E Pluribus Unum: Growing TFP From Regional Trade

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Abstract

This paper empirically investigates the new dynamics of firm productivity under regional trade conditions, characterized by significant productivity gains and reduced patent activity. By integrating administrative data, we find that Urban Integration Policy (UIP) significantly enhance firm productivity, especially for firms between the 50th and 80th productivity percentiles that engage in regional trade. We document substantial evidence of the dismantling of local protectionism and the rise of regional trade, discovering that UIP primarily boosts China's aggregate productivity by at least 8% through the dominant channel of knowledge diffusion, while changes in the firm composition account for an additional 2%. Our analysis helps to elucidate the puzzle of China's economic growth and clarify the direction for the systematic integration of trade and innovation models.
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A peasant becomes fond of his pig and is glad to salt away its pork. What is significant, and is so difficult for the urban stranger to understand, is that the two statements are connected by an and not by a but.

—- *John Berger*

1 Introduction

Total Factor Productivity (TFP) emerges as a cornerstone in understanding long-term economic expansion, 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 burgeoning perspective investigates the potential of regional trade to sculpt TFP landscapes via channels of innovation (Akcigit and Melitz, 2022; Melitz and Redding, 2023).

Two primary obstacles complicate the pursuit of a detailed empirical understanding of the subject. Initially, the analysis requires a precise comprehension of the dynamics between firms' behavioral adjustments and innovation motivations in response to fluctuations in trade costs. Prevailing literature, including studies by Andersson, Berger and Prawitz (2023); Donaldson (2018), primarily explores the impact of trade cost alterations through the lens of transportation infrastructure developments. Yet, the underpinnings of such infrastructural investments often trace back to non-exogenous factors, such as governmental decisions or historical instances of local protectionism. This entanglement notably affects firms' incentives to innovate, underscoring the necessity for an in-depth exploration into the essence of local protectionism to unravel the influences on innovation strategies (Akcigit, Ates and Impullitti, 2018). This complexity represents a significant analytical challenge. Additionally, identifying the causal effects of regional trade on firms' TFP amidst local protectionism entails overcoming considerable hurdles. These include navigating through cross-national geopolitical barriers, disparate institutional frameworks, and the difficulties in pinpointing exogenous factors of integration (Eaton and Kortum, 2002; Donaldson, 2015; Desmet, Nagy and Rossi-Hansberg, 2018). [1]

In this paper, we delve into an unexpected exogenous transition from entrenched local protectionism to regional integration within China. This exploration sheds light on the causal influences, scale, and mechanisms by which regional trade impacts TFP. To facilitate this investigation, we have curated a comprehensive dataset encapsulating the broad spectrum of Chinese firms, governmental initiatives, and innovation pursuits. By intertwining various micro-level firm databases with over 200 million business administrative data, we dissect diverse facets of firm operations. The inclusion of judicial documents, patent filings, land transaction data, and detailed government action records enables a transparent examination of the foundational elements driving TFP evolution in the context of local protectionism.

[1] The investigation into regional trade's functionalities is often jeopardized by threats to the Stable Unit Treatment Value Assumption (SUTVA).

This exogenous shift, implemented in a staggered manner by local governments in China and aimed at achieving regional integration, is referred to as the Urban Integration Policy (UIP). In each UIP cluster, it connects a core city with one to two peripheral cities to foster deep cooperation and break down entrenched local protectionism. By closely examining the policy's specific effects on local government actions and employing an instrumental variable strategy, we transparently demonstrate the historical origins and essence of local protectionism, thus linking it to the subsequent strong regional trade flows.

This setting is unique and useful. Historically, China has been deeply entrenched in local protectionism, which has led to observable 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 dawn of the 21st century, the Chinese central government focused its strategic priorities on regional coordinated development through the five-year plans[2]. Following the national agenda, local governments began implementing UIP to break the cycle of fragmentation and promote economic integration. In this context, our analysis is established within a unified institutional framework, allowing for a comparative assessment of how the emerging of regional trade flow within UIP clusters affect the dynamics of TFP under a constant control group scenario, and clarifying the determinants of shifts in firm 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.

Despite starting from a relatively low absolute level, the pace of TFP growth in China since the 21st century has been astonishing. From 2000 to 2013, productivity grew by 30.14% (Figure G.1)[3]. When grouped by UIP, our data seem to reveal a distinctive pattern underlying this productivity growth. As depicted in Figure 1, we observed that after the initiation of the UIP in 2003, the TFP of firms in treated cities significantly increased compared to control cities. However, simultaneously, the patent activities in treated cities were notably suppressed, and over time, their total patent filings began to significantly lag behind those of the control cities. Additionally, firm dynamics occurred more frequently near the city borders between treated cities, suggesting the critical influence of regional trade (See Figure F.6).

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 imita-

[2]At the turn of the century, the Chinese central government progressively incorporated urbanization strategies and regional synchronized development into the "Tenth Five-Year Plan," creatively deviating from the "Ninth Five-Year Plan" (see Appendix A).

[3]Concurrently, a noteworthy observation also indicates that developed nations have sustained stable TFP levels from 2000 to 2013. Conversely, countries characterized by prevalent domestic protectionism, such as Russia, Canada, Kazakhstan, India, Switzerland, and China, have witnessed rapid TFP growth (Sonin, 2010; Herrmann-Pillatha, Libman and Yu, 2014) (as illustrated in Figure G.1).

tive 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 disintegration of local protectionism'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. Simultaneously, trade flows also reduce the costs of imitation, accompanied by a dampening effect on subsidy-oriented independent innovation caused by subsidies reduction, calibrating the critical trade-off in firms' innovative behaviors. Consequently, the mechanism of knowledge diffusion becomes an endogenous driver of productivity growth on the intensive margin.

Our DID-based findings reveal that, under the influence of the UIP, firms located in treated cities exhibit a significant TFP surge of 7.8% compared to those in the control group. Concurrently, this effect strengthens over time, with the promotional impact exceeding 20% seven years after implementation. Furthermore, we identify that this facilitative effect is primarily driven by firms situated within the 50th to 80th percentile 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. It is noteworthy that 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 the bulk of total productivity growth is driven by the intensive margin effects of knowledge diffusion.

This TFP growth pattern reflects a fundamental prediction: namely, that robust regional trade flows emerge among treated cities. To confirm this and shed light on the mechanisms behind TFP growth, we empirically investigate the following questions: How does the UIP eliminate local protectionism between treated cities? Does this treatment satisfy several fundamental characteristics of regional trade expansion? Does the growth of firm TFP under regional trade conditions stem from imitative innovation and changes in firm composition? Building on this foundation, we conduct multiple sensitivity analyses on all outcomes and further employ an instrumental variable strategy to investigate the sources and relative importance of the two mechanisms. Finally, we link these mechanisms to trade and innovation theories, exploring several unresolved macroeconomic issues currently pending.

Eliminating Local Protectionism within the UIP: We demonstrate that the UIP shifts local government focus from industrial policy to regional coordinated development, thereby mitigating various dimensions of local protectionism. We observe a marked decline in the intensity of industrial policy actions by local governments[4], while public investment expenditures significantly increase, emphasizing the strengthening of transportation infrastructure[5]. Concurrently, the transparency of the land market in peripheral cities has significantly improved, reducing entry barriers caused by local protectionism. With the change in government behavior, in terms of economic outcomes, we notice

[4]There is a significant reduction in business subsidies, and a corresponding decrease in the prevalence of so-called "zombie firms"—a major distortion related to protectionism in the Chinese economic paradigm (Chen et al., 2021).

[5]The expansion of high-speed rail lines connecting UIP cooperative entities.

a clear upward trend in outside direct investment in governed cities, accompanied by increased labor mobility[6]. Therefore, TFP growth is mainly driven by firms that were not previously influenced by industrial policy incentives.

Regional Trade Expansion: As local protectionism waned, we documented substantial evidence of regional trade expansion in treated cities. Firstly, affected firms experienced rapid growth in output, sales revenue, profits, sales expenses, and advertising expenditures, with a significant decrease in markups as competition intensified. Secondly, the main drivers of production were those firms that exhibited a stronger preference for regional trade over international trade[7]. Simultaneously, we found that the UIP did not largely alter firms' export behaviors but significantly reduced import activities, consistent with the integration of internal markets within the UIP cluster.

Intensive Margin of TFP Growth: All evidence indicates that the growth in firms' TFP is driven by knowledge spillover effects at the intensive margin. As subsidies and trade cost decrease under the influence of UIP, there was a significant shift in the incentive mechanism for firm innovation, from independent innovation to more accessible imitative innovation activities facilitated by regional trade. Our empirical analysis reveals the role of two types of knowledge spillover effects. On one hand, there was a surge in formal patent transfers within treated cities, with a significant increase in transfers to cooperative cities within the province and a decrease in transfers to cities outside the province. On the other hand, due to the reduction of subsidies, we observe that firms in affected cities have significantly restrained their behavior of mislabeling R&D expenditures to deceitfully claim subsidies (Chen et al., 2021). Accordingly, we see a significant decline in patent activities, implied a suppression of potential strategic patent activities, leading to an increase in informal imitation activities.(Argente et al., 2020): We show that easier imitation, lower imitation costs, and greater technological consistency significantly enhance the UIP's facilitative effect on firm TFP,[8]consistent with the trade-off between imitative and independent innovation, thus growth in TFP under the effects of knowledge diffusion at the intensive margin[9]. Basically, this result highlights that under trade conditions, the optimal level of government R&D subsidies decreases (Akcigit, Ates and Impullitti, 2018).

Extensive Margin of TFP Growth: Our comprehensive study on the impact of UIP on firms' geographical choices further provides consistent evidence regarding 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

[6]This growth primarily comes from cooperative cities within the UIP cluster, indicating that UIP motivates businessmen in these cities to invest in cooperative cities.

[7]Specifically, this impact is particularly pronounced for non-exporting firms that are distant from ports and not situated along coastlines.

[8]Specifically, industries located in sectors with stronger potential knowledge spillover effects, easier to imitate (industries with lower average patent quality but higher knowledge spillover effects), cities with weaker intellectual property regimes, and industries where subsidiary cities have greater technological consistency with core cities, all experience faster TFP growth and a significant reduction in patent activities.

[9]We also demonstrate that the UIP did not change judicial litigations related to patents and ownership, thereby ruling out any impact from changes in the intellectual property regime.

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 threats to our empirical specifications. For all dependent variables, our covariate balance, event study estimates and alternative estimates consistently indicate that pre-treatment trends are parallel between the control group and all adopter of the UIP. Moreover, baseline results remain robust, controlling for several time-invariant or time-varying controls, using alternative measures of TFP, eliminating of several significant competitive assumptions related to TFP, placebo test for random adopter of UIP, applying different data windows and specifications, heterogeneous treatment effect under staggered DID design and the potential contamination under SUTVA[10].

To demonstrate that the adoption of UIP is unaffected by economic factors and to unveil its historical origins, thereby investigating the relative significance of the aforementioned mechanisms, we 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, policy factors appear to be the fundamental cause of local protectionism. When governments collaborate to eliminate trade barriers, the homoplasy of cultures facilitates the substantive dismantling of local protectionism, at which point the mechanism of knowledge diffusion dominates 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 employ these two mechanisms to empirically 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. Third, concerning competition and resource allocation issues. On the intensive margin, productivity growth in any scenario is driven by imitative innovation, but the degree to which it substitutes for patent activity depends on market size and competitive intensity; the larger the market size, the more likely it is to distribute the costs of firm innovation, and the more intense the competition, the more firms tend to rely on patents to evade competition. This heterogeneous innovation effort sustains the long-term

[10] An empirical finding shows that the scope of UIP spillover effects extends to approximately 80 kilometers. Therefore, we establish a control group located 80 kilometers away from the treated city, yielding slightly larger estimated effects that reinforce the robustness of the baseline results.

growth of TFP. On the extensive margin, the positive role of resource reallocation fundamentally originates from changes in the composition of firms (Hsieh and Klenow, 2009), that is, the reallocation between more and less efficient firms/industries.

This paper contributes to several strands of literature. Firstly, it aligns with the literature on the impact of local protectionism, highlighting the trade border phenomenon's effects on the economic performance of federations and decentralized states (Wolf, 2000; Sonin, 2010; Froot, Kim and Rogoff, 2019). Our formal analysis of government behavior and historical cultural factors elucidates the intrinsic roots of changes in local protectionism, providing robust empirical evidence for the perspective that trade border effects are influenced by local protectionism (Jones Luong, 2004; Sonin, 2010). Additionally, as a crucial element of the economic analysis concerning the impacts of local protectionism, we have supplemented recent studies on the political drivers of local protectionism (Fang, Li and Wu, 2022), automotive market protectionism (Barwick, Cao and Li, 2021), and the impacts of judicial protectionism reforms in China (Liu et al., 2022). As an initial effort to unveil the causal relationship between local protectionism and productivity dynamics, we have enriched a series of papers related to the determinants and impacts of TFP (Gai et al., 2021; Brandt and Zhu, 2010; Hsieh and Klenow, 2009; Sraer and Thesmar, 2023). Regarding policy implications, our findings strongly support the view that optimal R&D subsidies decrease as the level of trade openness increases (Akcigit, Ates and Impullitti, 2018). This suggests that addressing local protectionism and facilitating the transition from industrial policies to regional policies may be effective tools for developing countries to achieve long-term growth.

Secondly, 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), how trade is closely linked to development through innovation channels (Desmet and Rossi-Hansberg, 2014; Desmet, Nagy and Rossi-Hansberg, 2018), and resolving several outstanding issues related to comparative advantage, market size, competition escape, and resource allocation (Bernard, Redding and Schott, 2007; Melitz and Redding, 2023; Akcigit and Melitz, 2022; Hsieh and Klenow, 2009). Moreover, the conclusion that regional trade facilitates the migration of firms from core cities to peripheral cities provides new micro-level evidence for the literature on industrial location choice and core-periphery relationships in economic geography[11]. Essentially, our results serve as a crucial component in the integration of heterogeneous firm trade models and innovation models, inspiring

[11]Early studies on the determinants of industrial location primarily approached the issue from an industry perspective (Hanson, 1996, 1998; Holmes and Stevens, 2004; Amiti and Javorcik, 2008; Lu and Tao, 2009), while our study complements this by examining the micro-perspective of firm location choices. Additionally, we find that regional trade promotes the diffusion of industries from core cities to peripheral cities, thus highlighting the distortions of local protectionism on beneficial industrial transfers (Fujita and Thisse, 2009; Bo, 2020; Baum-Snow, Henderson et al., 2020).

a careful consideration of the key sources of productivity growth in quantitative spatial models and emphasizing the endogenous and customized design of the knowledge diffusion function.

Finally, 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 dedicated to linking trade theory with innovation, quantifying the specific magnitude of dynamic economic benefits brought by regional trade, and distinguishing the relative importance of different mechanisms. Contrary to the views of Bau and Matray (2023), we find that trade flows are not only related to the improvement of resource misallocation but also profoundly alter firms' innovation incentives. This perspective complements the findings of Bloom, Draca and Van Reenen (2015), who demonstrated that advanced entities strengthened their innovation incentives due to trade expansion. In contrast, our findings demonstrate that trade expansion enables firms in latecomer entities to more readily access firms in advanced entities, thereby extensively benefiting from knowledge diffusion. Consequently, this leads to the achievement of imitative innovation and more dynamic firm activities, resulting in significant improvements in TFP. This result aligns with the view in macroeconomic research that imitative innovation has driven China's economic growth, while the decay of knowledge diffusion has led to the stagnation of firm dynamics in the United States (König et al., 2022; Akcigit and Ates, 2023). Furthermore, our evidence of reduced patent activity accompanied by an increase in TFP also responds to the literature that has raised concerns about strategic patenting activities suppressing economic welfare (Argente et al., 2020; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020; Akcigit and Ates, 2023).

The structure of this paper is as follows: Section 2 introduces the our conceptional framework. Section 3 covers UIP's background and identification. Data, statistics, and baseline results are in Sections 4 and 5. Section 6 details the analysis of mechanisms. Section 7 assesses the robustness of our findings and mechanisms relative importance. Section 8 response to the trade, and resource allocation theory, along with macroeconomic implications. Section 9 is the conclusions. Supplementary materials are provided separately.

2 Conceptional 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. 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 the sake of analytical tractability without sacrificing generality, the main text focuses solely on key implications related to TFP dynamics, while the derivations can be found at Appendix I.

2.1 Setup

Environment

We commence 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 categories of public expenditure: firm subsidies, denoted as τ, and public investments, pi, targeted at infrastructure development aimed at reducing the so-called iceberg costs in regional trade, ι, where $\iota = 1/pi$. We introduce the term o to define the government's fiscal allocation ratio. In scenarios where local protectionism is adopted, o decreases, thereby amplifying subsidies extended to firms and concurrently reducing public investments designed to mitigate iceberg costs.

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 $\sigma > 1$.

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

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 [12], 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:

$$\log(a_{i,t+1}) = \log(a_{i,t}) + \tilde{g}, \tilde{g} > 0 \quad \& \quad a_r \equiv \log(a)/\tilde{g}. \tag{2}$$

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

[12] 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).

written as:

$$F_{a_r} = \sum_{j=1}^{a_r} \mathfrak{T}_j \tag{3}$$

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[13]. 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:

$$I_i \geq T(a, \tau, \iota; \mathfrak{T}) \equiv \frac{m(\iota)(1 - c(\tau))(1 - F_{a_r})}{1 - c(\tau)m(\iota)(1 - F_{a_r})} \tag{4}$$

We purpose a threshold, T, independent innovation occurs only when the expected probability of independent innovation is greater than T, defined by its own productivity level a, iceberg costs ι, and subsidy τ. Intuitively, 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.

$$\chi_{\text{im}}(a, I, \tau, \iota; \mathfrak{T}) = 1 - \chi_{\text{in}}(a, I, \tau, \iota; \mathfrak{T}) = \begin{cases} 1 & \text{if } I \leq T(a, \tau; \mathfrak{T}) \\ 0 & \text{if } I > T(a, \tau; \mathfrak{T}) \end{cases} \tag{5}$$

2.2 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):

[13]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.

$$V(a) = \max\left\{0, \sum_{t=0}^{\infty}(1-\kappa)^t\pi(a)\right\} = \max\left\{0, \frac{1}{\kappa}\pi(a)\right\} \tag{6}$$

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 [14] over entry cost f:

$$a^e, a^x = \begin{cases} a^e = \inf\{a : V(a) > 0\} & \text{if Successful Entry} \\ a^x = \inf\{a : a > a^e, \quad \pi_x(a) > 0\} & \text{if Regional Trade} \end{cases} \tag{7}$$

$$a^x = a^e \iota(\frac{f_x}{f})^{\frac{1}{\sigma-1}} \tag{8}$$

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:

$$F(a) = \begin{cases} \frac{z(a)}{1-\mathcal{Z}(a^e)} & \text{if } a \geq a^e \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

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

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:

$$\tilde{a}_t = \left(\frac{1}{M_t}\left[M\tilde{a}(a^e)^{\sigma-1} + nM_x\left(\tau^{-1}\tilde{a}(a^x)\right)^{\sigma-1}\right]\right)^{\frac{1}{\sigma-1}}, \quad M_t = M + nM_x = M + nx_rM \tag{10}$$

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:

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

$$\frac{\alpha a^e}{\alpha o} > 0, \frac{\alpha a^x}{\alpha o} < 0, \frac{\tilde{a}}{\alpha o} > 0 \tag{11}$$

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.*

2.3 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 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, $\alpha a^i/\alpha T > 0$. We argue that the equilibrium productivity threshold for independent innovation a^i not only exceeds the firm's exit productivity threshold a^e, but also surpasses the firm's trade productivity threshold a^x.

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

$$\begin{aligned}
&\mathfrak{T}_{a_r}(t+1) - \mathfrak{T}_{a_r}(t) \\
&= \int_0^{\bar{I}} \left[\begin{array}{c} \chi^{\text{in}}\left(a_r - 1, I, \tau, \iota; \mathfrak{T}\right) \times \left(I + (1-I)c(\tau)m(\iota)\left(1 - F_{a_r-1}(t)\right)\right)\mathfrak{T}_{a_r-1}(t) + \\ +\chi^{\text{im}}\left(a_r - 1, I, \tau, \iota; \mathfrak{T}\right) \times m(\iota)\left(1 - F_{a_r-1}(t)\right)\mathfrak{T}_{a_r-1}(t) \\ -\chi^{\text{in}}\left(a_r, I, \tau, \iota; \mathfrak{T}\right) \times \left(I + (1-I)c(\tau)m(\iota)\left(1 - F_{a_r}(t)\right)\right)\mathfrak{T}_{a_r}(t) \\ -\chi^{\text{im}}\left(a_r, I, \tau, \iota; \mathfrak{T}\right) \times m(\iota)\left(1 - F_{a_r}(t)\right)\mathfrak{T}_{a_r}(t) \end{array} \right] dB(I),
\end{aligned} \tag{12}$$

Equation (14) 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 $v'(m) > 0, v'(c) = 0 \; if \; a < a^i; < 0, \; otherwise.$

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:

$$\frac{\alpha a^i}{\alpha o} > 0, \quad \frac{\alpha v}{\alpha o} = \begin{cases} = 0 & \text{if } a < a^x \\ > 0 & \text{if } a^x <= a < a^i \\ < 0 & \text{if } a >= a^i \end{cases} \tag{13}$$

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.*

2.4 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 5. These equilibrium are represented by the cumulative distribution 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 $a^{i(\mathrm{UIP})}$, a regional trade cutoff point $a^{x(\mathrm{UIP})}$, relative to a counterfactual regional trade cutoff point a^x in a no-innovation scenario, a firm exit cutoff point $a^{e(\mathrm{UIP})}$ and corresponding counterfactual exit cutoff point a^e. And the explanations for the dynamics are provided in the figure's annotations.

