A Note on Place-based Land Policy and Spatial Misallocation: Firm-level Evidence*

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Supplementary Note to
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Abstract

This note provides firm-level evidence for Fang et al. (Forthcoming) on the causal effect of place-based land policy and spatial misallocation. More specifically, we leverage the same research design that combines difference-in-differences and regression discontinuity at the policy border around the implementation of China's 2003 inland-favoring land policy, but using firm-level data. Our findings are as follows. First, the policy achieved regional growth convergence by reducing the gap in firm-level productivity across regions. Second, however, the relative changes are mainly due to slower productivity growth in eastern firms rather than faster productivity growth in inland firms. Both of the above findings are consistent with Fang et al. (Forthcoming). Furthermore, our mechanism analysis of firm-level variables shows that the policy increased land costs, decreased new-firm entry, and consequently reduced agglomeration and knowledge spillovers in the east; as a result, eastern firms responded by reducing their R&D expenditures, potentially harming their productivity in the long term.

Keywords: Place-based Policy; Land Policy; China; Firm Productivity; Misallocation;
JEL Classification Numbers: R58, R52, D24;

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1 Introduction

Many countries implement place-based policies to promote balanced national development by supporting underdeveloped regions through cash transfers, tax reductions, and land allocation regulations (Neumark and Simpson, 2015). Such policies, especially place-based land or migration policies in China, are shown to lead to spatial misallocation and lower aggregate productivity at the national level in quantitative spatial equilibrium models (Yu, 2019; Deng et al., 2020; Wu and You, 2025; Fang et al., Forthcoming). In our previous paper (Fang et al., Forthcoming), we show that, at the city level, using difference-in-differences and regression discontinuity at the policy border around the implementation of China's 2003 inland-favoring land policy, such a place-based land supply policy increases spatial misallocation. We extend the analysis to the firm level here.

Our analysis draws on the same design as in Fang et al. (Forthcoming) and the implementation of China's place-based land policy. The background information is that, in China, all urban land is state-owned, and the central government enforces strict quotas on construction land for each prefecture. Following the 1978 reforms, these quotas were allocated based on demand, primarily benefiting the rapidly expanding eastern coastal regions. However, the growing economic disparity between the eastern regions and the rest of the country became a significant concern. As a result, in 2003, the policy was dramatically shifted from a demand-driven approach to a development-promoting strategy, reallocating land quotas from the east to inland regions. This inland-favoring land supply policy has been in effect ever since. This dramatic shift in place-based land policy provides us with the potential exogenous variations for identification.

However, we still face the typical identification problem that firms in eastern regions often differ markedly from those in other regions in both observed and unobserved characteristics. To alleviate this endogeneity issue, we employ a method that combines Border Regression Discontinuity Design (Black, 1999) with the Difference-in-Differences approach (RD-DID). The basic idea is that firms within a narrow bandwidth along the border are very similar, regardless of which side they are on. Thus, firm-level productivity should have similar time trends. This allows us to implement an RD-DID strategy on these border firms to identify the effects of the inland-favoring land policy at the firm level. Compared with the prefecture-level regression, the advantage of this firm-level regression is that it exploits more variation and provides detailed micro evidence.

The main estimation results show that the inland-favoring policy reduced the firm-level productivity gap between firms in the eastern and inland regions by approximately 8%. The results remain robust across various robustness exercises. Moreover, we do not observe significant productivity improvements among inland firms, suggesting that the relative changes are mainly due to slower productivity growth among eastern firms rather than faster growth among inland firms. Our empirical analysis demonstrates that the inland-favoring land policy narrowed the productivity gap between eastern and inland firms by adversely affecting eastern firms without significantly benefiting inland firms, suggesting that land constraints could be a potential cause. These results are consistent with the city-level empirical results in Fang et al. (Forthcoming). Below, we add additional results that are not feasible in the city-level empirical analysis.

We find that these changes in firm productivity patterns could potentially stem from two channels. First, the policy may have directly impeded the productivity of eastern firms by constraining their land usage, slowing their innovation, and diminishing agglomeration benefits. We term this the "direct effect." Second, a more restrictive land policy in eastern regions could precipitate the exit of lower-productivity firms from the market or compel them to downscale their operations below the National Industrial Enterprise Database (NIED) survey threshold or even cease operations. We refer to this as the "selection effect."

We further investigate these two channels separately and find that the direct effect dominates. The inland-favoring land policy significantly increased land prices in the east, forcing firms to cut costs by reducing their R&D expenditures. Additionally, the land supply limitation deterred further firm entry into eastern regions and potentially reduced agglomeration effects. On the contrary, we find no evidence for the selection effect. Consequently, we find that the inland-favoring land supply policy narrowed the productivity gap between inland and eastern firms by reducing eastern firms' productivity growth. This reduction in productivity growth is accompanied by a decline in new firm entry and a decrease in R&D expenditure among eastern firms, potentially harming their long-term development. However, this policy affects both equality and efficiency.

