'(\iota) < 0\ if\ a >= a^x$, and $c(\tau) < 1$, we have:

$$\frac{\partial T}{\partial o} > 0, \quad \frac{\alpha a^i}{\alpha o} = \frac{\alpha a^i}{\alpha T}\frac{\alpha T}{\alpha o} > 0 \tag{45}$$

Based on the analysis of König et al. (2022), the $v = v(m, c, b(I))$ can only be defined implicitly and solved for numerically. And the numerical results show that $v'(m) > 0, v'(c) = 0 \; if \; a < a^i; < 0, \; otherwise$, therefore:

$$\frac{\alpha v}{\alpha o} = \frac{\alpha v}{\alpha m}\frac{\alpha m}{\alpha \iota}\frac{\alpha \iota}{\alpha o} + \frac{\alpha v}{\alpha c}\frac{\alpha c}{\alpha \tau}\frac{\alpha \tau}{\alpha o} \tag{46}$$

$$= \begin{cases} = 0 & \text{if } a < a^x \\ > 0 & \text{if } a^x <= a < a^i \\ < 0 & \text{if } a >= a^i \end{cases} \tag{47}$$

Then we conclude the proof.

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