3 Empirical Strategy

3.1 The Background of UIP

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[15]. On the other hand, many scholars argue that China's decentralized administrative system has fostered a competitive milieu among local governments, contributing to

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

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 policy divergences appeared between the Tenth Five-Year Plan and the Ninth Five-Year Plan. They innovatively emphasized the need to *break administrative segmentation*, *utilize regional comparative advantages*, and promote *rational construction of the urban system*. These highlights reflect the central government's growing focus on eliminating local protectionism and achieving regional common prosperity.

In accordance with the directives set forth by the central government, certain local government leaders have demonstrated exceptional political acumen by embarking upon endeavors aimed at political innovations that are geared towards facilitating coordinated regional development, and the UIP being one of the most noteworthy. As of 2013, a total of 14 provinces including Hunan, Guangdong, Henan, Liaoning, Xinjiang, Anhui, Gansu, Jilin, Jiangsu, Fujian, Guizhou, and Hubei had adopted UIP, encompassing 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 urban integration and 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.

The promotion of UIP continues in China, yet we are unaware of any studies that have examined the implications of UIP. The main reason for this oversight is that UIP is a strategic cooperation agreement, signed independently by local governments and typically acknowledged by the central government only after it has been implemented for some time and achieved specific results. It is then elevated to a national project status and serves as a template. Consequently, to study China's UIP, extensive data collection of the contracts signed by various local governments is required, along with a systematic organization of their main content, which poses a research challenge.

The central philosophy of UIP involves eliminating trade barriers within clusters and establishing integrated urban agglomerations. We observed that the vast majority of policy documents accentuate the imperative of fortifying cooperation amongst cities, suggesting a pre-adoption scenario where inter-city collaboration was constrained. These documents predominantly pertain to infrastructure development, industrial linkages, and the sharing of resources. In order to augment interactions between entities involved in urban planning, there is a frequent advocacy for bolstering the construction of transportation networks. This could efficaciously diminish the geographical separation amongst cooperating cities, thereby mitigating iceberg costs. Regarding industrial linkages, there is a common emphasis on the synchronicity and structural advancement of industries, potentially indicating that historical protectionist barriers precluded industries from aligning with local comparative advantages, thus hampering the industries' capacity for efficient progression. In the realm of resource sharing, the documents discuss the establishment of a unified, reciprocally open market predicated on infrastructure development, aimed at dismantling regional monopolistic enclosures, curtailing the mobility of resources, and enhancing the efficiency of resource allocation.[16]. Generally, the objective of UIP is to achieve urban integration and dissolve local protectionism, making UIP a valuable quasi-natural experiment for testing our theoretical predictions.

3.2 Identifying Strategy

Based on theoretical predictions, the implementation of UIP enhances a firm's TFP within affected cities. Consequently, we employ the Two-Way Fixed Effects with Difference-in-Differences (TWFE-DID) estimator to ascertain the causal effect. This model is delineated in equation (14).

$$TFP_{ict} = \alpha + \beta \times UIP_{ict} + X_{ict} + \gamma_t + (\lambda_i \quad or \quad \theta_c) + \varepsilon_{ict} \tag{14}$$

Where TFP_{ict} is the TFP of firm i in year t of city c. We measure it by adopting the method from Ackerberg, Caves and Frazer (2015) in baseline estimation. And further adopt the method from Olley and Pakes (1996); Levinsohn and Petrin (2003); Gandhi, Navarro and Rivers (2020) for robustness check. UIP_{ct} is a dummy variable for measuring if a firm is affected by UIP (1 after UIP, otherwise 0). We focus on the coefficient of the interaction term, which captures the Average Treatment Effect on the Treated (ATT) of UIP on a firm's TFP.

Recognizing that a host of factors contribute to the heterogeneity of TFP, we incorporate the variable X into the model. This variable stands in for control variables that describe firm and city attributes, including the firm's age. The age is gauged via the logarithm of the temporal distance between the firm's 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

[16] 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.

variable indicating its engagement in export activities, is also included. Furthermore, three pre-established city parameters[17] – population size, per capita GDP, and the secondary industry's citywide share – are multiplied by the annual trend, respectively. Unobservable variables are also accounted for in the model, such as time-fixed effects γ_t, firm-fixed effects λ_i, and city-fixed effects θ_c. Here, UIP permits the utilization of a versatile array of fixed effects combinations, yielding insights into the marginal effects on varying dimensions. When firm fixed effects are accounted for, the coefficient 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. Moreover, standard errors are clustered at the city-year level. Lastly, ε_{ict} denotes the error term within the model.

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. Notably, existing literature demonstrates that the traditional method for identifying a common trend is unsuitable in the context of staggered policy implementation. Consequently, 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. This is done by creating 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):

$$TFP_{ict} = \beta_0 + \sum_{d=-5}^{7} \delta_d \cdot \mathbb{I}(Year_{ct} = t + d) \cdot UIP_{ic} + X_{ict} + \gamma_t + (\lambda_i \quad or \quad \theta_c) + \epsilon_{ict} \tag{15}$$

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 (14).

4 Data

One of the key advantages in studying the changes in China's TFP lies in our access to extensive data sources, encompassing virtually all micro-firms in China, namely, the China Industrial Enterprise Database, guided by the National Bureau of Statistics. This database includes a wide range of industrial firms across various regions of China[18], and incorporates specific details such as output,

[17] Value taken in 2002, prior to the initial adoption of UIP.

[18] 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. This evolving standard is closely aligned with China's economic development levels. As is well-known, by the post-2010 era, China's GDP had already ranked among the top in the world. The standard is based on actual revenues without adjustment for inflation. Consequently, to our knowledge, the majority of such firms, provided they have not exited the market, have been continually subject to tracking and investigation. Of course, to validate that our design is unaffected by this change in survey scope, we have employed different specifications

costs, firm characteristics, subsidies, etc. It should be noted that this is currently the most extensive, significant, and comprehensive confidential micro-level database in China. However, it is not without flaws, exhibiting some deficiencies in certain indicators and representativeness.

To comprehensively understand the dynamics and underlying mechanisms of Chinese enterprises, our study leverages a multifaceted approach. Utilizing over 200 million 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, creating unique micro-panels. Concurrently, we develop innovative panels to analyze urban, judicial, and land system features. 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)[19]. 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)[20], site selection activities (Panel G)[21], government land leasing and industrial policies (Panel H)[22], and patent transfers between firms (Panel I)[23]. 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 experimental and control groups. It is distinctly evident that the mean TFP of the firms in the treatment group exceeds that of the control group. 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. Concurrently, we also report the covariate balance between treatment and control firm or city in Table C.3 and C.4. Evidence consistently support that all important and relevant factors are remain balance between the two groups before

of data structure for robustness checks.

[19]Additionally, to identify the spillover effect of UIP, we collected geographic coordinate information of the center of mass for both firms and cities. This involved extracting geographical locations and names of individual firms from our database and using Stata to interface with AMAP for precise longitude and latitude details. For city center of mass coordinates, we used R to compute geographic coordinates based on vector data of Chinese cities, enabling accurate assessment of spatial dynamics in urban integration.

[20]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.

[21]This approach mitigates endogeneity problems caused by changes in the sampling objects of the industrial enterprise database and firms' discretion.

[22]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.

[23]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.

UIP, which indicates our design is suitable for a DID estimation.

5 Baseline Results

In this section, we investigate our key empirical implications using cross-firm data and establish a robust positive association between the implementation of UIP and firm's TFP.

We initially identified a positive correlation between UIP and TFP. To investigate this, we estimated the equation (14), wherein the implementation of UIP is regressed on TFP, serving as the dependent variable, for the period from 2000 to 2013.

Table 1 presents the OLS estimates for equation (14). Across all three columns of Table 1, 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.[24]

Figure 2A shows the full set of estimated δ coefficients in equation (15), 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 20%. 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.

Importantly, as depicted in Figure 2B [25], our regression analysis of the TFP distribution of firms in city-year level reveals evidence also consistent with theoretical predictions. Specifically, the UIP exhibit a positive effect on TFP only for firms above the 50th percentile, implying that the regional trade cut-off point is near this percentile. However, the UIP's promotion effect on firm TFP attenuates for those above the 80th percentile, suggesting that the innovation cut-off point is near the 80th percentile. Firms situated between these two percentiles of treated cities realize rapid TFP advancement through imitative innovation[26], and we will provide detailed evidence for this subsequently.

[24]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 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.

[25]In the figure, the gray bars represent a comparison of treated firms above a given percentile with control group firms, while the red bars represent a comparison of treated firms below that percentile with control group firms.

[26]This resonates with the prediction that low-productivity firms, by engaging in trade, find it easier to learn from other high-TFP firms, while those predominantly reliant on independent innovation witness a deceleration in TFP advancement

6 Mechanisms

In this section, we aim to substantiate several pivotal assumptions and principal forecasts within our model, elucidating the conduits through which UIP bolsters firms' TFP. Specifically, our investigation logically scrutinizes a sequence of variations: initially, we must associate UIP with the robust phenomenon of regional trade expansion, necessitating answers to two questions. First, as the cornerstone for dismantling regional trade barriers, has UIP precipitated the disorganization of local protectionism? Second, has the decline in local protectionism genuinely facilitated the enlargement of regional trade markets, and to what extent? Building upon this, we probe the impact of such regional market expansion on firm-level TFP from two distinct margins. The intensive margin concerns whether firms, under the aegis of trade expansion, reap augmented productivity gains through imitation innovation. The extensive margin examines the influence of entry and exit by firms of varying productivities on the aggregate productivity.

6.1 Nature of Local Protectionism: Foundation of Regional Trade Expansion

Within the ongoing discourse lacking a consensus on the quintessence of local protectionism, our framework endeavors first to clarify its origins may from government market interventions and delineates several observable manifestations through the lens of UIP. In a comprehensive examination from Panels A to C, we elucidate the ramifications of UIP on the system, as exhibited in Table 3.

Government Behavior: We document the pivotal shifts in governmental decisions across three dimensions.

Firstly, we find that governments have reduced the adverse economic distortions they imposed through decreasing fiscal interventions. According to Columns 1-2, compared to the control group, the implementation of the UIP has resulted in a significant decrease of approximately 16% in the average subsidies allocated to firms. On one hand, this could imply a shift in governmental policy focus. On the other hand, from the firms' perspective, this may reflect an increasing cost for independent innovation. Under this, the average number of "zombie" firms in the treated cities has significantly reduced, echo to the above-mentioned variations.[27]

Secondly, the government has redirected its focus vigorously towards infrastructural development. According to columns 9 and 11-14, there's a 4.5% surge in government investments in the public sector, implying infrastructural advancements. To validate this, we employed a manually-collected sample of high-speed railway construction practices to study the causal relationship between UIP and infrastructure development. The results resonate accordingly. Specifically, under the influence of UIP, the speed of high-speed rail in treated cities increased by 20.545 km per hour, and the length of the railway tracks extended by 130.875 km. More importantly, the growth in speed and track lengths are almost entirely driven by those lines encompassing UIP clusters (see columns 13 and 14).

due to reduced subsidies.

[27] Evidence provided in Appendix F, Table F.1, indicates a positive correlation between firms receiving subsidies and their transition into "zombie" status.

Lastly, additional evidence suggests that the governments of treated cities are elevating the fairness of the land market. 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: In line with the aforementioned shifts in governmental decisions, we identify a series of resonating economic outcome variations, substantiating the decline in local protectionism.

First, as shown in Table 3, Panel B, UIP has substantially augmented the proportion of investments that treated cities receive from outside cities while within the same province, approximately by 11550 RMB for each firm. (measured in proportion, it's similarly 0.3%). We clarify this outcome primarily originates from the diminishing inter-city local protectionism in two ways. On one hand, we present robust descriptive findings that, since the introduction of UIP in 2002, treated cities' external investments have surpassed other cities, and this gap is widening over time (see Appendix F, Figure F.1). On the other hand, it's pivotal to observe a counterfactual that we believe UIP will not alter inter-provincial local protectionism. Thus, we do find that investments received by treated cities from outside the province remain unchanged (Table 3, Columns 7 and 8).

Next, due to the substantial expansion in infrastructure, we observe a surge of over 10% in labor mobility within treated cities (Table 3, Column 10). Simultaneously, related changes in industrial policy directly mirror the pivot in decision-making by the treated city governments. According to columns 3-4, the UIP-driven boost in firms' TFP predominantly emanates from those not situated within industries that the government fervently supports or incentivizes. These firms, outside the ambit of industrial policy incentives, are less likely to receive subsidies and consequently less likely to transition into "zombie" firms [28]. Therefore, with the decline in local protectionism and subsequent regional trade expansion, they are more poised for growth.

In summary, our findings present a comprehensive picture of how UIP has dissolved local protectionism. Specifically, with the implementation of UIP, there's a substantial shift in governmental decision-making, transitioning from a focus on industrial policy to regional coordinated development[29]. This subsequently leads to the dismantling of local protectionism, whereby investors, particularly affluent businessmen from core cities, are more inclined to invest in the corresponding cooperative cities, exploring new ventures. Concurrently, labor mobility starts to surge, and the TFP of firms not contingent on industrial policy thrives swiftly.

[28] Evidence provided in Appendix F, Table F.1, indicates that zombie firms are often associated with lower productivity, and firms that receive subsidies are more likely to transform into zombie firms.

[29] This encompasses the transparency in the land market and infrastructure development.

6.2 Regional Trade Expansion

Subsequently, we empirically demonstrate that the dissolution of local protectionism has led to a significant expansion of intra-regional trade markets. Specifically, the expansion of intra-regional trade markets exhibits several fundamental characteristics: (1) firms increase production and sales, thereby achieving higher profits; (2) firms less likely to benefit from regional trade experienced slower production growth; (3) firms' sales expenses (including transportation costs) increase, while the unit cost of production is likely to remain constant, but there is an increase in advertising per unit product; (4) increased competition reduces firms' markup; (5) the expansion of intra-regional trade may lead to a reduction in firms' import demands.

In Table 4, we test these hypotheses by examining the impact of UIP on several firm-level outcomes. We find a range of evidence consistent with theoretical predictions: Firstly, UIP significantly increases firms' output, sales, and profits by more than 15%, primarily driven by firms with higher TFP (see Figure 4C). Secondly, the positive effects of UIP on firms' outputs are mainly driven by those firms that are far from ports, do not export, and are not located on coastlines, which are more likely to engage in regional trade (columns 7-9). Thirdly, firms' sales expenses increase significantly while maintaining the same unit production costs, with increased advertising per unit product (columns 4-6). Fourthly, 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, columns 11-12), continuing to suggest the expansion of the regional trade market[30]. Accordingly, we observe that UIP significantly suppresses firms' markup by about 3% (column 10), 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 higher TFP 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.

6.3 Intensive Margin: Knowledge Diffusion

Thus far, we have demonstrated that UIP leads to the dissolution of local protectionism, thereby expanding regional trade markets. Building on this, our theoretical model suggests that as government subsidies and iceberg costs decrease, low-productivity firms achieve productivity growth through imi-

[30]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.

tative innovation[31]. Meanwhile, high-productivity firms see a reduction in subsidy-driven independent innovation due to decreased subsidies.

Basing on the combination of industrial firm-patent match data, patent transfer data, and judicial document universe[32], the empirical results outlined in Tables 6 and 5 indicate the following:

On one hand, we observe a significant decline in patent activity; relative to the control group, patent applications decreased by an average of 0.335 per firm.[33] However, there was no significant change in the quality of patents (see Table 6, columns 1-2).[34] Concurrently, focusing on the heterogeneity of firm-level productivity, we find that as firm productivity increases, the negative impacts weaken, consistent with the hypothesis that higher-productivity firms rely more on independent innovation rather than imitation (columns 3-4). Moreover, considering the percentile levels of firm productivity in a yearly urban context, as illustrated in Figure E.3A, the negative impacts of the UIP on patents begin with firms above the 50th percentile of productivity and intensify with increasing productivity, becoming significant beyond the 80th percentile.

This outcome is associated with three relevant facts: First, in China, government subsidies are often linked to the number of patents a firm holds, and as the intensity of industrial policies decreases, the returns from applying for patents diminish. Consistent with this, using the method recommended by Chen et al. (2021), which employs the ratio of administrative expenses to sales expenses as a proxy for firms reclassifying expenditures as R&D expenses, we find a significant reduction in such reclassification activities, at least by 6.2% as shown in column 8. Second, patents often serve as a declaration to disclose the innovative activities and details they target to protect future innovative outputs. Hiowever, with the rise of regional trade, competitors are likely to deconstruct each other's traded products and combine this with patent disclosures to mimic their products. This reduces the motivation for high-productivity firms to disclose patents. Corresponding suggestive evidence is that we find an increase in R&D investments by treated firms, enhanced by 6.4% (column 8), consistent with the strategy of later firms investing resources in imitation, while pioneering firms invest in R&D but do not disclose. Equally important is that, as the implementation of UIP, there is no evidence suggesting any reform in institutions related to the overall legal environment and property rights protection (Columns 8-10 of Table 5). Therefore, it is unlikely that the property rights system will alter the incentives for firm patent activity.

On one hand, the decline in iceberg costs facilitates easier access for firms to high-productivity enterprises. On the other hand, the reduction in subsidies suppresses subsidy-driven independent

[31]In fact, this refers to learning from higher-productivity firms. This learning occurs primarily in two ways: firstly, by transferring patents and formally learning from trade partners; secondly, through informal imitation, which directly leads to technological progress.

[32]Appendix F, Figure F.5A illustrates the annual trend of judicial decision quantities, where the total number of litigations, those related to property rights, and those connected to patent rights all exhibit similar fluctuations. This demonstrates that the collected judicial data aptly reflect the universe of the adjudication system.

[33]A relevant hypothesis supporting this argument is that regional trade facilitates the expansion of technology exchange markets, thereby enhancing the efficiency of technological innovation, which could reduce the number of entities participating in innovation activities (Spulber, 2008).

[34]Given other types of patent activities, the results are robust. Research in Table E.4 of Appendix E indicates that the reduction in patent applications was mainly driven by a decrease in invention patents and utility model patents related to inventions. Design patent activity did not change significantly, as it is less associated with innovative inventions.

innovation activities, which leads to a decrease in strategic patent activities used to curb competition (Argente et al., 2020; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020). Both aspects make imitation activities more attractive for low-productivity firms, thereby promoting productivity advancements achieved through imitation. Our empirical results are consistent with this. According to Columns 1-3 of Table 5, firstly, due to the innovation diffusion effect of intra-industry trade under trade expansion, firms in industries with higher potential knowledge diffusion effect experience faster TFP growth under the influence of UIP (Column 1). Secondly, an improvement in patent quality typically signifies an increase in the difficulty of imitation, which may suppress imitative innovation (Column 2). Therefore, evidence consistently indicates a negative correlation between patent quality and the increase in TFP. Most crucially, productivity grows fastest in firms located in industries with higher potential knowledge diffusion effect but low patent quality (Column 3). These suggestive pieces of evidence highlight the significant role of imitative innovation.

Building on this, we identify the specific patterns and characteristics of imitative innovation. As shown in Columns 7-8 of Table 6, with the implementation of UIP, the probability of treated cities transferring patents to other cities within the province increases relative to the control group, while the probability of transferring patents outside the province significantly decreases. Additionally, as shown in Figure F.5B, the increase in intra-provincial patent transfers is almost entirely driven by patent transfers between cooperating cities. This implies that formal imitative innovation activities become more vibrant. Moreover, as shown in Columns 4-5 of Table 6, in cities with weak intellectual property protection systems, influenced by UIP, firms are less likely to apply for patents but benefit more from the TFP improvement brought about by imitative innovation.

More directly, utilizing the method proposed by Dechezleprêtre et al. (2023), we calculated the technological similarity at the industry level between each peripheral city and its corresponding core city. This enabled us to formally identify the industries that benefit more from regional trade due to technological consistency[35]. As shown in Columns 6-7 of Table 5, under the influence of UIP, industries with higher technological consistency with corresponding core cities see a significant reduction in patent activities, while their TFP significantly increases.

In summary, the evidence depicts intensive margin growth in firm total factor productivity. 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.

[35]Specifically, firms with a higher degree of technological alignment are more likely to improve their TFP through imitative innovation, as this alignment increases the possibility of achieving this innovation through trade.

6.4 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[36]. 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 [37]. 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 7, we utilize both firm administrative data and the matched data between industrial firm and firm administrative data to capture the dynamics of firm activities. The former encompasses all enterprises in China, while the latter identifies the dynamic activities of surveyed firms above a designated size and, with the aid of richer internal performance information, identifies their specific characteristics. Using firm administrative data, Columns 1-3 indicate that under the influence of UIP, compared to the control group, the probability of firm entry within the counties of treated cities increased by 0.192%, the exit probability decreased by 1.5%, and the transfer probability was unaffected. According to the matched data, Columns 4-6 demonstrate that for firms above a designated size, the entry rate significantly declines, the probability of exit remains unchanged, but the likelihood of relocation increases. These findings suggest that UIP tend to promote the development of small, emerging firms, while some large incumbent firms are more likely to relocate to regions more conducive to their production operations, namely cooperative cities. At the same time, the magnitude of these results is not significantly large, which is consistent with the results identified in the baseline regression where the intensive margin plays a dominant role.

Simultaneously, Columns 7-9 of Table 7 further indicate that for firms with higher productivity, the probability of entry is higher, while the probabilities of exit are lower. This aligns with the model predictions that extensive margin effects contribute to shifting the composition of firms towards those with higher productivity.