Finally, we implement two sets of heterogeneity analyses to further validate the mechanism. First, we categorize industries into land-intensive and non-land-intensive groups. We find that the impact of the 2003 inland-favoring land policy is limited to firms in land-intensive industries, further confirming that land constraints play an important role in reducing these firms' productivity. Second, we examine heterogeneity across ownership types and find that state-owned enterprises (SOEs) were not affected by the inland-favoring land policy. In contrast, non-state-owned enterprises (non-SOEs), particularly private firms, were significantly affected. This result can be attributed to SOEs typically enjoying preferential access to land allocation and credit, making them less vulnerable to land-supply policy shocks than private firms.

Literature Our study contributes to three strands of literature. First, we investigate the direct causal effect of place-based land policy on firm productivity in a developing country. Many studies have investigated different kinds of place-based policies in developed countries from different perspectives (Neumark and Simpson, 2015), including enterprise zones (Neumark and Kolko, 2010; Ham et al., 2011; Busso, Gregory, and Kline, 2013), discretionary grants (Crozet, Mayer, and Mucchielli, 2004; Devereux, Griffith, and Simpson, 2007), infrastructure investment (Kline and Moretti, 2014; Becker, Egger, and Von Ehrlich, 2010), and community development (Eriksen and Rosenthal, 2010; Accetturo and De Blasio, 2012). This paper extends the literature by examining a large-scale, place-based policy in a developing country.

Second, our study contributes to the extensive literature on spatial misallocation. The literature has investigated various frictions that result in spatial misallocation, including housing constraints (Hsieh and Moretti, 2019), tax policies (Fajgelbaum et al., 2019), migration frictions (Wu and You, 2025), farmland frictions (Fu, Xu, and Zhang, 2021; Yu, 2019), and various combinations of the above frictions (Li, Ma, and Tang, 2024; Deng et al., 2020; Chen et al., 2019). We further investigate the spatial misallocation of land supply due to urban land regulation and its consequences for firm productivity growth.

Third, this paper contributes to the literature on migration and regional development in China. Other scholars have investigated the Hukou restriction and regional trade barriers (Tombe and Zhu, 2019; Pi and Chen, 2019), labor mobility (Ma and Tang, 2020; Tian, 2024; Fan, 2019; Zi, 2025; Fang et al., 2025), housing constraints (Fang and Huang, 2022), air quality (Khanna et al., 2025), and local public services for migrants (Sieg, Yoon, and Zhang, 2023; Huang and Zhang, 2022). This study contributes to the literature by connecting land misallocation and firm productivity.

Specifically, this study is closely related to Fang et al. (Forthcoming), which investigates the impact of China's inland-favoring land policy on the spatial economy through distorting the land and labor markets. This paper differs in several important ways. First, we provide micro-level (firm-level) causal evidence of reduced productivity resulting from China's inland-favoring land policy, using an RD-DID design. Second, we offer additional firm-level empirical evidence on the underlying mechanisms, including both a direct effect on innovation and an indirect selection effect. Third, we conduct extensive heterogeneity analyses to further support our findings. Overall, our paper contributes to the literature by zooming in on the firm-level consequences of the inland-favoring land policy and providing richer micro evidence on the mechanisms at play.

2 Background and Data

2.1 Background

In China, agricultural land is collectively owned by villages, while urban land is state-owned. Citizens cannot own land privately. To convert agricultural land to urban use, the local government first collects it from rural collectives (villages). Construction companies then purchase "use rights" from the local government to develop urban land. As a result, the central government can tightly control urban expansion by setting land usage plans for each region. Each year, each prefecture receives an annual quota for new urban construction land, which was primarily based on demand before 2003. Thus, developed coastal regions would receive more land quota and supply more construction land. However, after 2003, the central government changed its strategy to balance development across regions in response to the steadily widening regional development gap between eastern and inland regions. Specifically, they aimed to spur economic growth in inland regions by increasing land quotas for underdeveloped inland provinces (Lu and Xiang, 2016; Han and Lu, 2017; Fu, Xu, and Zhang, 2021; Fang et al., Forthcoming). Land quota sets a tight constraint on land usage each year.

2.2 Data

The primary dataset utilized in this study is the National Industrial Enterprise Database (NIED), published by the National Bureau of Statistics. This database includes all state-owned and non-state-owned enterprises classified as "above scale" (main business revenue exceeding 5 million RMB, which is about $700,000 USD), accounting for over 90% of all industrial production in China from 1998 to 2007. The dataset provides comprehensive enterprise-level information, including firm name, four-digit industry category, year of establishment, number of employees, total payroll, and total fixed assets. To address potential data anomalies, we apply a 1% censoring rate to exclude anomalous observations. Table 1 presents the descriptive statistics of the enterprise data. Our primary TFP measurement is based on the OP (Olley and Pakes, 1996) estimation method. Additionally, we calculate TFP using the LP (Levinsohn and Petrin, 2003) method in Appendix A, which yields similar results.