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 enterprise composition operates heterogeneously in treated core and peripheral cities, illustrating how it serves as the microfoundation for the macroeconomic explanation of productivity enhancement-

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

[37]Figure F.3 in Appendix F illustrates that prior to 2003, industrial firms were predominantly concentrated in core cities. Post-2003, industrial firms in peripheral cities began to emerge.

Enhancemeant in resource allocation efficiency.

7 Robustness Check and The Source of Mechanisms

In this section, we, on one hand, demonstrate the identification assumptions and address several issues pertinent to our model specification to robustly maintain our baseline estimates. On the other hand, we employ an instrumental variable strategy to identify the specific sources of the mechanisms proposed in the previous section and elucidate their relative importance in different scenarios.

7.1 The Robustness of Baseline Results

Assumption of DID: Common Trend

We provided parallel trend tests for the results reported in all tables within the document, which can be found in Appendix D. The results robustly demonstrate that for all our estimates, there were no pre-existing trend differences between the treatment and control groups, and the magnitude and direction of changes are essentially consistent with the results presented in the tables.

Assumption of DID: SUTVA

The potential spillover effect may pose a risk to our baseline estimation(See Appendix D, Table D.3). To assess this, we furnish formal evidence demonstrating that the boundary of the spillover effect for UIP is 80 km. (See Appendix D, Figure D.6). As a result, 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 1, 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.10), 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, we prove the impact of UIP is not driven by contemporaneous other policies related to TFP (Appendix D, Tables D.10). Finally, in Appendix D's Tables D.5 to D.7 and Figure D.7, we demonstrate that the UIP's influence on TFP is not contaminated by heterogeneous treatment effects.

7.2 The Exogeneity of the UIP Selection and Mechanisms Discussions

In this section, we employ instrumental variable strategy to rigorously model the selection process of UIP. On one hand, we further addressing the endogeneity problem of non-random allocation, and on the other hand, we leverage the property of instruments to investigate the intrinsic logic behind the mechanisms discussed previously.

Regarding the issue of non-random allocation, 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[38]. 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.6, 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 instrumental variables.

The first is the inherent cultural characteristics of a city. 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 subsidiary 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. According to our theory, 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 post offices 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. Operationally, we further interact these with time trends to allow for changes over time.

Regarding exogeneity, 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

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

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.9). Finally, it's reasonable to assume that the adoption of UIP is closely related to the instrumental variables, as Figure 3 shows, where all three instrumental variables demonstrate potential geographical correlations with the actual distribution of UIP.

As shown in Table D.8, the instruments are significantly correlated with the adoption of UIP, evidenced by sufficiently high first-stage F-statistics. Concurrently, Table 2 provides the second-stage results of our IV specification, with the Wald test p-values nearing zero, except for columns 8-9. From columns 1-3, we observe that using dialect similarity as an instrument, UIP significantly enhances both the extensive and intensive margins, yet the impact of knowledge diffusion is considerably stronger. This underscores that beyond the previously mentioned governmental actions, local protectionism determined by historical culture exerts a significant influence on changes in firms' TFP. Additionally, the findings suggest that if the collapse of local protectionism triggered by UIP is driven by cultural factors, then TFP growth is primarily facilitated through knowledge diffusion channels, with changes in the composition of firms playing a secondary role. Columns 4-9 indicate that if the own trade conditions (or with higher firm's productivity compositions) are more favorable before the adoption of UIP, the knowledge diffusion channels on the intensive margin of UIP find it challenging to be effective (as in columns 5-6 and 8-9), but the reduction in local protectionism brought about by UIP becomes the leading mechanism for TFP growth through favorable changes in firm composition (columns 4 and 7). These pieces of evidence profoundly illustrate the relative importance and sources of shifts in firm composition and knowledge diffusion channels on firms' productivity across different regional trade conditions.

8 Further Analysis

Up to this point, we have substantially verified several principal propositions posited by our model—that UIP fosters TFP growth under regional trade conditions. Specifically, it dismantles local protectionism and fosters regional trade expansion, thus primarily promoting firm-level TFP through the intensive margin (imitation innovation) effects of regional trade, and elevating the aggregate TFP by changing firm compositions to higher levels through extensive margin effects. In this section, our objective is to explore how these mechanisms can address some unresolved issues in trade model as highlighted by Akcigit and Melitz (2022); Melitz and Redding (2023); Bai, Jin and Lu (2019), including: Who benefits more from regional trade, the lagging parties? Does comparative advantage play a role? Are there any other explanations associated with TFP growth? Based on this, we provided quantification of the economic consequence of UIP.

8.1 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 4A and 4B 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) [39]. 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 4C). This implies a transference of secondary industries from core to peripheral cities[40]. 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.

[39] Drawing upon the core-periphery theory posited by Friedmann (1966), regional economic growth unfolds alongside spatial imbalances in the economic system, distinguishing between core and peripheral zones within the regional economy. This paradigm underscores the rapid industrial ascendancy initially observed in core cities, followed by an industrial migration towards peripheral cities.

[40] 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.

Thirdly, concerning the intensive margin: We find that the extent to which UIP constrains patent activity in core city firms substantially outweighs its impact in peripheral cities (Appendix E, Table E.4). Taken together, this aligns with the hypothesis that firms in core cities, exhibiting higher TFP and a greater reliance on independent innovation, are more adversely affected by subsidy reductions, in contrast to enterprises in peripheral cities which primarily enhance their total factor productivity through imitative innovation.

Synthesizing the evidence at hand, we can address which entities derive greater benefit from regional trade expansion: on one hand, firms of participants with a lower average productivity level can drive an overall productivity increase through imitation-driven innovation when intensive marginal effects of knowledge diffusion are present; on the other hand, under the extensive marginal effects of regional trade, firms are incentivized to transition from advanced to latecomer entities, attracted by the more favorable production conditions of the latter cities, and in this process, the lower productivity firms phase out, thereby stimulating an overall elevation in aggregate productivity.

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

The role of comparative advantage in economic welfare remains a point of contention, with economic models predicting that regional specialization according to comparative advantage could lead to static welfare losses (Lucas, 1988), potentially secure static welfare benefits at the expense of dynamic welfare (Young, 1991), or possibly yield benefits in dynamic welfare (Lucas, 1993). The objective of this section is to address this issue[41]. As Melitz and Redding (2023) points out, if comparative advantage influences productivity through endogenous innovation, that is, through learning effects of knowledge spillover, trade could potentially lead to rapid growth similar to South Korea after the 1960s.

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 (intensive margin effects) and the shifting composition of firms (extensive margin effects). 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 indicates that UIP primarily foster TFP growth in local industries with Revealed Comparative Advantage (RCA industries, as illustrated in Figure 4D). Building upon this base, several corresponding outcomes help explain this phenomenon. As depicted in Figure 4E, industries that align with comparative advantage have led the surge in output, sales, and profit growth in the wake of regional trade expansion. This trend corroborates the hypothesis that comparative advantage-driven trade benefits industries conforming to local strengths, suggesting they gain disproportionately from regional trade dynamics. Thus, regional trade helps shape industries towards development in alignment with local comparative advantages.

Therefore, columns 10-12 in Table 7 provide further evidence, reinforcing the notion that RCA firms

[41] It is noteworthy that although comparative advantage commands considerable attention, our theoretical model simplifies the heterogeneity of comparative advantage across sectors. This is because the model by Bernard, Redding and Schott (2007) has already tackled this aspect, and our core predictions are consistent with theirs. Hence, our model focus is solely on elucidating the factors most pertinent to the shifts in the distribution of TFP.

are less likely to relocate to other markets, but are more likely to enter and exit markets compared to NRCA firms. This finding is consistent with the extensive margin effects associated with UIP, suggesting that regional trade plays a crucial role in shaping the industry's development towards RCA sectors. In this process, intense competition within RCA industries prompts less productive firms to exit, thereby sustaining the long-term trend of TFP growth.

In term of innovation activities, Table 6, columns (1), (5), and (6) show that although overall patent activity decreases, RCA industries reduce their patent activities insignificantly, and patent quality remains unaffected by comparative advantage. This negative aspect highlights the pattern observed earlier, where knowledge spillover effects stimulate TFP growth. However, a notable distinction is that RCA industries seem to engage more in independent innovation activities, which may be related to the competition avoidance mechanism to be mentioned later, potentially serving as a source of long-term TFP growth.

To recapitulate, our analysis illustrates the pivotal role of comparative advantage in shaping the dynamic welfare gains from regional trade. Specifically, industries that align with local comparative advantages are spearheading TFP growth due to knowledge diffusion's spillover effects and a stronger incentive for independent innovation. Concurrently, this growth is propelled by a continuous industry realignment towards sectors that align with comparative advantages, spurred by changes in the composition of firms.

8.3 Alternative Explanations And Discussions

Besides the issues previously discussed, on one hand, trade theory accentuates the role of market size and competition in shaping the dynamics of welfare growth through innovation, yet their effects 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 and Competition: 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 and competition under regional trade help illuminate the heterogeneous long-term growth of TFP. As demonstrated by Melitz and Redding (2023); Akcigit and Melitz (2022), on one hand, the expansion of market size allows firms to more broadly distribute the fixed costs of innovation, thereby encouraging innovation incentives. On the other hand, the impact of intensified competition on innovation incentives is ambiguous and may either weaken innovation incentives (by reducing expected future profits) or strengthen them (as a strategy to avoid competition, following Schumpeter's approach). Below, we will explain how the dynamics of TFP respond to these two assumptions.

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.4). 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.

Indeed, the competition mechanism exhibits heterogeneous effects on firms' innovation incentives. As shown in Appendix E, Table E.3 indicates that only RCA industries experience a decrease in markup[42]. Consequently, we find that UIP does not significantly suppress patent activities in RCA industries (see Table 6, columns 5-6). This suggests that despite a reduction in innovation incentives due to decreased subsidies, the intensifying competition encourages innovators within RCA industries to actively seek patents as a means to circumvent competition. Therefore, this also implies that the more significant TFP growth observed in RCA industries may either be attributed to their relatively higher levels of innovation activity, or that the disclosure of patents has facilitated easier imitation by follower firms within these industries.

In summary, we have once again demonstrated the crucial role of imitative innovation in fostering the growth of TFP. Simultaneously, as documented by the assumptions regarding market size and competition, we indeed find that innovation incentives at the city and industry levels are affected to varying degrees, thereby further explaining the observed heterogeneity in long-term productivity dynamics between core-periphery and RCA-NRCA industries. Despite a reduction in patent activity, it is much less pronounced in peripheral cities and RCA industries. Thus, this targeted imitative-innovation dynamic enables the possibility of long-term TFP growth.

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 4G - 4J demonstrates that under the influence of UIP, firms with higher TFP levels are

[42] This is due to UIP making the dynamics of firms within RCA industries more active, thereby intensifying internal competition within these industries.

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.[43]

In essence, when combined with previous evidence, these findings reveal the comprehensive picture of resource allocation under the influence of UIP. Specifically, under UIP, resources naturally gravitate towards firms with sustainable growth potential—as competition intensifies and subsidies decrease, these firms are more likely to survive the escalating competition. Consequently, high-productivity, non-zombie firms within industries that have comparative advantages and do not rely on subsidies gain more resources during this process, thereby driving an increase in overall productivity.

8.4 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[44]. This arises from a directional shift in firm composition, indicating a transition of the industrial structure towards a stable growth path characterized by specialization[45]. (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: Firstly, we consider the quasi-natural experiment estimation method of TFP growth under capital misallocation studied by Sraer and Thesmar (2023). This method quantifies policy effects on aggregated TFP growth through alleviating resource misallocation, considering general equilibrium effects. Secondly, our approach leverages the strengths of our firm-level data. We also back-of-the-envelope the growth of aggregation TFP simply using the coefficients from the reduced form regression. Although this method assumes stronger assumptions regarding general equilibrium effects and overlooks changes in the market environment, it is capable of capturing the growth in firm-level TFP under the imitation innovation mechanism at the intensive margin.

Scale up under general equilibrium effects

According to the modeling and rigorous proof by Sraer and Thesmar (2023), variations in TFP associated with capital reallocation can be determined by examining the distribution of Log-MRPK,

[43] 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.

[44] 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.

[45] This refers to industries evolving towards comparative advantages and firm compositions moving towards less distortion.

the ratio of industry value-added to the capital stock in log. A detailed explanation of this method can be found in Appendix G.

$$
\begin{aligned}
\Delta \log(a) \approx & \underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1,c=1}^{S,C} Cap\%_{s,c}\Delta\widehat{\Delta\sigma^2(s},c)}_{-5.64\%} \\
& \underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1,c=1}^{S,C}(Sale\%_{s,c}-Cap\%_{s,c})\left(\Delta\widehat{\Delta\mu(s},c)+\Delta\Delta\widehat{\varsigma_{logMRPK,logValueAdd}}(s,c)+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\Delta\widehat{\Delta\sigma^2(s},c)\right)}_{7.64\%} \\
& \approx 2\%
\end{aligned}
\tag{16}
$$

The results, as demonstrated in Equation 16, 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, suppressing it by 5.64%.

Scale up based on in-sample inference

Benefit from our access to the universe of Chinese firms, we conduct a back-of-the-envelope calculation, assuming that the control group and the treatment group are strictly isolated, disregarding the potential general equilibrium effects caused by interactions between them, to directly estimate the contribution of UIP to TFP growth. Given that both the treatment and control groups of firms had equivalent productivity levels in 2003[46], 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. Initially, the UIP facilitated the dissolution of local protectionism, as evidenced by the reduction in government subsidies and increased land market transparency, followed by extensive investment flows among cooperative cities. Although the reduction in subsidies generally decreased the capital stock accumulation of firms, under the competitive pressures of trade, the industries in core and peripheral cities continued to develop according to their comparative advantages, reflecting the cross-sectoral reallocation

[46]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.

of capital resources[47]. This reallocates resources preferentially to companies with potential for long-term productivity growth[48]. This pattern is amplified under general equilibrium effects, leading to the conclusion that cross-sectoral reallocation is a driver of productivity enhancement. Furthermore, if we consider the impact of both intensive and extensive margins, that is, based on reduced-form coefficients and within-sample structural characteristics, the overall magnitude of productivity growth reaches 11.9%, underscoring the significant economic implications of the UIP for China's productivity. It is noteworthy that the capital reallocation we observed promoting total productivity aligns with the predictions noted by Hsieh and Klenow (2009), reflecting two implications: 1. The method of Sraer and Thesmar (2023) demonstrates strong accuracy in assessing the impact of resource reallocation on productivity. 2. The increase in productivity is indeed not primarily due to changes in the composition of firms on the extensive margin, but stems from the intensive margin effects of knowledge diffusion.

9 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

[47] Clearly, this reallocation pattern was driven by knowledge diffusion mechanisms, as firms could enhance efficiency through imitation and benefit from product transactions, especially when organized in regions with lower production costs.

[48] On one hand, this refers to so-called non-zombie firms and those that can thrive without subsidies. On the other hand, it also refers to firms with strong imitation innovation capabilities, such as industries with high technological consistency with core cities.

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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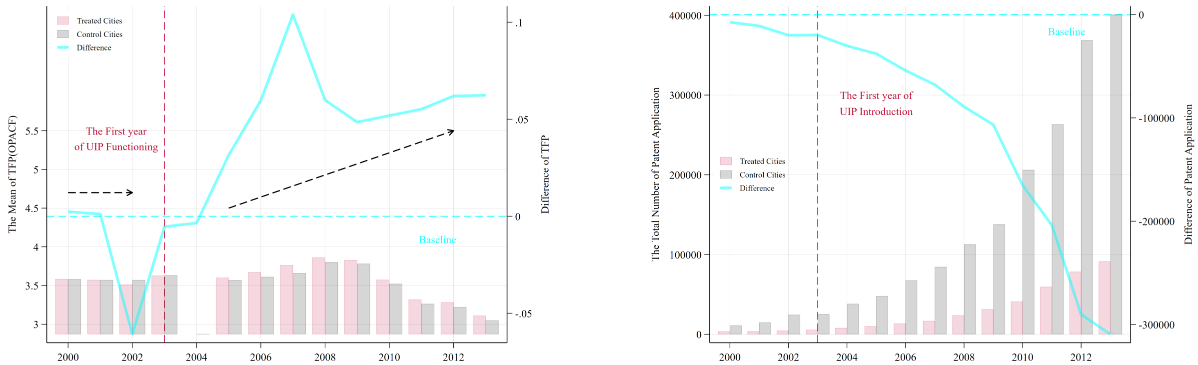
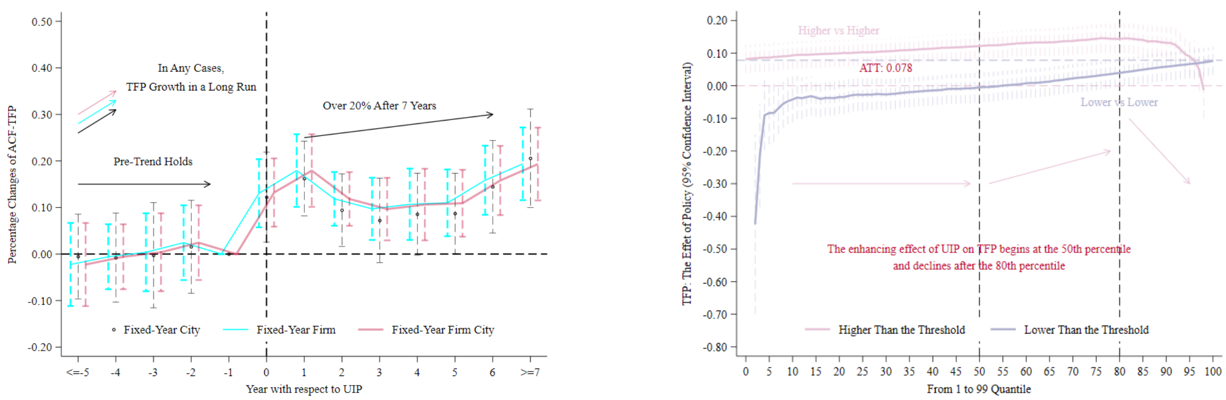


A. TFP

B. Patent Activities

Figure 1: Stylized Facts Under UIP: Motivation

Notes: The objective of these figures is to establish the primary insights regarding the economic impact of the UIP, specifically focusing on TFP and patent activities. We depict the annual trends in firm's TFP, measured by the OPACF method, for both the treatment cities and the control group.