Furthermore, we employ other datasets to provide additional evidence. We utilize the China Land and Resources Statistical Yearbook to obtain province-level land quota data. Published by the Ministry of Land and Resources of China, this yearbook contains data on land, minerals, oil, natural gas, and various other natural resources. Unfortunately, prefecture-level construction land quota data remains confidential and is not publicly available. We also use the Firm Registration Data in China to investigate firm entry behavior. This comprehensive dataset includes information on all Chinese firms, such as their industry, location, and entry dates. We also examine the policy's impact on ROA and R&D. After excluding missing values for these two variables, the sample contains 29 fewer observations than the sample used in Fang et al. (Forthcoming).

Table 1: **Summary Statistics**

Variable	Description	Observations	Mean	Std. dev.	Min	Median	Max
Ln(tfp_op)	TFP(OP)	877354	3.25	1.02	-0.04	3.27	5.63
Ln(tfp_lp)	TFP(LP)	877354	6.36	1.09	3.08	6.32	9.02
Ln(output)	Ln(1k yuan)	877354	8.62	1.29	5.31	8.51	12.22
Ln(wage)	Ln(1k yuan)	876120	2.39	0.63	0.39	2.41	4.14
Age	Year	877354	9.66	9.22	1	7	48
Employee	Person	877354	192.37	293.80	12	97	1985
East	Dummy	877354	0.80	0.40	0	1	1
Firm Distance	Km	877354	76.06	102.32	-199.99	102.52	200

Notes: East is a dummy variable set to 1 if the firm is in the eastern region. Firm distance is from the firm's location to the east–inland provincial boundary, which is positive for eastern firms and negative for inland firms. All chosen observations are within 200 km of the boundary. We also examine the impact of the policy on ROA and R&D. After excluding missing values for these two variables, the sample contains 29 fewer observations than the one used in Fang et al. (Forthcoming).

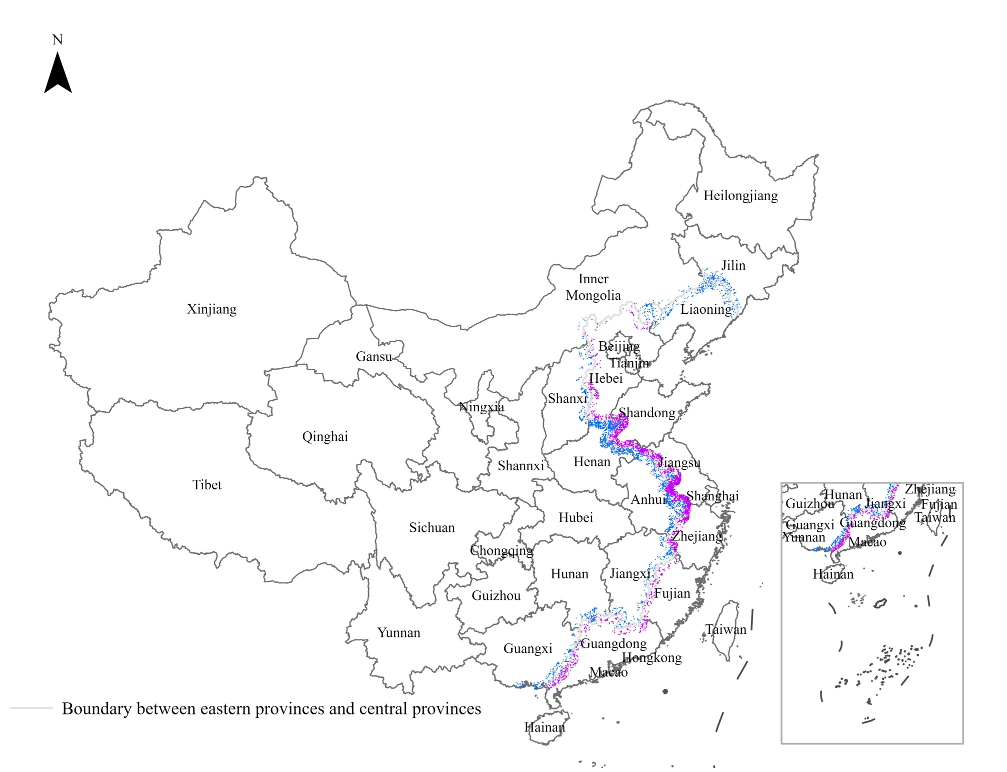
3 Main Empirical Analysis

We empirically analyze how the inland-favoring land supply policy affected firm performance, emphasizing the effects on firm-level TFP. We provide causal evidence that this policy shrank the TFP gap between eastern and inland firms. This reduction in the gap can be primarily attributed to the decreased TFP of eastern firms.