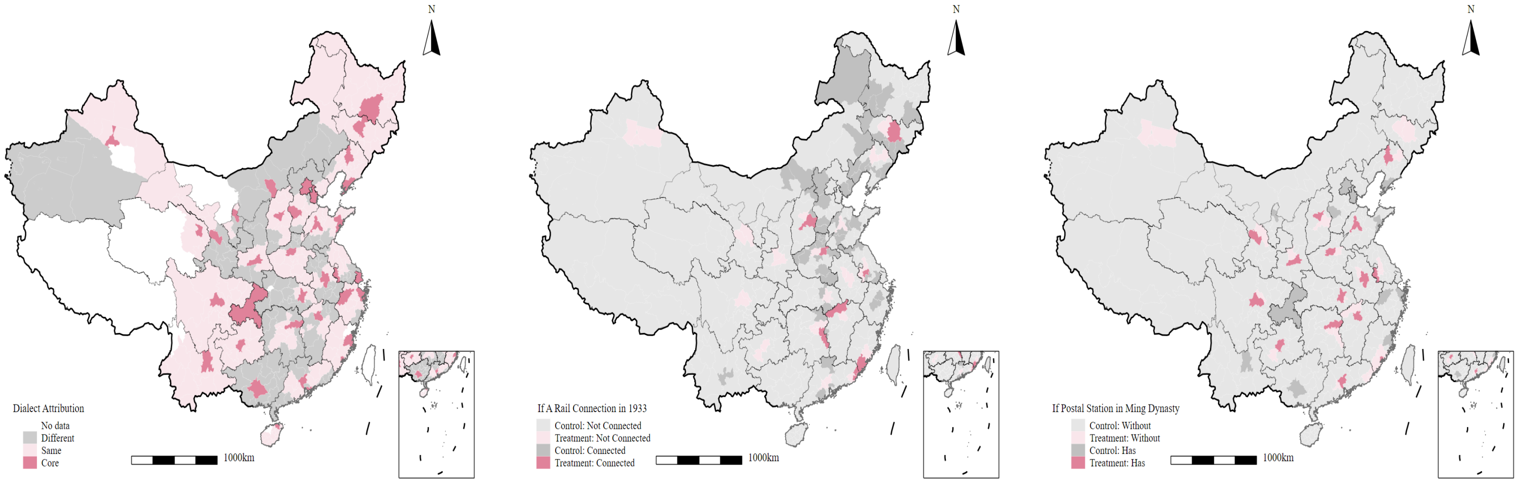


A. Pre-Trend Parallel and Dynamic

B. TFP: Grouped by TFP Quantile

Figure 2: Pre-trend Parallel and TFP Quantile

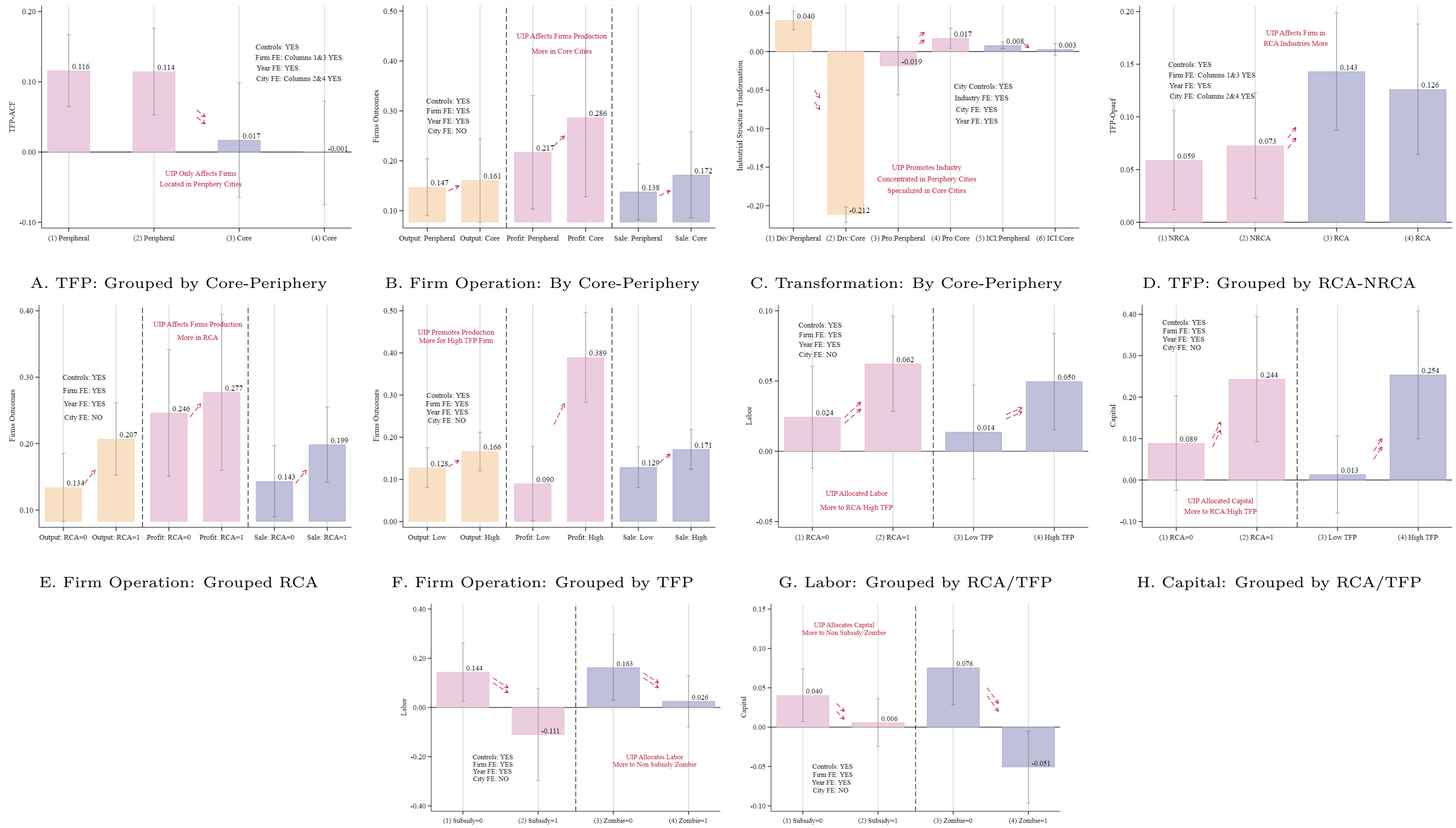
Notes: For Panel A, the event study-style analysis examines the relationship between UIP and a firm's TFP, corresponding to Columns (1)-(3) in Table 1. The panel is used for the dependent variable employing the ACF method, and we adopted three specifications by adding different permutations and combinations of year, firm, and city fixed effects. For Panel B, the graph displays the regression results of using UIP on TFP as dependent variables, split by TFP percentile at the year - city level, select each 9 percentile from 10 to 90. The red line represents comparisons below the percentile threshold, while the black line represents comparisons above the percentile threshold. The red line corresponds to the right axis, and the black line corresponds to the left axis.



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

Figure 3: 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.



A. TFP: Grouped by Core-Periphery B. Firm Operation: By Core-Periphery C. Transformation: By Core-Periphery D. TFP: Grouped by RCA-NRCA

E. Firm Operation: Grouped RCA F. Firm Operation: Grouped by TFP G. Labor: Grouped by RCA/TFP H. Capital: Grouped by RCA/TFP

I. Labor: Grouped by Subsidy/Zombie J. Capital: Grouped by Subsidy/Zombie

Figure 4: Cross-sectional Results

Notes: The table demonstrates a cross-sectional examination of firms' TFP, operational metrics, production factor, and industiral structure, segmented into RCA-NRCA industries, firm property, Subsidized/zombie firm or not, and High-TFP -Low-TFP firms. 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, we introduce the measurement strategies and dynamic effect for all variables.

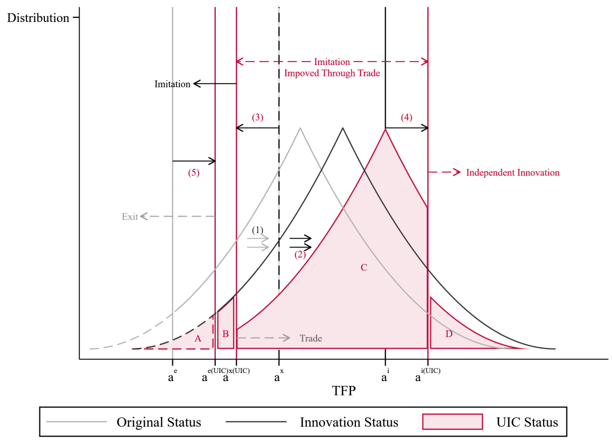


Figure 5: Comparative Static

Notes: Comparative static for explaining the implications and variations in our theoretical model in Section . 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. Contrasted with 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: Estimates of the Impact of UIP on a Firm's TFP

	Panel A: Universe of Industrial Firm		
	(1)	(2)	(3)
Dependent Variable		TFP-Opacf	
UIP	0.081***	0.078***	0.078***
	(0.024)	(0.022)	(0.022)
Observations	2640726	2485219	2485219
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 (14). 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. In Appendix B, we introduce the measurement strategies for all variables.

Table 2: IV-2SLS Estimation - Second Stage

	Second Stage: TFP								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	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 second-stage results, and the dependent variable employed is the ACF method, respectively. We report the p-value of the Anderson Rubin test for the coefficient on Dum being zero. 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 B and Appendix D, we introduce the measurement strategies and dynamic effect for all variables.

Table 3: UIP on Local Protectionism

	Panel A: Universe of Industrial Firm				Panel B: Universe of Business Registrations				Panel C: City Panel					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Subsidy	Zombie	TFP	TFP	OCIP	OCIP(%)	OP	OP(%)	PI	PV	Speed	Length	Speed	Length
UIP	-0.160***	-0.005**	0.041	0.042	1.155***	0.003***	0.388	0.000	0.045***	0.107***	20.545**	130.875***	-1.811	13.513
	(0.059)	(0.002)	(0.035)	(0.037)	(0.364)	(0.001)	(0.569)	(0.002)	(0.014)	(0.033)	(8.486)	(41.963)	(4.806)	(26.864)
UIP×IP			-0.091***	-0.087***										
			(0.032)	(0.032)										
UIP×Co-Line													45.712***	435.841**
													(11.415)	(170.234)
Observations	2055003	2640726	1543626	1543626	11144252	11137582	11144252	11137582	2917	3595	3606	3606	3606	3606
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Control	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Notes: The table represents an OLS estimation of the relationship between UIP and local protectionism, focusing on three dimensions of local protectionism, namely, firms, investment, and cities. Columns 1-2 pertain to the firm dimension, with the dependent variables measuring firms' subsidy income and the probability of zombification (defined as firms with negative profits for three consecutive years). Columns 3-4 show the heterogeneity of UIP on TFP based on whether firms supported by provincial industry policies. As we can only observe the policy after 2006, we use the waves from 2006 to 2013, and only keep the treated cities adopted UIP over 2006. Column 3 focuses on the main industry policy, while column 4 regarded a industry to be supported if the government working report positively mentioned the industry. Columns 5-8 relate to the investment dimension, with the dependent variables representing the amount or proportion of investment received by firms from different non-local attributes, including investment from outside the home city within the province (OCIP) and its proportion (OCIP%), and investment from outside the home province (OP) and its proportion (OP%). Columns 9-12 pertain to the city dimension, with dependent variables measuring government public investment, urban personnel mobility, The Speed of High-speed Rail and Length of High-speed Rail Line. In Columns 13 - 14, we further add the interaction term of Co-line (Whether the line to be built includes at least one UIP cluster) with UIP, while controlling for corresponding constituent terms. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. For the three dimensions, standard errors are clustered at the city-year level. In Appendix B and Appendix D, we introduce the measurement strategies and dynamic effect for all variables. In Appendix H, we provided alternative measurement strategies for the above-mentioned outcomes.

Table 4: UIP on Market Expansion and Regional Trade

	Panel A: Universe of Industrial Firm										Panel D: Custom Panel	
	(1) Sale	(2) Profit	(3) Output	(4) Selling Cost	(5) Unit Cost	(6) Unit ad	(7) Output	(8) Output	(9) Output	(10) Markup	(11) Export	(12) Import
UIP	0.160***	0.263***	0.156***	0.174***	0.006	0.054*	-0.539***	0.214***	0.170***	-0.030**	0.092*	-0.333***
	(0.025)	(0.047)	(0.024)	(0.027)	(0.028)	(0.028)	(0.165)	(0.027)	(0.027)	(0.013)	(0.053)	(0.053)
UIP×Distance of Port							0.061***					
							(0.015)					
UIP×If Exportor								-0.214***				
								(0.025)				
UIP×If Located at Coastline									-0.091**			
									(0.038)			
Observations	2387430	2089293	2387459	2485113	995387	114346	2382943	2387459	2386875	2427134	728087	728087
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
City FE												
Firm FE	X	X	X	X	X	X	X	X	X	X	X	X
Control	X	X	X	X	X	X	X	X	X	X	X	X

Notes: The table presents OLS estimates for UIP in relation to market expansion and competition. The dependent variables in columns 1-6 are the firm's sales, profits, output, selling cost, production cost, and unit ad cost respectively. For unit costs, our data only permits observations from the years 2000 to 2006. As for advertising expenditures, the data available covers only a subset of samples from 2004 to 2007, and we exclude those treatment groups that were treated prior to 2004. Therefore, we interpret these findings as suggestive evidence. The dependent variables in columns 7-9 are the firm's output, using the distance to the nearest port, whether the firm is exporter, and whether the firm is located in coastline as interaction terms, while controlling for all constituent terms. The dependent variables in column 10 is firm's markup, measured followed the method suggested by Gandhi, Navarro and Rivers (2020). The dependent variables in columns 11-12 are the firm's exports and imports, respectively. All time-varying variables are represented in log values, and ***, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. For these three dimensions, standard errors are clustered at the city-year level. In Appendix B and Appendix D, we introduce the measurement strategies and dynamic effect for all variables.

Table 5: UIP on Imitative Innovation

	Panel E: Universe of Industrial Firm & Chinese Patent							Panel F: Universe of Judicial Document		
	(1) TFP	(2) TFP	(3) TFP	(4) Patent	(5) TFP	(6) Patent	(7) TFP	(8) Total Lawsuit	(9) Patent Lawsuit	(10) Right Lawsuit
UIP	0.060**	0.083***	0.066***	-0.176**	0.066***	-0.182*	0.049*	-569.756	-1.725	-28.293
	(0.024)	(0.024)	(0.023)	(0.069)	(0.024)	(0.100)	(0.027)	(528.389)	(1.721)	(25.312)
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×Patent Right Risk				-0.908***	0.087*					
				(0.248)	(0.047)					
UIP×High Spillover						-0.262**	0.079**			
						(0.120)	(0.032)			
Observations	2485219	2485219	2485219	3348418	2485219	3348418	2485219	1774	1774	1774
Year FE	X	X	X	X	X	X	X	X	X	X
City FE								X	X	X
Firm FE	X	X	X	X	X	X	X			
Control	X	X	X	X	X	X	X	X	X	X

Notes: The following table presents the estimates of the impact on imitation innovation. In columns 1-2, we include interaction terms to assess if a firm is situated within an industry where the quantity of invention patent applications or the quality of patents surpasses the 80th percentile for that city in the given year. In columns 3-4, interaction terms are added to evaluate whether a city is more susceptible to infringement risks (cities with a patent-related litigation count exceeding the mean are coded as 1, and those below as 0). Consistency with these findings is seen in robustness checks presented in Appendix Appendix H, which focus on ownership. In columns 5-6, we further include interaction terms to reflect on whether firms belong to industries more likely to be influenced by the innovation spillover effects emanating from their core cities. Columns 7-9 employ UIP to regress on the total number of litigations at the city level, patent-related litigations, and ownership-related litigations. All control variables for the interaction and time-variant aspects are represented in logarithmic forms. The significance levels of ***, **, and * correspond to 0.01, 0.05, and 0.1, respectively. For Panel E and F, standard errors are clustered at the city-year level. Measurement strategies and the dynamic effects of all variables are discussed in Appendix B and Appendix D, respectively. Alternative measurement strategies for the interaction terms mentioned above are provided in Appendix H.

Table 6: UIP on Firm's Innovation

	Panel E: Universe of Industrial Firm & Chinese Patent Innovation								Panel J: Universe of Patent Transfer	
	(1) Patent	(2) Quality	(3) Patent	(4) Quality	(5) Patent	(6) Quality	(7) Relabeling	(8) R&D	(9) Non Local - Inside	(10) Non Local - Outside
UIP	-0.335***	-0.003	-2.191***	-0.040***	-0.447***	-0.003	-0.062***	0.064***	0.017***	-0.027***
	(0.118)	(0.002)	(0.263)	(0.004)	(0.119)	(0.002)	(0.020)	(0.024)	(0.004)	(0.007)
UIP×TFP			0.517***	0.010***						
			(0.080)	(0.001)						
UIP×RCA					0.397***	-0.003				
					(0.107)	(0.002)				
Observations	2485219	2485219	2485219	2485219	2485219	2485219	2371520	711412	98474	98474
Year FE	X	X	X	X	X	X	X	X	X	X
City FE									X	X
Firm FE	X	X	X	X	X	X	X	X		
Receiver City FE									X	X
Control	X	X	X	X	X	X	X	X	X	X

Notes: The table provides OLS estimates for the relationship between UIP and firm innovation. In columns 1-2, the dependent variables measure the number of patent applications by the firm and the breadth of knowledge as measured by the knowledge breadth method, respectively. Columns 2-6 further include interaction terms with the firm's TFP (Opacf) and whether the firm is located in an RCA industry, while controlling for corresponding constituent terms. In column 7, we reference Chen et al. (2021) and use the ratio of administrative expenses to sales expenses as a proxy for the firm's efforts to reclassify expenditures as R&D investments. In column 8, we provide suggestive evidence by using the observable corporate R&D investments from 2005 to 2007 as the dependent variable, and we exclude those treatment groups that were treated prior to 2005. Columns 9-10 are the non local intra-province patent transfer and patent transfer to the outside province as the dependent variables, respectively. All time-varying variables are represented in log values. ***, **, * 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 and Appendix D, we introduce the measurement strategies and dynamic effect for all variables.

Table 7: UIP on Firm's Location

	Panel B: Business Registrations			Panel G: Universe of Industrial Firm & Business Registrations								
	(1) Enter Rate	(2) Exit Rate	(3) Transfer Rate	(4) Enter	(5) Exit	(6) Transfer	(7) Enter	(8) Exit	(9) Transfer	(10) Enter	(11) Exit	(12) Transfer
UIP	0.192*	-1.502***	-0.003	-0.007***	0.005	0.002*	-0.029***	0.006**	0.009	-0.009***	0.001	0.003*
	(0.115)	(0.349)	(0.005)	(0.002)	(0.004)	(0.001)	(0.006)	(0.002)	(0.007)	(0.002)	(0.005)	(0.001)
UIP×ACF							0.008***	-0.001**	-0.002			
							(0.001)	(0.001)	(0.002)			
UIP×RCA										0.007***	0.014**	-0.002**
										(0.002)	(0.006)	(0.001)
Observations	3292934	3292934	3292934	2640726	2229559	2229844	2485219	2102425	2102533	2640726	2229559	2229844
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X				X	X	X
Firm FE							X	X	X			
Control	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table provides an OLS estimation of the relationship between UIP and the company's location. In columns 1, 4, 7, 10 the dependent variable measures whether the company enters the market; columns 2, 5, 8, 11 measure whether the company exits the market in the following year; columns 3, 6, 9, 12 measure whether the company relocates to another city in the following year. Columns 1-3 dependent variables adopted a county level measurement. In columns 7-9, we have added a series of interaction terms related to the company's TFP (Opacf), and columns 10-12 include a series of interaction terms related to RCA. All time-varying variables are represented in log values, and we further control for any relevant interaction terms. ***, **, 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 and Appendix D, we introduce the measurement strategies and dynamic effect for all variables.

Online Appendix - Not For Publication

E Pluribus Unum: Growing TFP From Regional Trade

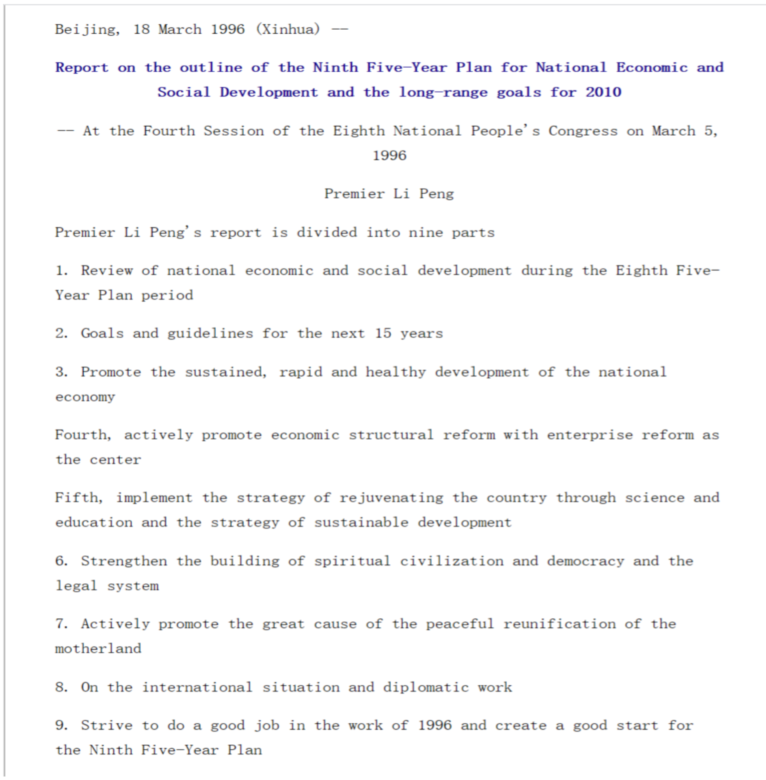
By Weizhe Aaron Wang, Zhong Zhao, Xianqiang Zou

In this appendix, we present additional information and figures which we can refer to but do not include in the paper's main text.

Contents

A Appendix A: The Information Related to UIP

A.1 Historical Background of UIP - Five-Year Plan



Beijing, 18 March 1996 (Xinhua) --

Report on the outline of the Ninth Five-Year Plan for National Economic and Social Development and the long-range goals for 2010

-- At the Fourth Session of the Eighth National People's Congress on March 5, 1996

Premier Li Peng

Premier Li Peng's report is divided into nine parts

1. Review of national economic and social development during the Eighth Five-Year Plan period

2. Goals and guidelines for the next 15 years

3. Promote the sustained, rapid and healthy development of the national economy

Fourth, actively promote economic structural reform with enterprise reform as the center

Fifth, implement the strategy of rejuvenating the country through science and education and the strategy of sustainable development

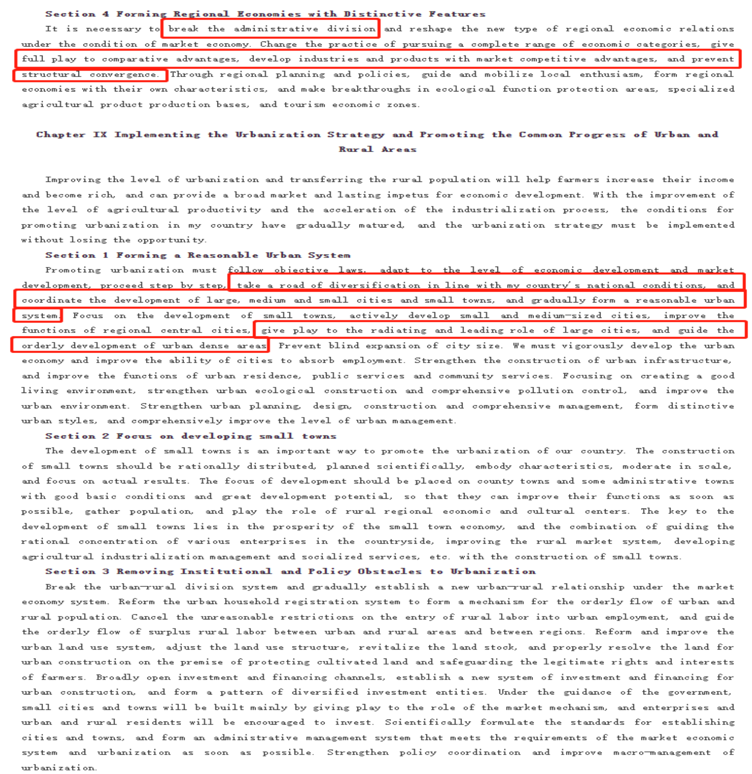
6. Strengthen the building of spiritual civilization and democracy and the legal system

7. Actively promote the great cause of the peaceful reunification of the motherland

8. On the international situation and diplomatic work

9. Strive to do a good job in the work of 1996 and create a good start for the Ninth Five-Year Plan

A. 9th Five-Year Plan



Section 4 Forming Regional Economies with Distinctive Features

It is necessary to break the administrative division and reshape the new type of regional economic relations under the condition of market economy. Change the practice of pursuing a complete range of economic categories, give full play to comparative advantages, develop industries and products with market competitive advantages, and prevent structural convergence. Through regional planning and policies, guide and mobilize local enthusiasm, form regional economies with their own characteristics, and make breakthroughs in ecological function protection areas, specialized agricultural product production bases, and tourism economic zones.