3.1 Empirical Specification

Our main empirical strategy in analyzing firm TFP combines a Border Regression Discontinuity Design as in Black (1999) and a Difference-in-Differences approach (RD-DID). The basic idea is to first compare firm TFP on the eastern and inland sides of the border. Then, we compare this border TFP difference over time, particularly before and after the year when the central government implemented the inland-favoring land supply policy. If the counterfactual time trend of TFP in the absence of the policy would have been similar across the neighborhoods on both sides of the border, the DID design can consistently identify the policy effect. Figure 1 shows the location of the boundary between the eastern and inland regions of China. Red dots represent firms on the eastern side of the boundary. Black dots represent firms on the inland side of the boundary. We use the region definitions published by the National Bureau of Statistics of China. Specifically, we categorize northeastern provinces as inland.

Figure 1: **China's Eastern-Inland Boundary**



Notes: The boundary is between eastern provinces and their inland neighbors. Purple dots represent firms on the eastern side of the boundary. Blue dots represent firms on the inland side of the boundary (To avoid confusion, the black dots on the eastern coastline are just islands, which are not part of our firm sample). The data source is the National Bureau of Statistics of China.

For firm i at border segment b in city c and year t, we have the following regression:

$$\begin{aligned}\ln(y_{ibct}) = \alpha &+ \beta_1 East_{ibt} + \beta_2 f(Dist_{ibt}) + \beta_3 East_{ibt} \times f(Dist_{ibt}) \\ &+ Post2003 \times [\delta_1 East_{ibt} + \delta_2 f(Dist_{ibt}) + \delta_3 East_{ibt} \times f(Dist_{ibt})] \\ &+ \beta_4 X_{ct-1} + \phi_b + \gamma_t + \psi_i + \epsilon_{ibct} \qquad (1)\end{aligned}$$

where y_{ibct} is the log TFP of firm i. $East_{ibt}$ is a dummy that equals one if the firm is located on the eastern side of the border, which carries a subscript t since firms can change their locations over time (although only very few do so). $f(Dist_{ibt})$ is a smooth function of the distance between the firm and the border, and $Post2003$ is a dummy that equals one if t is after 2003 (including 2003). X_{ct-1} is a set of lagged city-level control variables, including the log of GDP, the log of population, the log of city area, and the value added to the service sector. ϕ_b is the border segment fixed effect for the firm i, which can be different across years due to firms' location changes. We divide the border into five segments of equal length and assign each firm to the nearest segment. We check the robustness of the results when we use more granular segment fixed effects in Appendix Section A.13. γ_t is the year fixed effect. ψ_i is the firm fixed effect.

This regression combines RD and DID methods. First, consider the first three terms (except the intercept), that is, $\beta_1 East_{ibt} + \beta_2 f(Dist_{ibt}) + \beta_3 East_{ibt} \times f(Dist_{ibt})$. This comprises a border regression discontinuity design, with the running variable being the distance to the border. Using only the observations within a small bandwidth, we assume that firms just on the eastern side of the border are very similar to firms just on the inland side. By fitting a smooth function $f(Dist)$, β_1 captures the effect of being in the eastern region on outcome variable y. This study uses two fitting functions: local linear regression and linear regression.

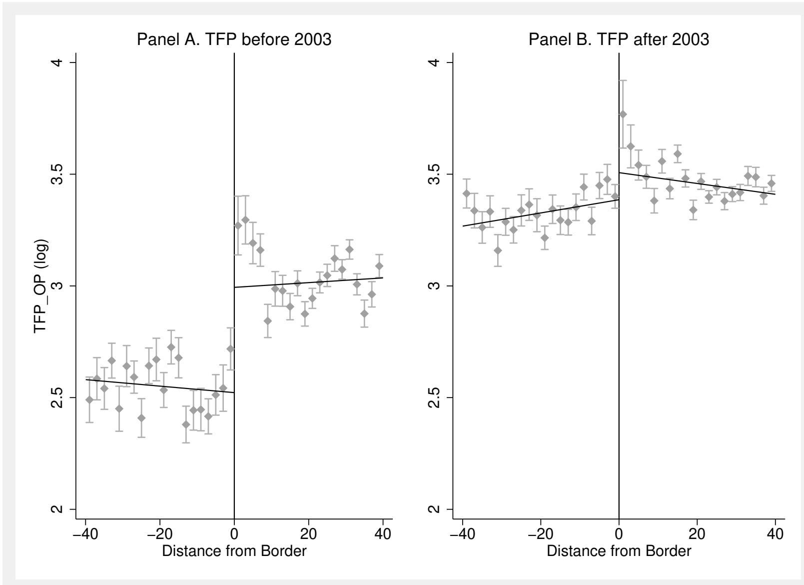
Second, we add interactions between the post-2003 dummy and all previous RD terms. Coefficient δ_1 then denotes the policy effect, which is interpreted as the change in the eastern region's TFP premium over the inland region before and after the 2003 inland-favoring land allocation policy. This is a difference-in-differences estimation. The first difference is between the eastern and inland regions (at the border). The second difference is between the before-policy and the after-policy periods.

It is important to clarify that the inland-favoring land policy can potentially affect the TFP levels of both regions. Therefore, the regression coefficient should be interpreted as the policy's effect on the regional gap (relative level) rather than on the absolute level of TFP for either region.

3.2 Regression Assumptions Validation

We validate our regression method by checking several important assumptions. First, we investigate the existence of the boundary discontinuity by drawing an RD figure. Panel A of Figure 2 shows data before 2003, and panel B data after 2003. The x-axis displays the distance of firms from the boundary, with a positive distance indicating firms located on the eastern side. The y-axis displays firm-level TFP, calculated using the Olley and Pakes (1996) method. This reveals a distinct discontinuity along the eastern-inland border in both panels. Notably, this gap narrowed following the implementation of the 2003 inland-favoring land policy.

Figure 2: **Regression Discontinuity Changes**



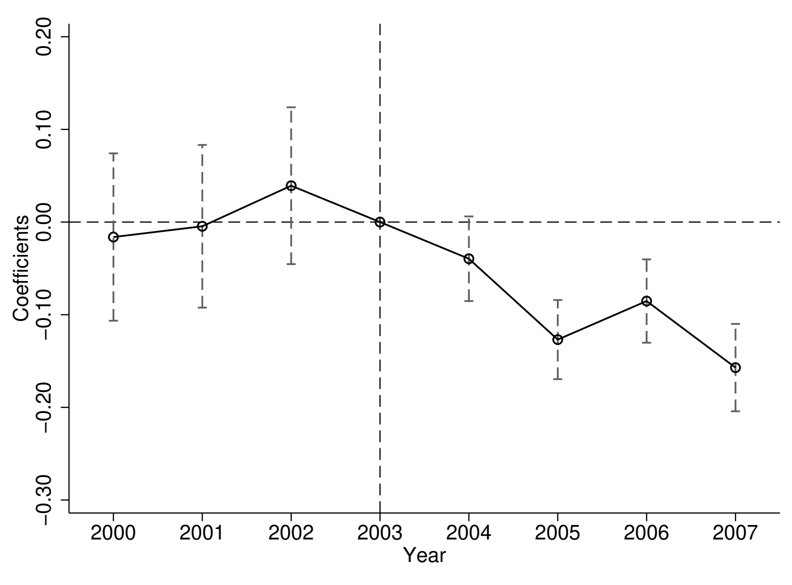
Notes: The dependent variable is firm-level TFP calculated using the Olley and Pakes (1996) method. The smoothing function is linear. The bandwidth is 40 km from the border.

Second, we investigate the eastern and inland time trends of firm TFP. Our regression specification assumes that firms on the eastern and inland sides of the border should share a similar time trend. We implement a traditional event study regression to investigate the evolution of the eastern region effect over time. We take 2003 as the baseline year and then run the following regression for the event study:

$$\begin{aligned}\ln(y_{ibct}) = \alpha &+ \beta_1 East_{ibt} + \beta_2 f(Dist_{ibt}) + \beta_3 East_{ibt} \times f(Dist_{ibt}) \\ &+ \sum_{s \neq 2003} \mathbf{1}(s = t) \times [\delta_{1s} East_{ibt} + \delta_{2s} f(Dist_{ibt}) + \delta_{3s} East_{ibt} \times f(Dist_{ibt})] \\ &+ \beta_4 X_{ct-1} + \phi_b + \gamma_t + \psi_i + \epsilon_{ibct} \end{aligned} \tag{2}$$

We plot the evolution of the coefficient δ_{1s} over time s in Figure 3, illustrating the changing effect of the eastern region over time, with 95% confidence intervals. We choose a linear smoothing function. We find that all coefficients are very close to zero before 2003. They became statistically and economically distinguishable from zero only after the policy was implemented. The results from this event study confirm the absence of a pre-trend in our data. These figures also give us a preview of the main results. After the central government implemented the inland-favoring land policy in 2003, the firm productivity gap between the eastern and inland regions decreased.

Figure 3: **Event Study - TFP (OP)**



Notes: The dependent variable is firm-level TFP calculated using the Olley and Pakes (1996) method. The bandwidth is 40 km from the border. The corresponding confidence interval is 95%.

3.3 Main Empirical Results

Table 2 shows the regression results based on TFP. In the first column, we use local linear regression as our fitting function. In the second column, we change the fitting function to be a global first-order polynomial (linear). We use the optimal bandwidth for the local linear fit based on Imbens and Kalyanaraman (2012). The bandwidth we use for the linear fit is 40 km. We also try other bandwidths, and the results are similar. Please refer to Appendix A for details. We find that the reduction in land supply after 2003 reduced the measured TFP of eastern firms relative to inland firms by about 8%.