Chapter IX Implementing the Urbanization Strategy and Promoting the Common Progress of Urban and Rural Areas

Improving the level of urbanization and transferring the rural population will help farmers increase their income and become rich, and can provide a broad market and lasting impetus for economic development. With the improvement of the level of agricultural productivity and the acceleration of the industrialization process, the conditions for promoting urbanization in my country have gradually matured, and the urbanization strategy must be implemented without losing the opportunity.

Section 1 Forming a Reasonable Urban System

Promoting urbanization must follow objective laws, adapt to the level of economic development and market development, proceed step by step, take a road of diversification in line with my country's national conditions, and coordinate the development of large, medium and small cities and small towns, and gradually form a reasonable urban system. Focus on the development of small towns, actively develop small and medium-sized cities, improve the functions of regional central cities, give play to the radiating and leading role of large cities, and guide the orderly development of urban dense areas. Prevent blind expansion of city size. We must vigorously develop the urban economy and improve the ability of cities to absorb employment. Strengthen the construction of urban infrastructure, and improve the functions of urban residence, public services and community services. Focusing on creating a good living environment, strengthen urban ecological construction and comprehensive pollution control, and improve the urban environment. Strengthen urban planning, design, construction and comprehensive management, form distinctive urban styles, and comprehensively improve the level of urban management.

Section 2 Focus on developing small towns

The development of small towns is an important way to promote the urbanization of our country. The construction of small towns should be rationally distributed, planned scientifically, embody characteristics, moderate in scale, and focus on actual results. The focus of development should be placed on county towns and some administrative towns with good basic conditions and great development potential, so that they can improve their functions as soon as possible, gather population, and play the role of rural regional economic and cultural centers. The key to the development of small towns lies in the prosperity of the small town economy, and the combination of guiding the rational concentration of various enterprises in the countryside, improving the rural market system, developing agricultural industrialization management and socialized services, etc. with the construction of small towns.

Section 3 Removing Institutional and Policy Obstacles to Urbanization

Break the urban-rural division system and gradually establish a new urban-rural relationship under the market economy system. Reform the urban household registration system to form a mechanism for the orderly flow of urban and rural population. Cancel the unreasonable restrictions on the entry of rural labor into urban employment, and guide the orderly flow of surplus rural labor between urban and rural areas and between regions. Reform and improve the urban land use system, adjust the land use structure, revitalize the land stock, and properly resolve the land for urban construction on the premise of protecting cultivated land and safeguarding the legitimate rights and interests of farmers. Broadly open investment and financing channels, establish a new system of investment and financing for urban construction, and form a pattern of diversified investment entities. Under the guidance of the government, small cities and towns will be built mainly by giving play to the role of the market mechanism, and enterprises and urban and rural residents will be encouraged to invest. Scientifically formulate the standards for establishing cities and towns, and form an administrative management system that meets the requirements of the market economic system and urbanization as soon as possible. Strengthen policy coordination and improve macro-management of urbanization.

B. 10th Five-Year Plan

Figure A.1: Five-Year Plan

A.2 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.3 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

Table A.1 Continued from previous page

Contract	Time	Cities	Province	Legitimacy Endorsing Authority	Strategic Target
					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 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[49]. Further, we also manually collected the construction details of high-speed railway in China [50], 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.

[49]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.

[50]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.

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

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 [51] 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 Chinese Industrial Enterprise

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).

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

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.

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[52].

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.

[52]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.

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):

$$\begin{aligned} LQ_{dct} &= \frac{\text{output }_{\text{dct}} / \text{ output }_{ct}}{\text{output }_{dt} / \text{ output }_{t}} \\ RCA_{\text{idct}} &= I\left(LQ_{dct} >= mean(LQ_{dct})\right) \end{aligned} \tag{17}$$

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:

$$ICI_{dct} = \frac{insh_{dct}}{insh_{dpt}} \tag{18}$$

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.

$$pro_{dct} = \frac{\frac{lab_{dct}}{lab_{ct}}}{\frac{lab_{dt}}{lab_{t}}} \tag{19}$$

$$\text{div}_{dct} = \frac{1/\sum_{d^1 \neq d}\left(\frac{lab_{d^1ct}}{lab_{ct}-lab_{dct}}\right)^2}{1/\sum_{d^1 \neq d}\left(\frac{lab_{d^1t}}{lab_{t}-lab_{dt}}\right)^2} \tag{20}$$

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.[53]

[53] 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.

Furthermore, Figure C.1 displays the geographical distribution of firms for which we can observe productivity, as well as the locations of the treatment group. It is evident that, although the distribution of firms remains consistent over the years, what changes is the density of these firms. The positioning of the treatment group is also uniform, implying a suitable basis for comparison.

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.

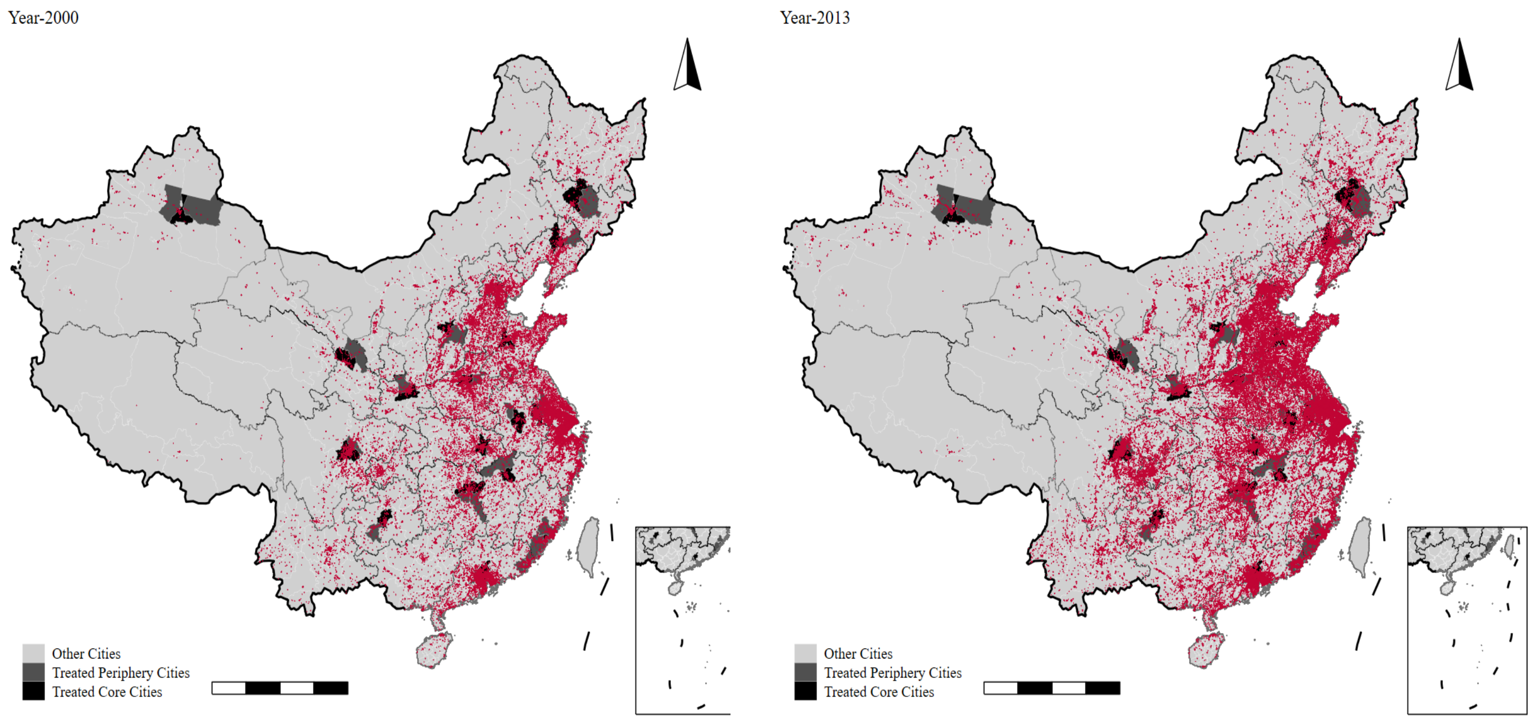
C.4 Covariate Balance Between Treatment and Control Cities

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.

C.5 Firm Location Landscape



A. Year: 2000

B. Year: 2013

Figure C.1: Firm Location Landscape

Notes: These images depict the geographical distribution of industrial firms from 2000 to 2013. In general, industrial firms are widely dispersed across all regions. Beyond the cities that pique our interest as treated entities, industrial firms have proliferated extensively in other cities. These characteristics furnish us with ideal conditions for estimating the impact of UIP on TFP, as we can identify analogous control firms for virtually every firm within the potential outcome framework.

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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Lp	Op	Gandhi	Lp	Op	Gandhi	Lp	Op	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.

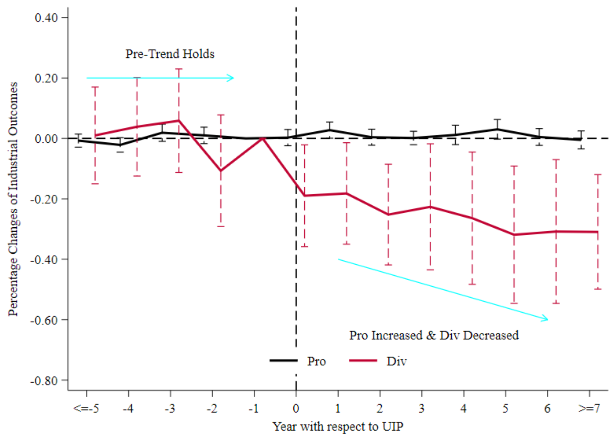
Table D.2: Regression Results: Alternative Control Variables and FE

	Panel A: Universe of Industrial Firm					
	(1)	(2)	(3)	(4)	(5)	(6)
	TFP-ACF					
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

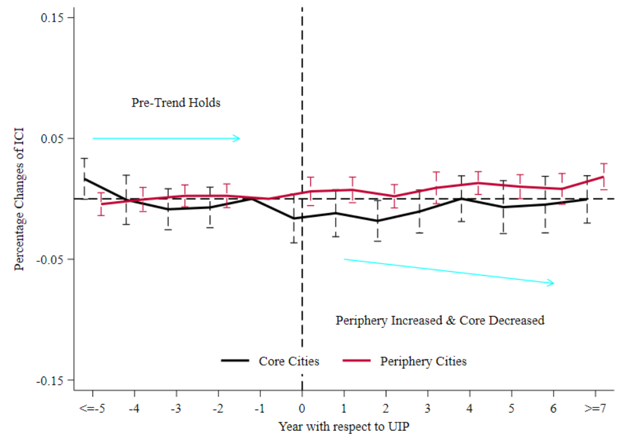
Notes: This table demonstrates a robustness check for regression using different specifications with the ACF method as the TFP measure. For columns 1-2, we attempt to include province-time dimension fixed effects; for columns 3-4, we attempt to include other pre-determined control variables at the city 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 Parallel For All Results Corresponding to the Main Text

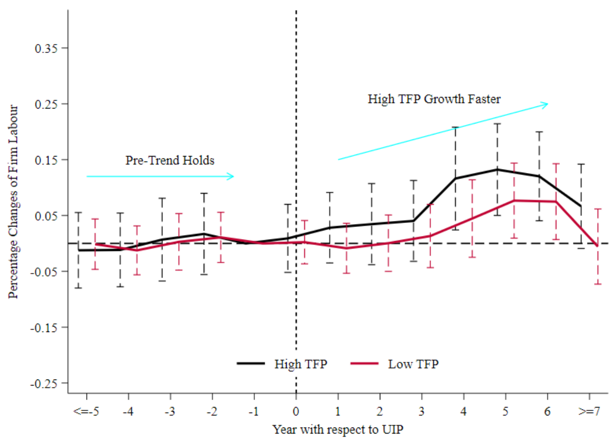
In order to ensure that all the estimated outcome variables, along with all the groups used for comparison, satisfy the assumption of parallel trends, thereby deriving results with causal interpretations, we conducted thorough examinations of parallel trends and dynamic effects across all regressions 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.



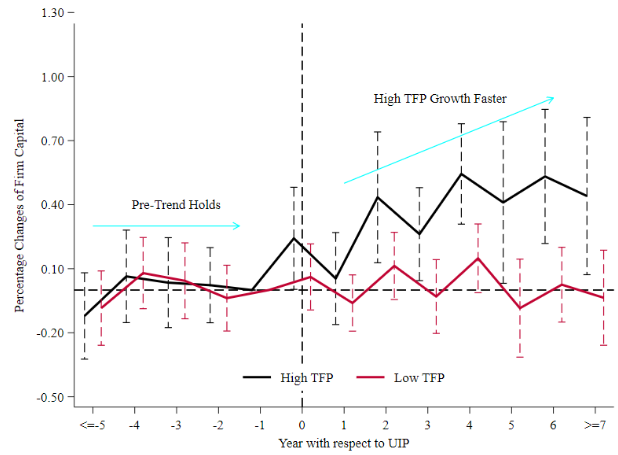
A. Industrial Transformation: Pro & Div



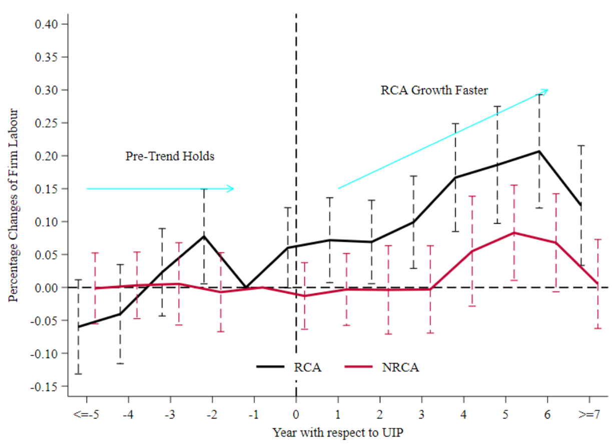
B. Industrial Transformation: ICI



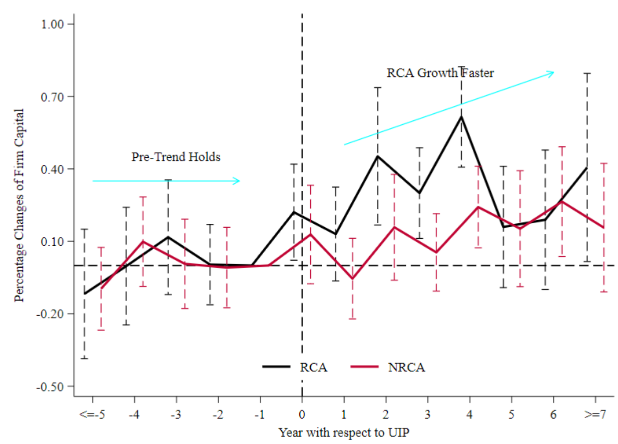
C. Labor allocation: Grouped by Firm TFP



D. Capital allocation: Grouped by Firm TFP



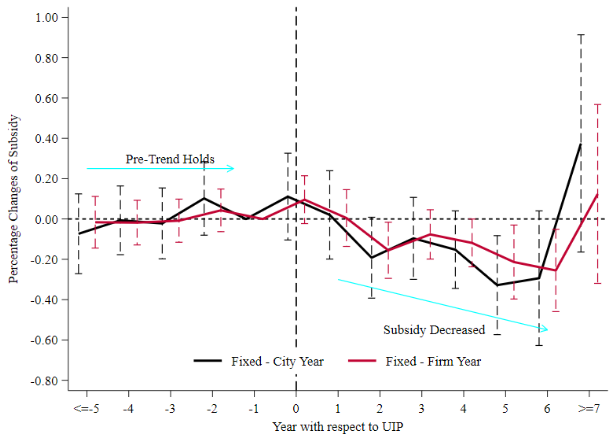
E. Labor allocation: Grouped by RCA



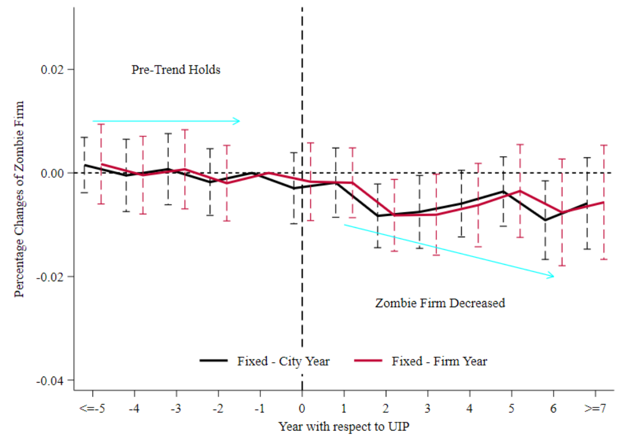
F. Capital allocation: Grouped by RCA

Figure D.1: Cross-sectional Results: Dynamic Effects

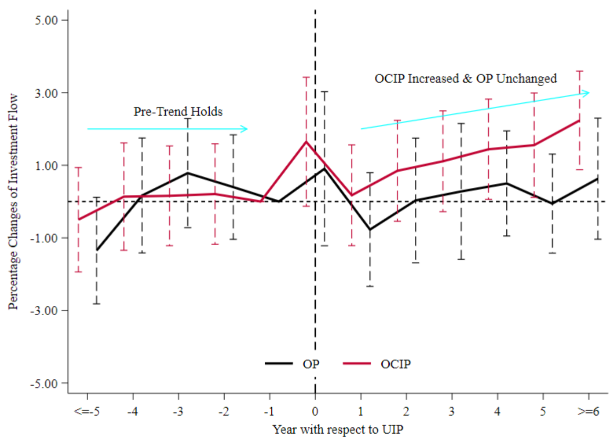
Notes: In this figure, we depict the dynamic effect results of the variables employed in the main text, utilizing regression equations analogous to those employed in the main text's Event Study Analysis (ESA). In particular, panel (b) employs core-periphery categorization as a grouping criterion; panels (c) and (d) employ annual mean TFP of firms as the grouping criterion; and panels (e) and (f) employ whether a firm belongs to an RCA industry as the grouping criterion. These outcomes correspond to Figures 4 in the main text.