3.4 Province-level Quota Regressions

To further validate our main results, we implement a province-level quota regression as follows:

$$\ln(Prod_{ijt}) = \alpha + \delta_1 Post2003_t \times QS_j + \phi_i + \gamma_t + \delta_2 X_{it} + \delta_3 X_{jt-1} + \epsilon_{jt} \tag{3}$$

where the subscripts i, j, and t refer to firm, province, and year, respectively. The dependent variable is firm-level TFP. QS_j represents the change in the quota share of the province where firm i is located before and after the policy (the 2000-2002 share minus the 2003-2007 share).

Table 2: **RD-DID Results on TFP (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0799**	-0.0766*
	(0.0356)	(0.0426)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7386	0.7348

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

This measures the exposure to the inland-favoring land supply policy. We also control for firm fixed effects (ϕ_i), year fixed effects (γ_t), tax and subsidy policies (X_{it}), and lagged city-level control variables (X_{jt-1}). While it would be better to run this regression at the prefecture level, prefecture-level land quota data is unavailable in China, so we have to use province-level quota data instead.

Table 3 shows that firms in provinces more exposed to the 2003 policy experienced a reduction in TFP relative to firms in less exposed provinces. This provides direct evidence that the 2003 changes in quota distribution affected firms in different provinces differently. Unfortunately, the lack of prefecture-level or county-level quota data prevents us from running regression discontinuity design (RDD) analyses.

3.5 Robustness Checks

We implement eleven groups of robustness analyses to address an extensive set of potential empirical concerns for our main regression. The results are available in Appendix A.

The first group addresses concerns with the robustness of our TFP estimates. We verify robustness by conducting the empirical analysis using firm-level TFP calculated with the methods proposed by Levinsohn and Petrin (2003). Table A1 shows that the results are very similar to the main results. The second group addresses concerns with the robustness of our bandwidth

Table 3: **Quota Regression**

	(1) OP	(2) LP
Post2003×QS	-0.0131***	-0.0126***
	(0.0012)	(0.0012)
City Lagged Controls	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Firm Controls	Y	Y
Observations	651,782	651,782
R-squared	0.7559	0.7940

Notes: The dependent variables are firm productivity measured by the Olley and Pakes (1996) and the Levinsohn and Petrin (2003) methods. We use quota changes in each province as the treatment variable. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the scale of the service sector. The set of firm-level control variables includes taxes paid and subsidies received by the firm. The standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

choice. We vary the bandwidths for the linear smoothing functions between 20 and 70 km in Tables A2 and A3. The results are very robust qualitatively. The third group addresses concerns with potential bad control issues. We estimate all main regressions without city-level lagged control variables to address any potential bad control issues. Tables A4 and A5 show that the resulting estimates are similar to those with control variables. Both the point estimates and R-squares exhibit minimal changes, validating our regression results according to Oster (2019). In the fourth group, we simplify the regression discontinuity functional form by keeping the slope of the smoothing function unchanged at the boundary. Table A6 shows minimal change compared with the baseline results.

In the fifth group, we alleviate potential contamination from special geographical characteristics at the provincial boundary by excluding firms within 10 km on either side. Table A7 shows that the results are unchanged. In the sixth group, we investigate the effect of firms changing location. In Figure A1 and Table A8, we show that the number of relocating firms is minimal, and no regression results change if we drop these firms. This is reasonable since the National Industrial Enterprise Database firms are all "above scale" large firms that rarely change their locations. In the seventh group, we perform a placebo test by shifting the boundary to the west or the east. We do not observe significant changes in firm TFP gaps for these artificial boundaries before or after 2003, as shown in Table A9. In the eighth group, we change the clustering level of the standard error to the province level. Table A10 shows that the results are still statistically significant. However, considering the negligible sample size compared with the population, this high level of clustering is inappropriate (Abadie et al., 2020, 2023). In the ninth group, we drop Liaoning Province from our sample. Northeastern China enjoyed certain favorable policies for regional development and Liaoning was not restricted by the land supply policy after 2003. Table A11 shows that our results are robust to this change.

We also addressed concerns about possible confounders around 2003. In the tenth group of robustness checks, we address the potential spatial effect of China's joining the WTO in 2001. To address this issue, we run regressions keeping only firms with zero exports and regressions controlling for firm-level exports to eliminate any WTO effect. The regression results in Tables A12, A13, A14, and A15 show that the main conclusions are unchanged. In the eleventh group, we try to rule out the effects of other subsidy and tax changes around 2003, which may distort our estimates. Tables A16, A17, and A18 show that the main results are maintained. In the twelfth group, we discuss the confounding policy of the Great Western Development Program (GWDP) in Appendix Section A.12. On the one hand, our boundary differs from that of the GWDP. On the other hand, the results are not changed if we drop all locations affected by the GWDP. In the thirteenth group, we change the 5-segment border fixed effects to a more granular 15-segment border fixed effects in Table A21. We do not find any qualitative change in our results.