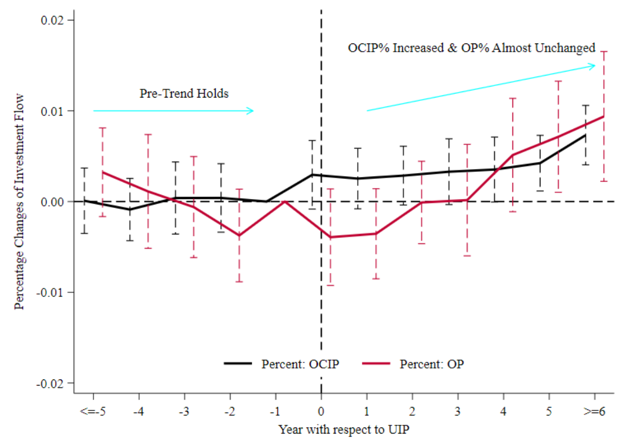
A. Subsidy Income



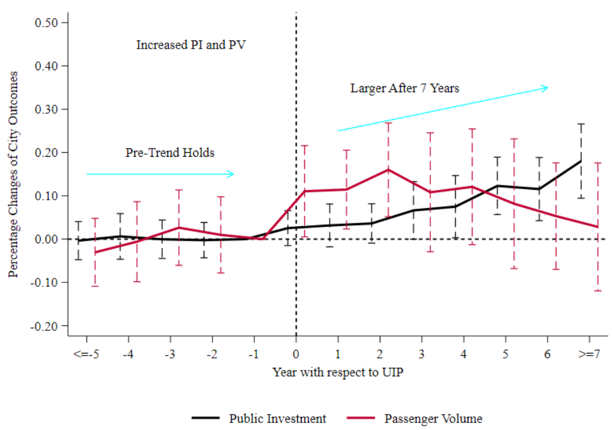
B. Zombie Firm Emerging



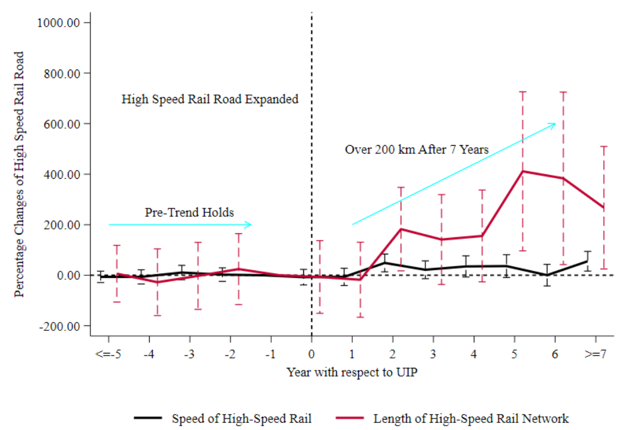
C. Investment: Outside City - Within Province



D. Investment: Outside City Or Province(%)



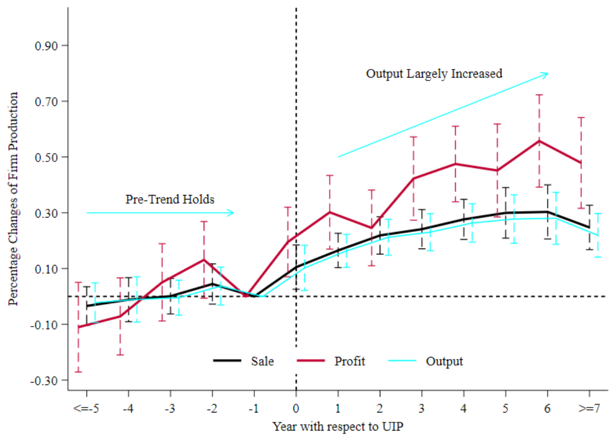
E. Public Investment and Passenger Volume



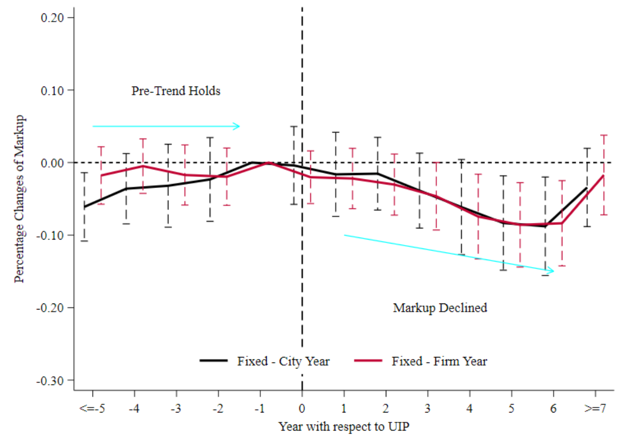
F. High-speed Rail: Speed and Length

Figure D.2: Results on Local Protectionism: Dynamic Effects

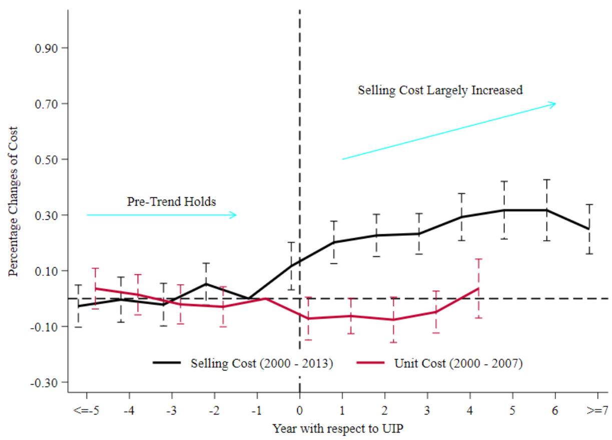
Notes: In this figure, we depict the dynamic effect results of the variables employed in the main text, utilizing regression equations analogous to those employed in the main text's Event Study Analysis (ESA). In particular, panel (a) and panel (b) employ different specifications, by adding year-city or firm-city fixed effect. These outcomes correspond to Table 3 in the main text.



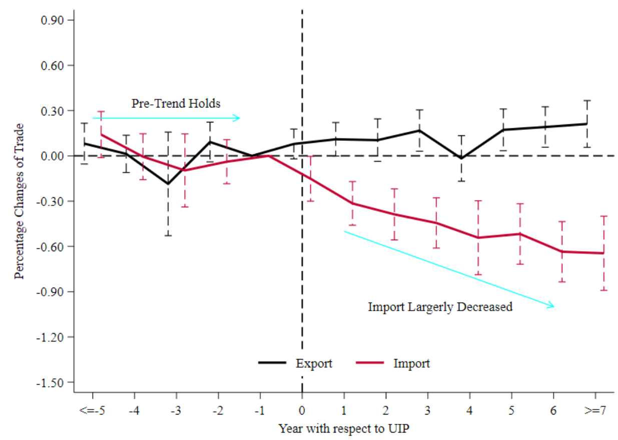
A. Firm Operation



B. Markup



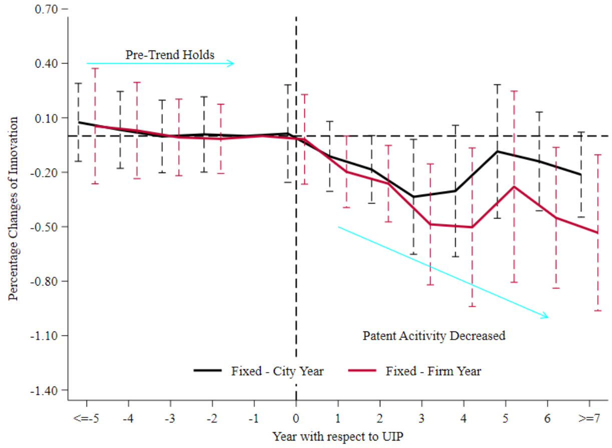
C. Selling Cost



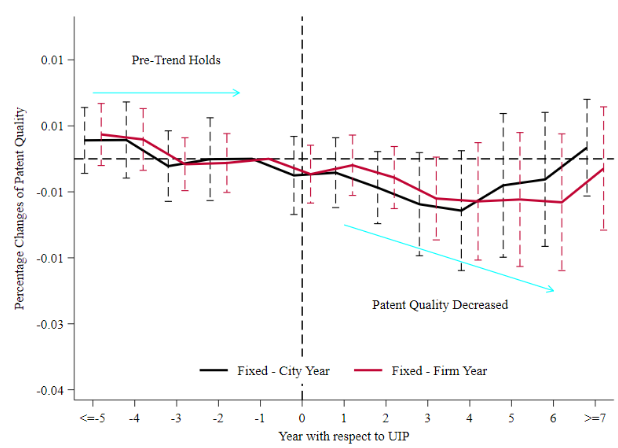
D. Export and Import

Figure D.3: Results on Market Expansion: Dynamic Effects

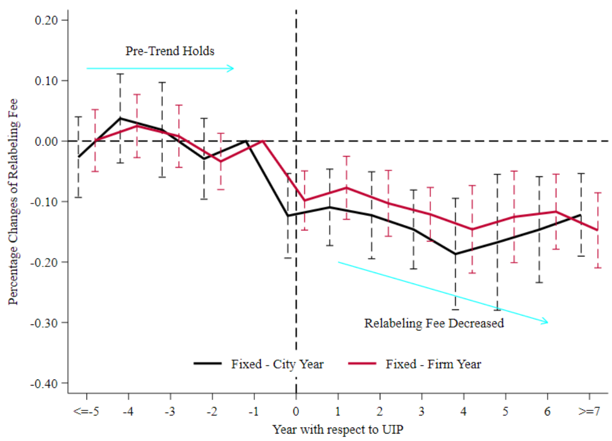
Notes: In this figure, we depict the dynamic effect results of the variables employed in the main text, utilizing regression equations analogous to those employed in the main text's Event Study Analysis (ESA). These outcomes correspond to Table 4 in the main text.



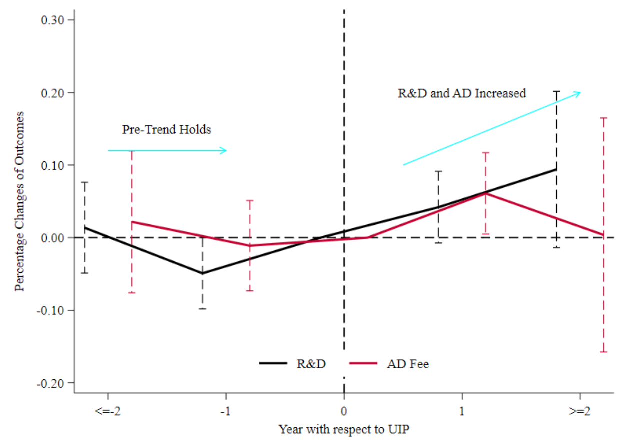
A. Patent



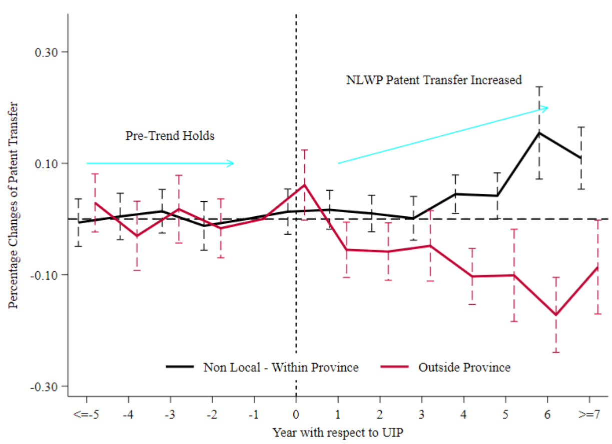
B. Quality



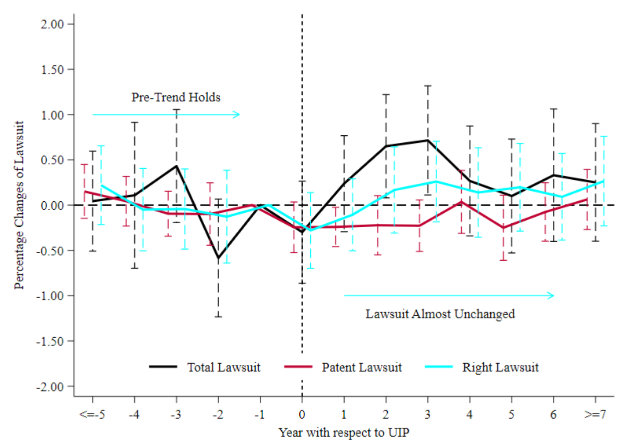
C. Relabeling Fee



D. R&D and AD Cost



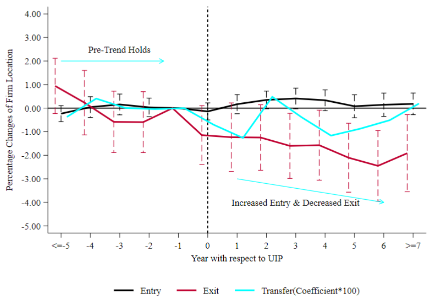
E. Patent Transfer



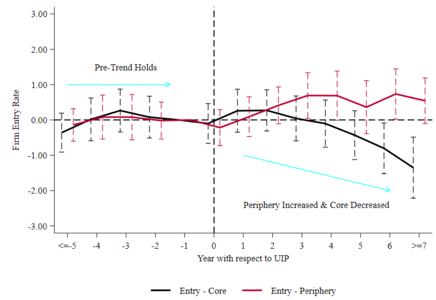
F. Lawsuit

Figure D.4: Results on Innovation and Lawsuit: Dynamic Effects

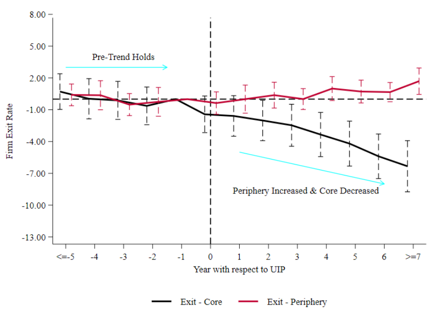
Notes: In this figure, we depict the dynamic effect results of the variables employed in the main text, utilizing regression equations analogous to those employed in the main text's Event Study Analysis (ESA). These outcomes correspond to Table 6 and 5 in the main text.



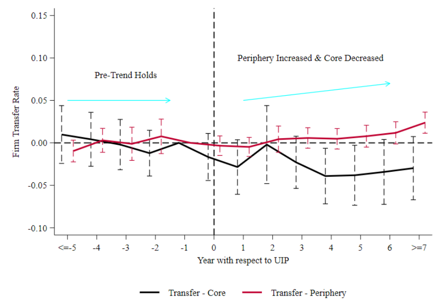
A. Firm Location: Full



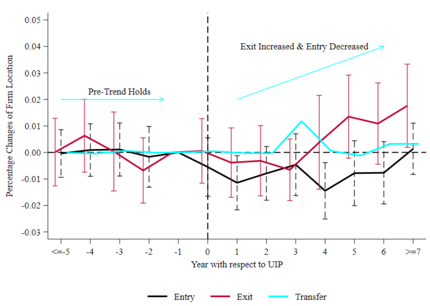
B. Entry: Full



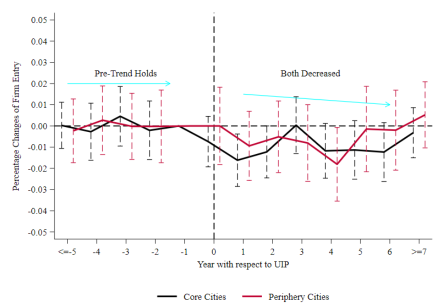
C. Exit: Full



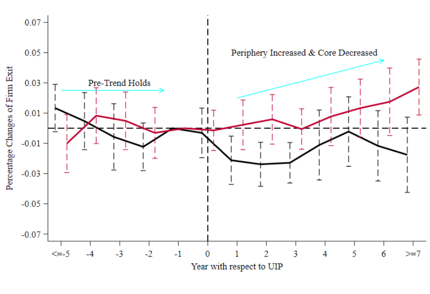
D. Transfer: Full



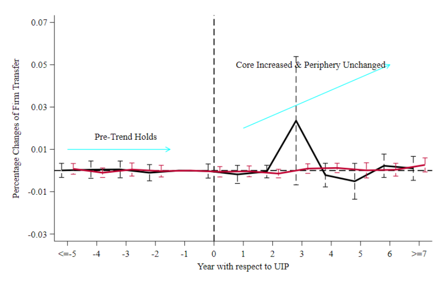
E. Firm Location: ASIEC



F. Entry: ASIEC



G. Exit: ASIEC



H. Transfer: ASIEC

Figure D.5: Results on Firm Location: 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 Figures 7 in the main text. Note that the definitions of 'transfer' differ between the full panel and the ASIEC panel. For the former, it denotes whether a firm moves in or out, while for the latter, it only indicates when a firm moves out.

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.6, 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.

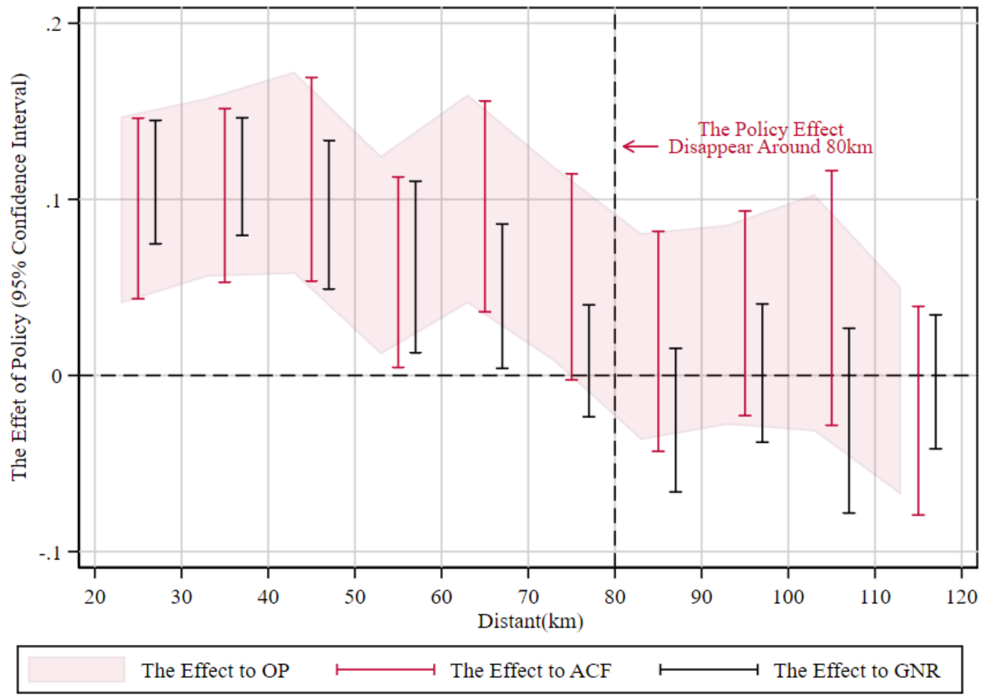


Figure D.6: The Geography Boundary of UIP Function

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-Opacf	
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.6, 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-Opacf	
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 (14). 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:

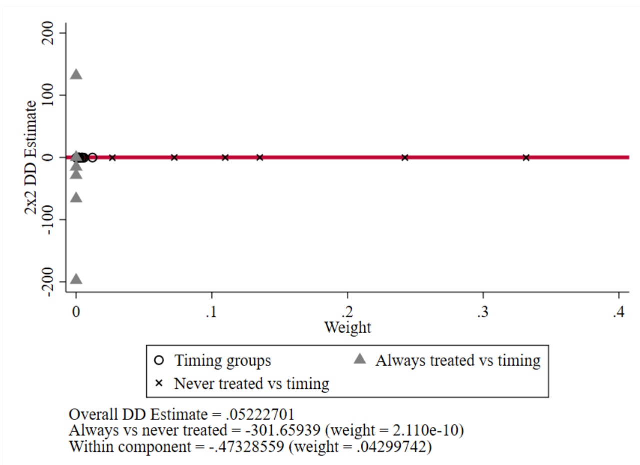
We run the same regression as our baseline specification to check whether the estimates are contaminated by the incorrect comparison of already treated units as controls. To do so, we first divide the data into two windows, 2000-2005 and 2008-2013, and consider the effect of UIP on TFP in 2002 and 2011, 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.7. 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.7A 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.7B and Table D.6, and the results are consistent with our baseline results.

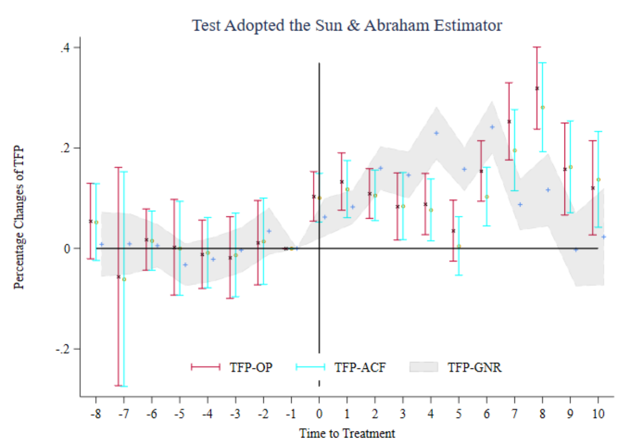
Table D.5: Check the Heterogeneous Treatment Effect

	2000-2005: Treated 2002		2008-2013: Treated 2011	
	(1) TFP	(2) TFP	(3) TFP	(4) TFP
	b/se	b/se	b/se	b/se
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.7: 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 The Robustness of IV-2SLS

As shown in Table D.8, 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.9 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.8: IV-2SLS Estimation - First Stage

	First Stage: UIP								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		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.9: The Exclusion Restriction

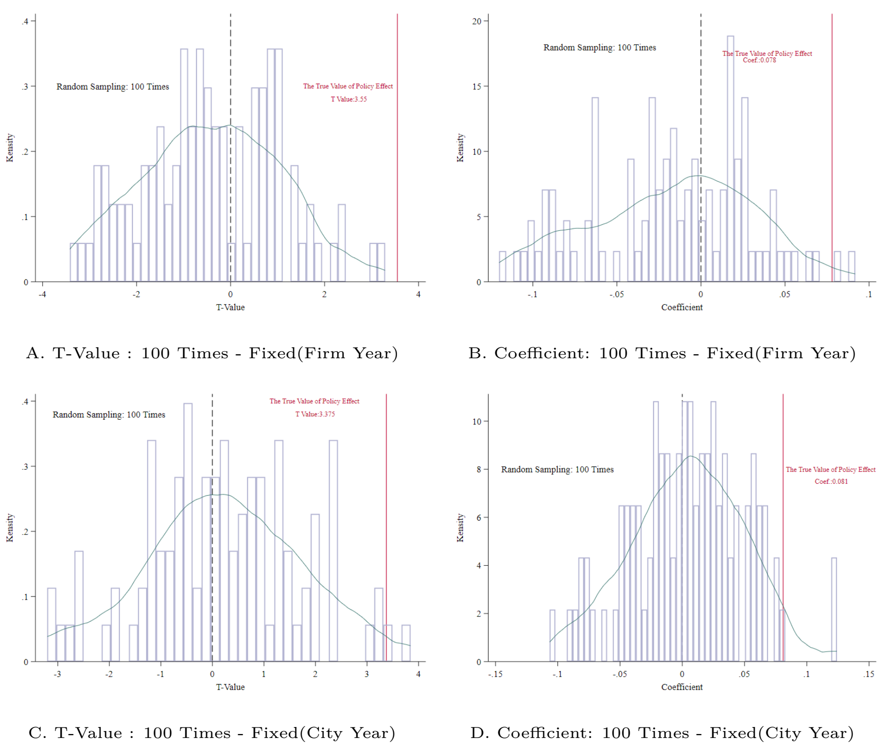
	2000-2003			2003-2013		
	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	TFP	TFP	TFP	TFP	TFP
Dialect	0.004	0.012	0.012	0.016***	0.016***	0.016***
	(0.009)	(0.009)	(0.010)	(0.005)	(0.005)	(0.005)
	2000-2003			2003-2013		
If Railway Between Periphery and Core City In 1933	-0.019***	-0.022***	-0.022***	-0.007	-0.002	-0.002
	(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.