3.6 Remarks on Main Results

We show that the inland-favoring land policy reduced the firm-productivity gap between developed eastern regions and underdeveloped inland regions. These findings indicate that although the government achieved the goal of shrinking the eastern-inland gap, it potentially came at a substantial cost of distorting land prices and decreasing the productivity of eastern firms. In other words, such regional convergence comes at the cost of spatial misallocation. In the next section, we will investigate the mechanism at the firm level in more detail.

4 Mechanism Analysis

In this section, we further investigate the mechanism by which the inland-favoring land policy affects firm productivity. At the firm level, the policy influences TFP through three distinct channels. First, such a policy could directly damage the productivity of existing eastern firms by increasing production costs, decreasing R&D expenditure, reducing new-firm entry, and consequently reducing regional agglomeration. We label this the "direct effect". Second, a more restrictive eastern land policy could precipitate the exit of lower-productivity firms from the market, compel them to downscale their operations below the NIED survey threshold, or even to cease operations. This could, in turn, elevate the location's average TFP, a process we refer to as the "selection effect". Thus, it may offset part of the policy's direct negative productivity effect. Third, in our TFP calculation using the OP method, land input is naturally included as one of the production factors. Therefore, this policy reduces land input and, as a result, mechanically lowers the measured TFP. We refer to this as the "mechanical effect". This effect is simply a measurement issue and does not carry a meaningful economic interpretation. Accordingly, we examine the first two channels separately.

4.1 Direct Effect

First, we investigate the policy's direct effect on firm productivity by running the same main regression but using firms' factor inputs and total outputs as the dependent variables. By scrutinizing changes in inputs and outputs, we can determine why firm productivity fell in the east relative to the inland region. In Table 4, we consider four variables: return on assets in columns (1) and (2); log of labor input (employment) in columns (3) and (4); log of capital input in columns (5) and (6); and log of total output in columns (7) and (8). In Table 5, we consider two R&D-related variables: the log of R&D expenditure in columns (1) and (2); and a dummy of whether R&D expenditure is larger than zero in columns (3) and (4). In the odd columns, we use a local linear smoothing function. In the even columns, we use a linear smoothing function.

We find that after 2003, eastern firms reduced their output and R&D expenditures compared to their inland counterparts. No significant effects were observed for return on assets, labor input, and capital input. Consequently, we do not find evidence that the 2003 inland-favoring land policy led eastern firms to reduce their traditional labor and capital factor inputs. Rather, the primary factor behind the decrease in the relative TFP and output of eastern firms is the reduction in their R&D expenditures. Firms decide to sacrifice innovation when land is more expensive.

Besides this decline in R&D expenditure, the negative impact of the policy could also stem from diminished agglomeration. We additionally investigate the policy effect on firm entry using the administrative Firm Registration Data in China. The dependent variable is the firm entry rate at the prefecture level, which is defined as the ratio of the number of newly entered firms to all existing firms in a prefecture. We keep only prefectures along the eastern-inland border and run a simple prefecture-level DID regression by controlling for prefecture and year fixed effects. Table 6 shows that the inland-favoring land policy led to more than a one percentage point decrease in the firm entry rate for the eastern region. This effect is notably salient for the manufacturing

Table 4: **RD-DID Results on Firm Inputs**

	ROA		Ln(Labor)		Ln(Capital)		Ln(Output)	
	(1) LL	(2) Poly	(3) LL	(4) Poly	(5) LL	(6) Poly	(7) LL	(8) Poly
Post2003×East	0.0000	0.0057	0.0124	0.0326	-0.0594	-0.0658	-0.0947**	-0.0862*
	(0.0051)	(0.0064)	(0.0237)	(0.0280)	(0.0397)	(0.0476)	(0.0393)	(0.0468)
City Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
Border FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	119,633	90,742	119,633	90,742	119,633	90,742	119,633	90,742
R-squared	0.6994	0.6953	0.9087	0.9081	0.8842	0.8848	0.8120	0.8108

Notes: The dependent variables are the return on assets, labor input, capital input, and total output, respectively. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD cases is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5: **RD-DID Results on Firm R&D**

	Ln(R&D)		R&D > 0	
	(1) LL	(2) Poly	(3) LL	(4) Poly
Post2003×East	-0.3352*	-0.1804	-0.1003**	-0.0586*
	(0.1978)	(0.1530)	(0.0407)	(0.0317)
City Lagged Controls	Y	Y	Y	Y
Border FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	32,246	47,674	32,246	47,674
R-squared	0.7122	0.7081	0.6507	0.6485

Notes: The dependent variables are the logarithm of R&D expenditure and the dummy of whether R&D expenditure is larger than zero. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD cases is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

sector. As less land supply and higher land prices raised the entry threshold, the agglomeration effect was reduced by the land-use policy. Reducing agglomeration and knowledge spillovers can also explain why firms are less incentivized to invest in innovation.