D.7 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.8 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.10, 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.11, 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.10: 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-Opacf					
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 (14) 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.11: Adopt Balance Panel

Life Span	=10	=11	=12	=13	=14
	(1)	(2)	(3)	(4)	(5)
Dependent Variable			TFP-Opacf		
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 (14). 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.9 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.12 In Table D.13, 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.12: 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

Continued on next page

Table D.12 continued from previous page

Category	Timing	Details
	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
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

Continued on next page

Table D.12 continued from previous page

Category	**Timing**	**Details**
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.13: Control the Concurrent Polices

	City level				Industry level		All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable				TFP-Opacf			
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.

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 (14). 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-Opacf		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.

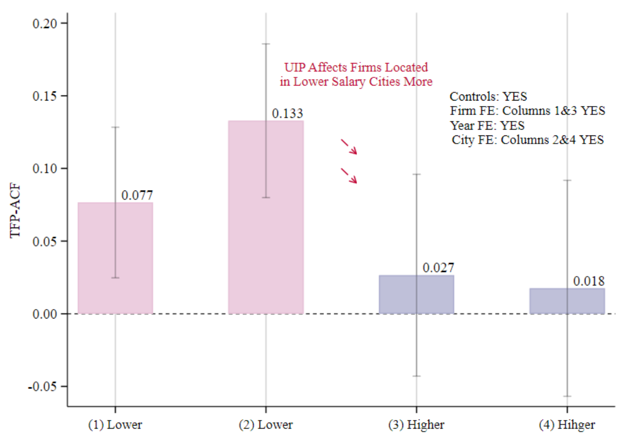


Figure E.1: TFP: Grouped by City's Salary Level

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 Markup

Table E.3: Heterogeneity on Markup

	RCA		NRCA	
	(1)	(2)	(3)	(4)
Dependent Variable	Markup			
UIP	-0.053***	-0.034***	-0.005	-0.019
	(0.016)	(0.011)	(0.014)	(0.015)
Observations	683566	621504	1930711	1796219
Year FE	X	X	X	X
City FE	X		X	
Firm FE		X		X
Control	X	X	X	X

Notes: The table presents OLS estimates of the relationship between UIP and a firm's Markup by adopting the model (14). 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 B, we introduce the measurement strategies for all variables.

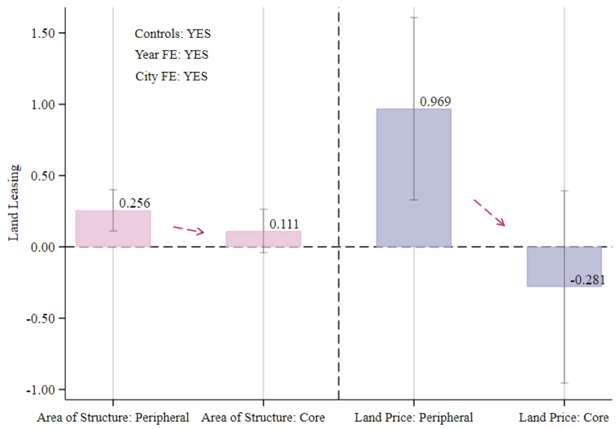
E.4 The Heterogeneity of Innovation

Table E.4: Heterogeneity on Patent Activity

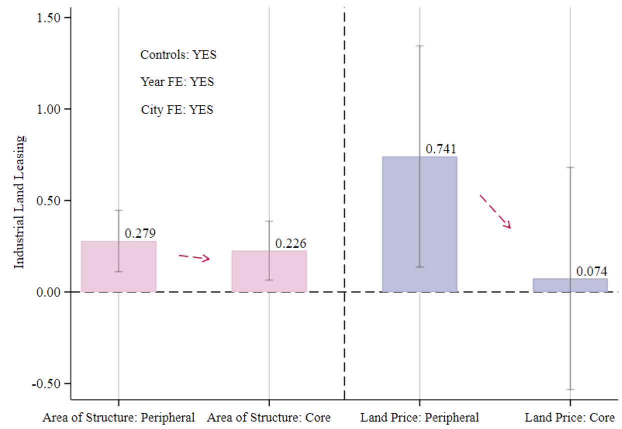
	Core	Periphery	Full Panel			
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Patent		Design	Innovation	Utility	Total
UIP	-0.473**	-0.345***	-0.123***	-0.188***	-0.024	-0.335***
	(0.207)	(0.100)	(0.040)	(0.066)	(0.046)	(0.118)
Observations	793527	1691572	2485219	2485219	2485219	2485219
Year FE	X	X	X	X	X	X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

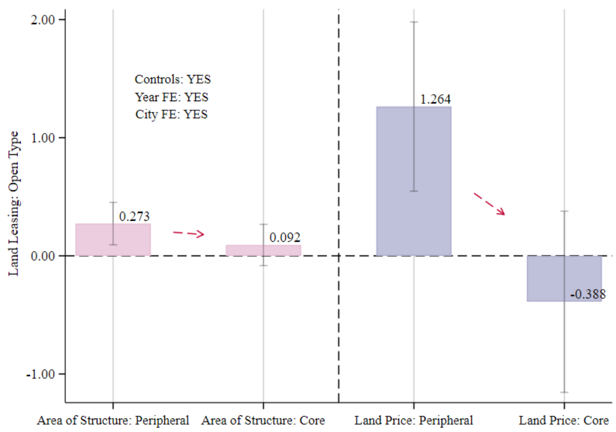
E.5 Land Leasing of Government



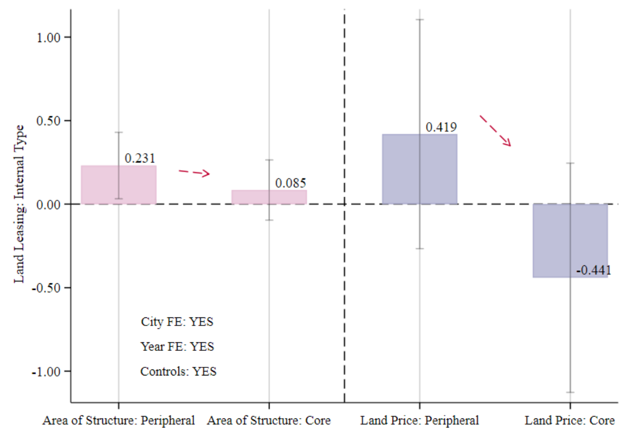
A. Land Leasing: New Land



B. Industrial Land Leasing: New Land



C. Land Leasing: New Land & Open Type

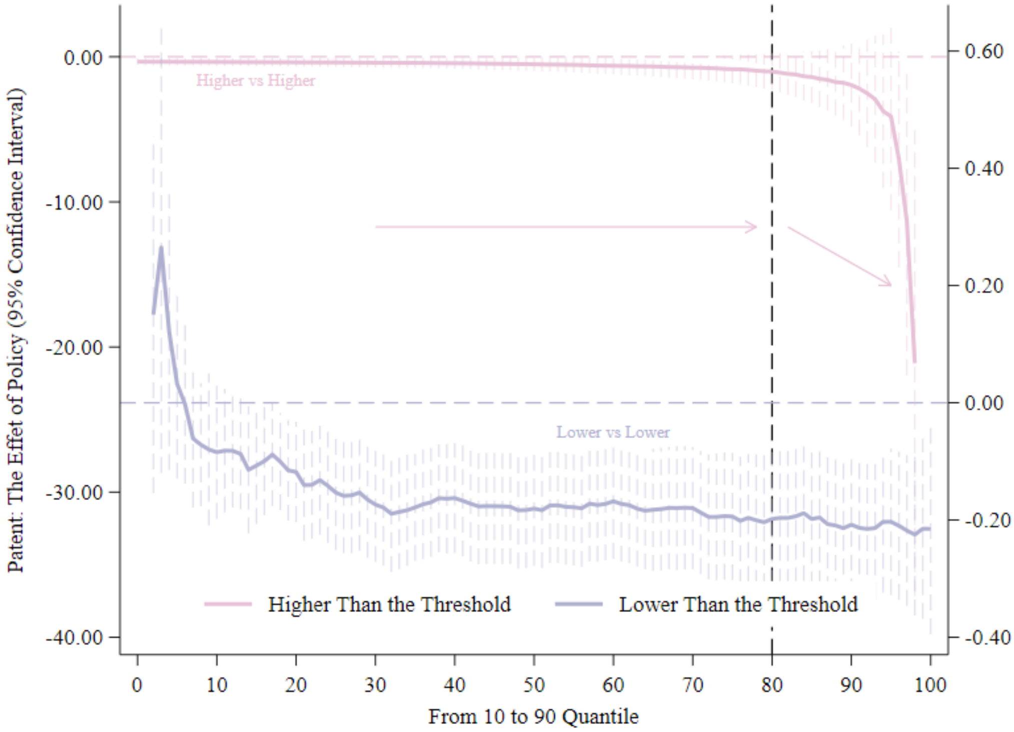


D. Land Leasing: New Land & Internal Type

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.

E.6 Regression on Innovation By TFP Quantilie



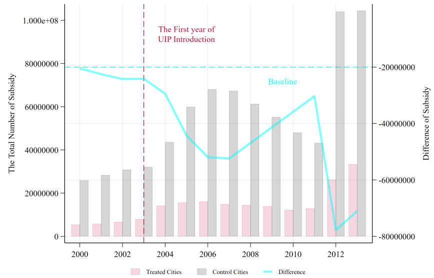
A. Patent: Grouped by TFP Quantile

Figure E.3: Quantile Estimator: Patent

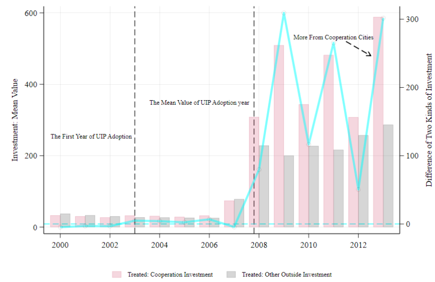
Notes: The graph displays the regression results of using UIP on Patents as dependent variables, split by TFP percentile at the year - city level, select each 9 percentile from 10 to 90. The red line represents comparisons below the percentile threshold, while the black line represents comparisons above the percentile threshold. The red line corresponds to the right axis, and the black line corresponds to the left axis.

F Appendix F: Stylized Facts

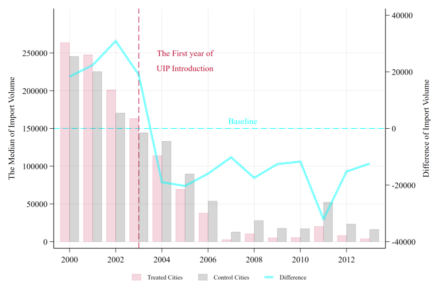
F.1 Main Variations in Mechanism Analysis



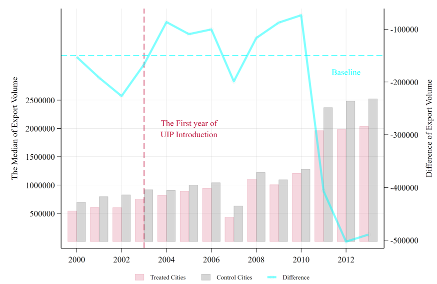
A. Subsidy



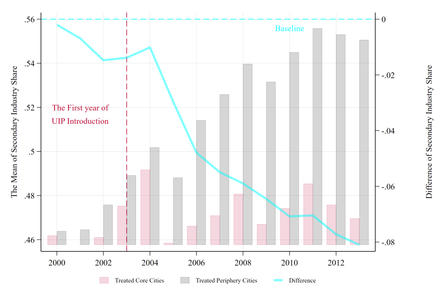
B. Outside Investment



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 Subsidies on Firm's Zombified

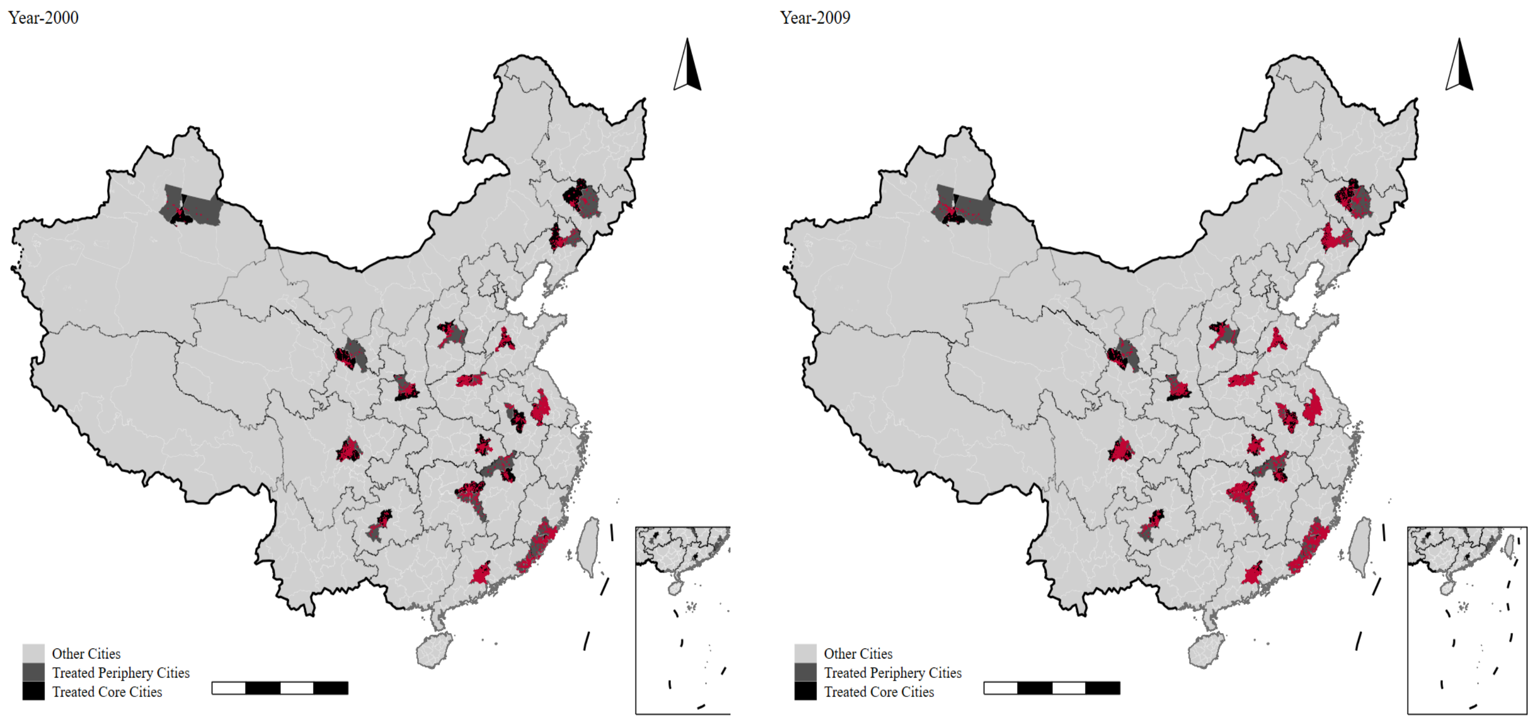
We demonstrate that UIP reduces government subsidies to firms, thereby decreasing the proportion of zombie firms. Herein, we uncover substantial evidence of a correlation indicating that zombie firms have significantly lower productivity. As illustrated in columns 2-4, should a firm transition into a zombie state, its productivity declines by at least 20%. Concurrently, evidence from columns 5-8 suggests that government subsidies appear to act as a catalyst for the creation of zombie firms. This aligns with our main text's assertion that UIP reduces government subsidies, leading to fewer observed zombie firms and consequently less distortion in the macroeconomy.

Table F.1: Stylized Facts of Zombitization

	Panel A: Universe of Industrial Firm							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	TFP				Zombie		Zombie-Alter	
Zombie	-0.678***	-0.251***						
	(0.009)	(0.007)						
Zombie-Alter			-0.498***	-0.220***				
			(0.008)	(0.006)				
Subsidy					0.011***	0.004***	0.013***	0.011***
					(0.000)	(0.000)	(0.000)	(0.000)
Observations	2640726	2485219	2640726	2485219	2093383	1937959	2093383	1937959
Year FE	X	X	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	X	X

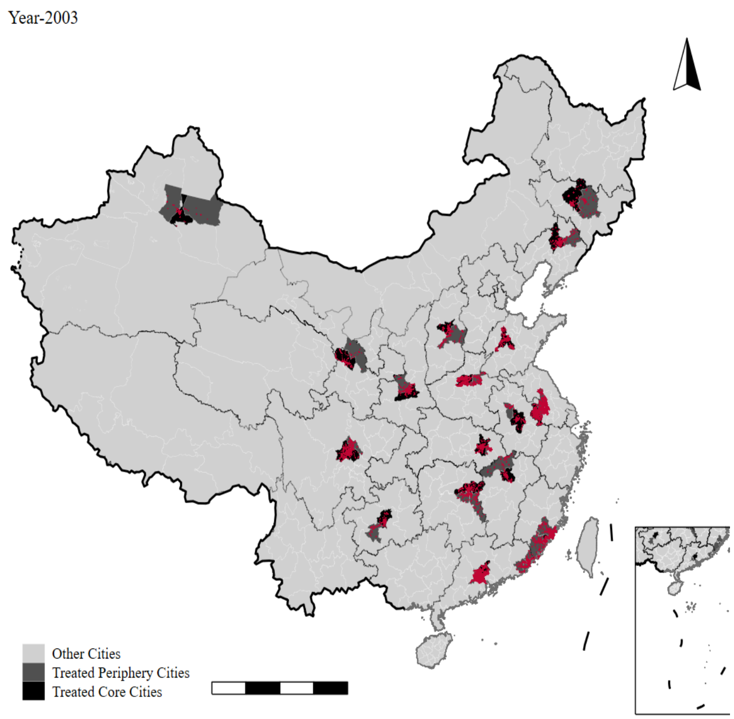
Notes: The table presents the relationship between zombie firm and TFP, subsidy and zombitization. In columns 1-4, the dependent variable is the firm's TFP employed using the ACF method. In columns 5-8, we regress subsidy on firm zombitization. For the baseline measurement of zombie firms, we adhere to the specification of the baseline results, namely, firms with negative profits for three consecutive years. Concurrently, we also provide an alternative specification, identifying as zombie firms those with a debt-to-asset ratio exceeding the industry average, coupled with an increase in debt compared to the previous year, and with a negative net profit in the current period. 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.

F.3 The Changes of Firm Location in Treated Core and Periphery Cities

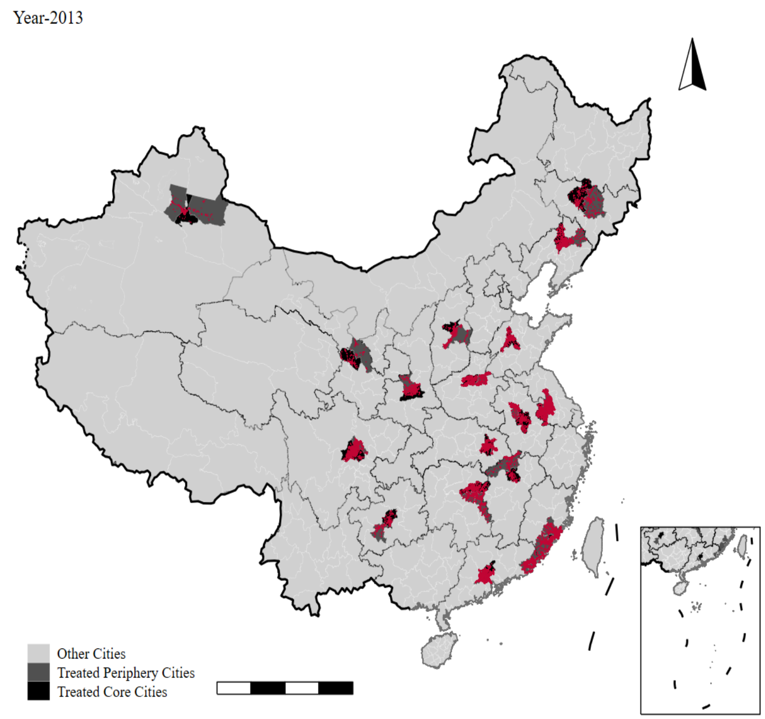


A. Year: 2000

B. Year: 2009



A. Year: 2003

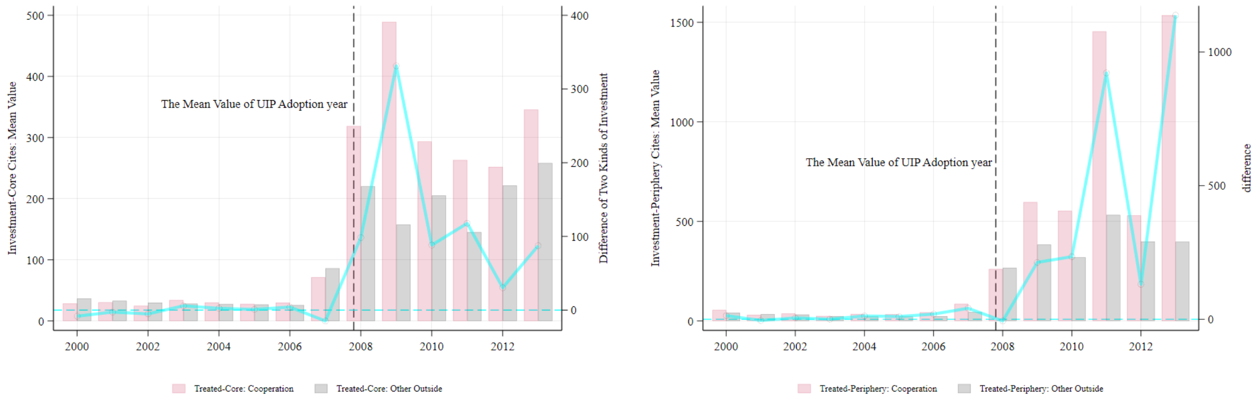


B. Year: 2013

Figure F.3: Firm Location Landscape at Core-Periphery Cities

Notes: These images show the geographical distribution of industrial firms from 2000 to 2013 in the treated cities. (a) and (b) compares 2000 and 2009, while (c) and (d) compares 2003 and 2013. In general, in the absence of UIP (2000 and 2003), industrial firms were clustered mainly in the core cities. After the UIP was introduced, industrial firms started to cluster more in the peripheral cities. More interestingly, many industrial firms sprang up in the urban junctions. These characteristic facts are consistent with the Core-periphery Theory regarding the pattern of industries clustering in core cities in the early stages of urbanization and moving to peripheral cities in the later stages. Alternatively, dense industrial firms at city boundaries may be associated with regional trade.

F.4 The Investment Flow Between Core-Periphery Cities



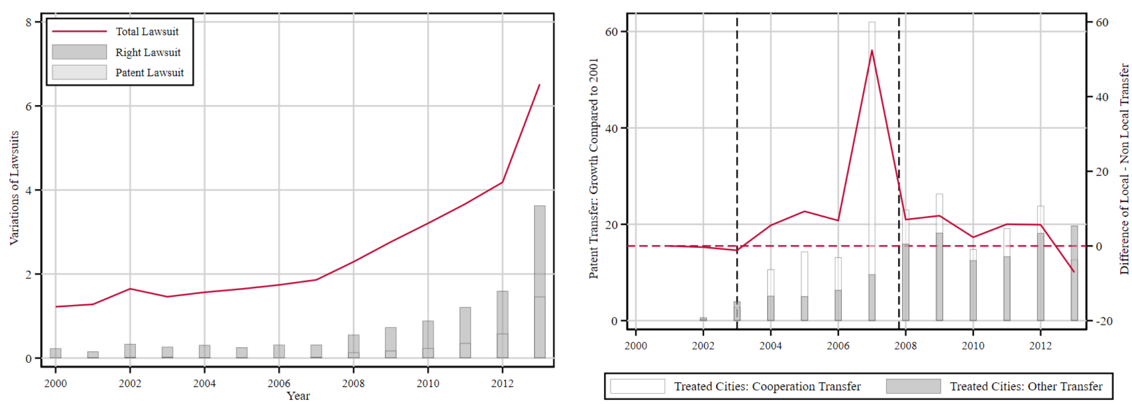
A. Treatment: Core Cites

B. Treatment: Periphery Cites

Figure F.4: 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.5 The Dynamics of Lawsuit and Patent Transfer in China



A. Lawsuit Dynamics

B. The Patent Transfer of Treated Cities

Notes: The figure shows the stylized facts of lawsuit and patent transfer changes in china. For the lawsuit, we present the mean value of lawsuit for each city per year, divided to three types, total, patent and right. For the patent transfer, we present the patent transfer of treated cities and divided the transfer into two type, transfer to cooperated cities or other non-local transfer.

F.6 A Stylized Case Related to the Firm Dynamic Pattern and UIP Adoption

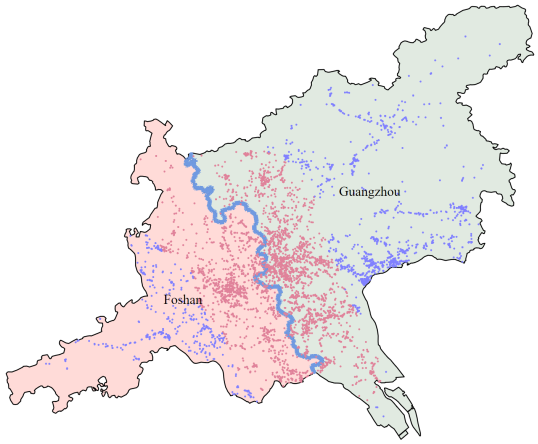
We provide a representative case of a UIP cluster to illustrate two key points:

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.

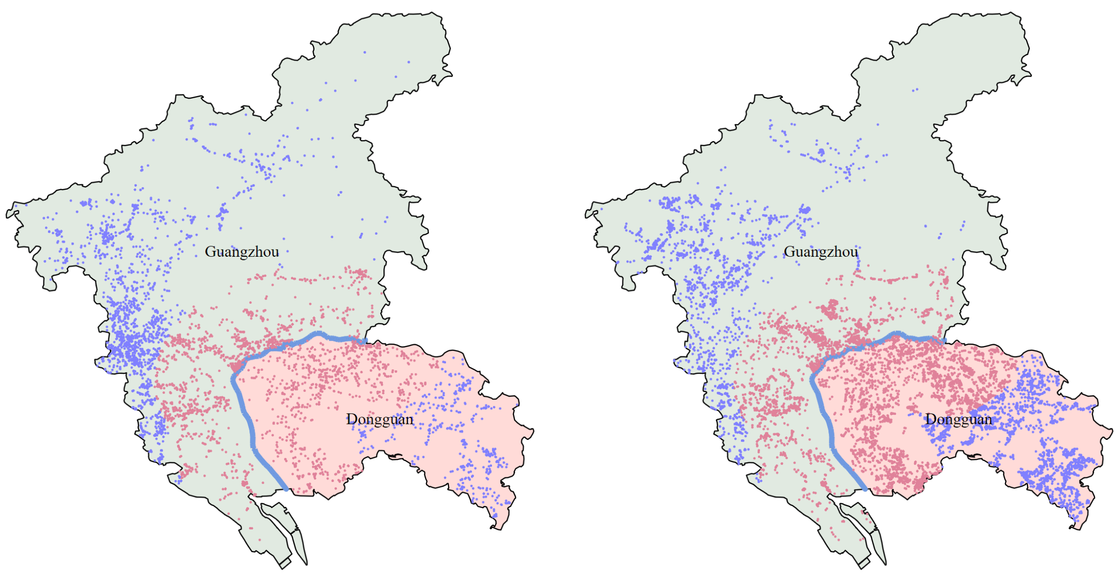
The following figure F.6 shows the firm dynamics within the UIP cluster formed by Guangzhou and Foshan, as well as the non-UIP cluster of Guangzhou and Dongguan. This figure conveys two main implications:

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.

Second, we observe that after the formation of the UIP cluster between Guangzhou and Foshan, many firms emerged within 20km of the city border (indicated by red dots), while no such emergence is seen near the border of Guangzhou and Dongguan. This reflects a situation where regional trade is facilitated by proximity, leading to firm emergence near areas where local protectionism is effectively dismantled. Consequently, we capture the strong firm dynamics and robust 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.6: 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 21.

$$\Delta \log(a) \approx \underbrace{-\frac{\alpha^*}{2}\sum_{s=1,c=1}^{S,C} Cap\%_{s,c}\left(1+\frac{\alpha_s\theta_s}{1-\theta_s}\right)\widehat{\Delta\Delta\sigma^2}(s,c)}_{\text{The Change of within-industry reallocation caused by UIP}}$$
$$\underbrace{-\sum_{s=1,c=1}^{S,C}(Sale\%_{s,c}\alpha_s - Cap\%_{s,c}\alpha^*)\left[\widehat{\Delta\Delta\mu}(s,c)+\Delta\Delta\widehat{\varsigma_{logMRPK,logValueAdd}}(s,c)+\frac{1}{2}\frac{\alpha_s\theta_s}{1-\theta_s}\widehat{\Delta\Delta\sigma^2}(s,c)\right]}_{\text{The Change of cross-industry reallocation caused by UIP}} \tag{21}$$

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, $\Delta\widehat{\Delta\varsigma(s,c)}$. 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[54]. 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.

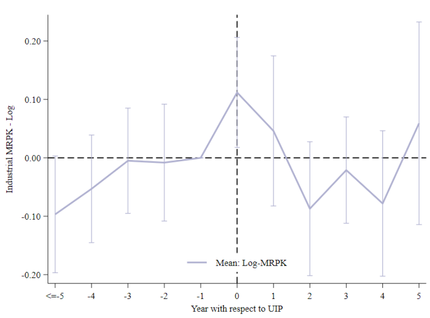
Now, based on the estimated DID parameters from columns 1-3 of Table G.1, namely $\widehat{\Delta\Delta\mu}(s,c) = 0.077$, $\widehat{\Delta\Delta\sigma^2}(s,c) = 0.004$, and $\widehat{\Delta\Delta\varsigma}(s,c) = -0.004$, we can formally scale up the TFP growth. Given the presence of several other undetermined 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.

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

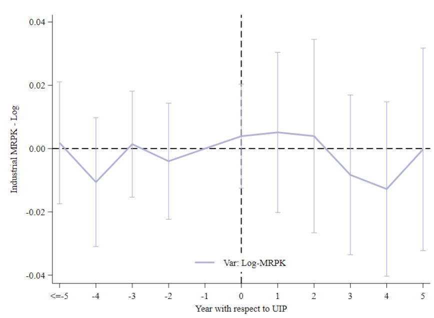
Table G.1: Estimates of the Impact of UIP on MRPK

	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

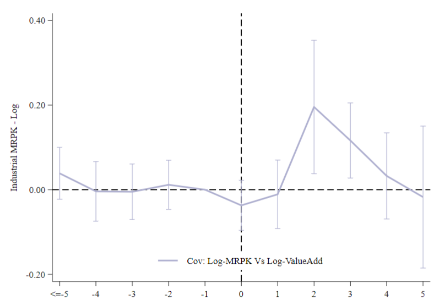
Notes: The table presents OLS estimates of the relationship between UIC and the moments of Log-MRPK. The dependent variable is the average, variance and the covariance between Log-MRPK and Log-ValueAdd. All time-varying variables are presented in log values. ***, **, and * represent statistical significance 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.



A. Mean: Log MRPK



B. Var: Log-MRPK



C. Cov: Log-MRPK Vs Log-ValueAd

Figure G.1: Results on MRPK: 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 G.1 in the main text.

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.

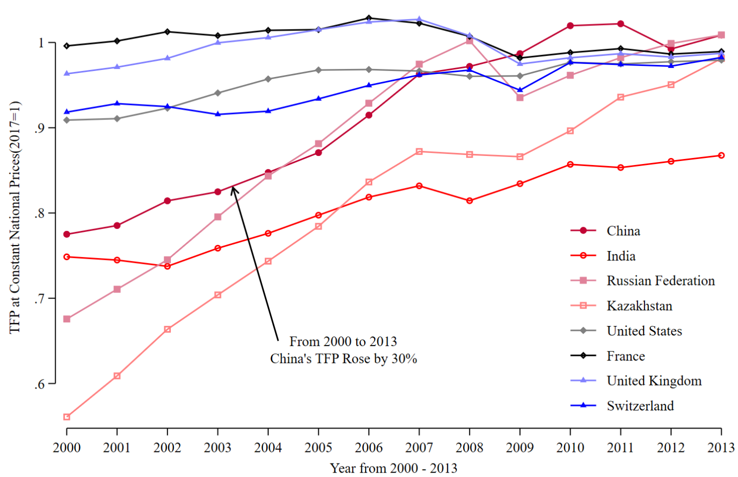


Figure G.1: TFP Variations Across Country

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)).

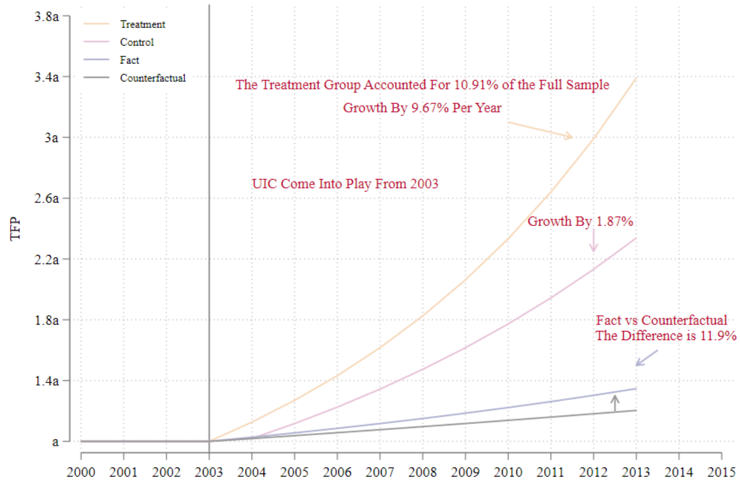


Figure G.2: The Simulation of TFP Variations

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%	1.1265a	1.0187a	1.0272a	0.0085a
2005	Both: 1.87%	1.0377a	T: 9.67% C: 1.87%	1.2698a	1.1172a	1.0557a	0.0180a
2006	Both: 1.87%	1.0572a	T: 9.67% C: 1.87%	1.4321a	1.2252a	1.0857a	0.0286a
2007	Both: 1.87%	1.0769a	T: 9.67% C: 1.87%	1.6162a	1.3437a	1.1172a	0.0403a
2008	Both: 1.87%	1.0971a	T: 9.67% C: 1.87%	1.8252a	1.4737a	1.1504a	0.0534a
2009	Both: 1.87%	1.1176a	T: 9.67% C: 1.87%	2.0626a	1.6162a	1.1855a	0.0679a
2010	Both: 1.87%	1.1385a	T: 9.67% C: 1.87%	2.3326a	1.7724a	1.2224a	0.0839a
2011	Both: 1.87%	1.1598a	T: 9.67% C: 1.87%	2.6399a	1.9438a	1.2615a	0.1017a
2012	Both: 1.87%	1.1815a	T: 9.67% C: 1.87%	2.9902a	2.1318a	1.3029a	0.1215a
2013	Both: 1.87%	1.2035a	T: 9.67% C: 1.87%	3.3898a	2.3380a	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: Robustness Check For the Mechanisms Analysis

In this section, we provide alternative tests for the variables of interest in our mechanism analysis, demonstrating that our results are not dependent on the specific measures of variables. As shown in Table H.1, we use the receipt of subsidies rather than the amount of subsidies as the dependent variable, alternative measures of zombie firms, and define investment flows by the number of investments rather than the amount, with results consistent with those in the main text. As indicated in Table H.2, we define regional patent infringement risk using the number of property rights infringements instead of the number of patent infringements, and measure the intensity of industrial technology spillover using different thresholds of technological consistency, with results remaining consistent with those in the main text.

Table H.1: UIP on Local Protectionism: Robustness

	Panel A: Universe of Industrial Firm				Panel B: Universe of Business Registrations	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Subsidy Number		Zombie-Alt		OCIP%:Num	OP%:Num
UIP	-0.029***	-0.025***	-0.008***	-0.006**	0.003***	-0.000
	(0.010)	(0.010)	(0.002)	(0.003)	(0.001)	(0.003)
Observations	2055968	1902409	2640726	2485219	11144252	11144252
Year FE	X	X	X	X	X	X
City FE	X		X		X	X
Firm FE		X		X		
Control	X	X	X	X	X	X

Notes: The table represents robustness check corresponding to the Table 3 in the main text. Columns 1-4 pertain to the firm dimension, with the dependent variables measuring firms' subsidy number and the probability of zombification(identifying as zombie firms those with a debt-to-asset ratio exceeding the industry average, coupled with an increase in debt compared to the previous year, and with a negative net profit in the current period.). Columns 5-6 relate to the investment dimension, with the dependent variables representing the number or proportion of investment number received by firms from different non-local attributes, including the proportion of investment from outside the home city within the province (OCIP%:Number), the propotion of investment from outside the home province (OP%:Number). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. For the two dimensions, standard errors are clustered at city-year levels.

Table H.2: UIP on Imitative Innovation

	Panel A: Universe of Industrial Firm			
	(1)	(2)	(3)	(4)
Dependent Variable	Patent	TFP	Patent	TFP
UIP	-0.169**	0.021	-0.216**	0.062***
	(0.070)	(0.029)	(0.088)	(0.024)
UIP×Patent Right Risk	-0.248**	0.127***		
	(0.103)	(0.041)		
UIP×High Spillover			-0.314**	0.082***
			(0.130)	(0.029)
Observations	3348418	2485219	3348418	2485219
Year FE	X	X	X	X
City FE				
Firm FE	X	X	X	X
Control	X	X	X	X

Notes: The table represents robustness check corresponding to the Table 5 in the main text. In columns 1-2, we adopted the measurement method based on the number of ownership-related litigations. In columns 3-4, we modify the criterion for segmenting industries by the spillover effects from corresponding core cities to the 90th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors are clustered at the city-year levels.

I Appendix I: Details of Conceptional Framework

In this section, I 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, I provide proof supporting the assertions made in the main text.

Equilibrium Condition: Regional Trade

$$q(n) = Q\left(\frac{p(n)}{P}\right)^{-\sigma} \tag{22}$$

$$r(n) = R\left(\frac{p(n)}{P}\right)^{1-\sigma} \tag{23}$$

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:

$$\bar{\pi} = \pi_d(\tilde{\varphi}) + x_r n \quad (FE) \tag{24}$$

$$\tilde{\pi} = fk(a^e) + x_r n f_x k(a^x), \quad Where \quad k(a) = \left[\left(\frac{\tilde{a}(a)}{a}\right)^{\sigma-1} - 1\right] \quad (ZCP) \tag{25}$$

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.

$$p(a) = \begin{cases} p_d(a) = \frac{1}{\rho a} & \text{if Local Market} \\ p_x(a) = \frac{\iota}{\rho a} = \iota p_d(a) & \text{if Regional Trade} \end{cases} \tag{26}$$

$$r(a) = \begin{cases} r_d(a) = R(P\rho a)^{\sigma-1} & \text{if Local Market} \\ r_d(a) + n r_x(a) = (1 + n\iota^{1-\sigma}) r_d(a) & \text{if Regional Trade} \end{cases} \tag{27}$$

$$\pi(a) = \begin{cases} \pi_d(a) = \frac{r_d(a)}{\sigma} - f & \text{if Local Market} \\ \pi_x(a) = \frac{r_x(a)}{\sigma} - f_x & \text{if Reginal Trade} \end{cases} \tag{28}$$

Aggregation

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

$$\bar{r} = r_d(\tilde{a}) + x_r n r_x\left(\tilde{a}(a^x)\right) \quad \text{and} \quad \bar{\pi} = \pi_d(\tilde{\varphi}) + x_r n \pi_x\left(\tilde{a}(a^x)\right) \tag{29}$$

$$P = \left[\int_0^{\infty} p(a)^{(1-\sigma)} M F(a)\, d(a)\right]^{1/(1+\sigma)} \tag{30}$$

$$\tilde{a} = \left[\int_0^{\infty} a^{\sigma-1} F(a) da\right]^{\frac{1}{\sigma-1}} \tag{31}$$

$$\begin{aligned} &P = M^{\frac{1}{1-\sigma}} p(\tilde{a}), \quad R = PQ = Mr(\tilde{a}), \\ &Q = M^{1/\rho} q(\tilde{a}), \quad \Pi = M\pi(\tilde{a}), \end{aligned} \tag{32}$$

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

$$\frac{\alpha[q_x(a > a^x)]}{\alpha o} > 0, \frac{\alpha[r_x(a > a^x)]}{\alpha o} > 0, and\ \frac{\alpha[\pi_x(a > a^x)]}{\alpha o} > 0 \tag{33}$$

Proof of Proposition 1

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:

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

$$\frac{\partial a^x}{\partial \tau} = -\frac{f j'(a^e)}{n f_x j'(a^x)}\frac{\partial a^e}{\partial \tau} > 0$$

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:

$$\tilde{a}_t = \left(\frac{1}{M_t}\left[M\tilde{a}(a^e)^{\sigma-1} + nM_x\left(\tau^{-1}\tilde{a}(a^x)\right)^{\sigma-1}\right]\right)^{\frac{1}{\sigma-1}}, \quad M_t = M + nM_x = M + nx_rM \tag{34}$$

Where we have

$$\frac{\partial \tilde{a}(a^e)}{\partial o} > 0, \quad \frac{\partial \tilde{a}(a^x)}{\partial o} < 0, \quad \frac{\partial M_x}{\partial o} > 0, \quad \frac{\partial M_t}{\partial o} > 0 \tag{35}$$

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:

$$\frac{\tilde{a}}{\alpha o} > 0 \tag{36}$$

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:

$$\frac{\partial T}{\partial \iota} = \frac{[m'(1-c)B + m'cA]K}{B^2} < 0, \quad \text{Conditional on} \quad a >= a^x \tag{37}$$

$$\frac{\partial T}{\partial \tau} = \frac{[A-B]c'Km}{B^2} < 0, \quad \text{Where} \quad A - B < 0 \tag{38}$$

Where

$$T = \frac{m(\iota)(1-c(\tau))K}{1-c(\tau)m(\iota)K}, \quad K = (1 - F_{a_r}), \quad B = 1 - c(\tau)m(\iota)K, \quad A = m(\iota)(1-c(\tau))K \tag{39}$$

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:

$$\frac{\partial T}{\partial o} > 0, \quad \frac{\alpha a^i}{\alpha o} = \frac{\alpha a^i}{\alpha T}\frac{\alpha T}{\alpha o} > 0 \tag{40}$$

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:

$$\frac{\alpha v}{\alpha o} = \frac{\alpha v}{\alpha m}\frac{\alpha m}{\alpha \iota}\frac{\alpha \iota}{\alpha o} + \frac{\alpha v}{\alpha c}\frac{\alpha c}{\alpha \tau}\frac{\alpha \tau}{\alpha o} \tag{41}$$

$$= \begin{cases} = 0 & \text{if } a < a^x \\ > 0 & \text{if } a^x <= a < a^i \\ < 0 & \text{if } a >= a^i \end{cases} \tag{42}$$

Then we conclude the proof.