In Appendix B, we further analyze the first-order effect of the inland-favoring land policy on

Table 6: **RD-DID Results on Firm Entry**

	All Firms		Manufacturing Firms	
	(1)	(2)	(3)	(4)
Post2003×East	-0.0174***	-0.0172***	-0.0234***	-0.0232***
	(0.00515)	(0.00512)	(0.00624)	(0.00609)
City Lagged Controls	N	Y	N	Y
Year FE	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y
Observations	1,281	1,259	1,280	1,258
R-squared	0.8188	0.8232	0.8066	0.8146

Notes: The dependent variable is the proportion of newly-entered firms over all existing firms in a prefecture. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the scale of the service sector. The sample includes only prefectures at the border of the eastern and inland regions. The standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

land prices using land parcel level transaction data collected from the China Land Market Website (http://www.landchina.com/). Using a simple difference-in-differences model, we find that the inland-favoring land policy widened the land price gap between eastern and inland regions by 50 percentage points. Therefore, firms in the eastern region respond to this massive increase in land prices by reducing their R&D expenditure to cut costs. The firm entry rate is also reduced.

4.2 Selection Effect

In the NIED dataset, we classify firms that are present in year t but absent from the survey in year $t + 1$ as exiting firms. Conversely, firms that are present in both years are categorized as surviving firms. Figure 4 illustrates the proportion of exiting firms relative to the total number of firms for each year. On average, the exit rate ranges from 10% to 20%, with inland firms more likely to exit. Notably, there was a significant spike in 2003, where the exit rate for firms in both regions rose to over 25%.

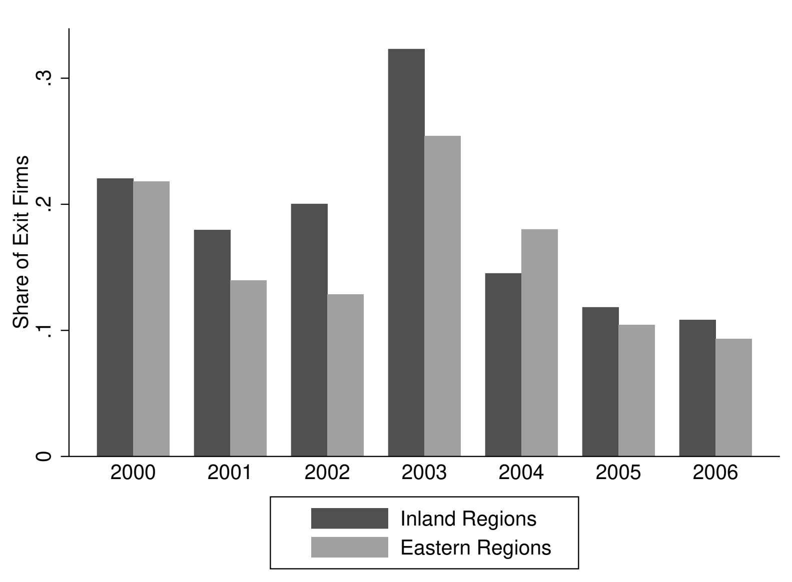
Figure 5 shows the average TFP for exiting firms (red solid line) and surviving firms (blue dashed line) across years. Subfigure (a) illustrates inland firms, and subfigure (b) illustrates eastern firms. We find that the productivity gap between existing and surviving firms is smaller in the east than in the inland. Furthermore, the gap shrank by similar magnitudes after 2003, both inland and in the east. Therefore, there is no evidence in our data supporting a regional difference in the selection of firms after the 2003 inland-favoring land supply policy. The offsetting effect from the exit of firms with lower productivity does not exist. In Figures 6 and 7, we further investigate the trends of firms' total assets and employment. We detect no evidence for a larger positive selection of surviving firms in eastern regions after 2003.

To precisely estimate the changes in selective pressure for firm i in year t, we run the following Difference-in-Differences-in-Differences (DDD) regression:

$$\begin{aligned} y_{it} = \beta_0 + &\beta_1 Exit_{it} \times Post2003_t \times East_j + \beta_2 Exit_{it} \times Post2003_t + \beta_3 Post2003_t \times East_j \\ &+ \beta_4 Exit_{it} \times East_j + \phi_i + \gamma_t + \beta_5 Exit_{it} + \epsilon_{it} \end{aligned} \tag{4}$$

$Exit_{it}$ indicates whether firm i in year t is an exiting firm that will disappear in the next year's survey. β_1 is the parameter of interest, which evaluates whether the eastern-inland productivity gap between exiting and surviving firms changed after 2003. It represents the effect of the inland-favoring policy on firm selection. If we detect a significantly negative coefficient, it means that this policy led to more selection and drove firms with low productivity growth out of the market in eastern regions, causing the remaining firms to have higher productivity growth than the firms that exited. Table 7 shows the results of this DDD regression, and we do not find any evidence for discrepancies in selection across regions.

Figure 4: **Exit Rate of Firms from NIED**

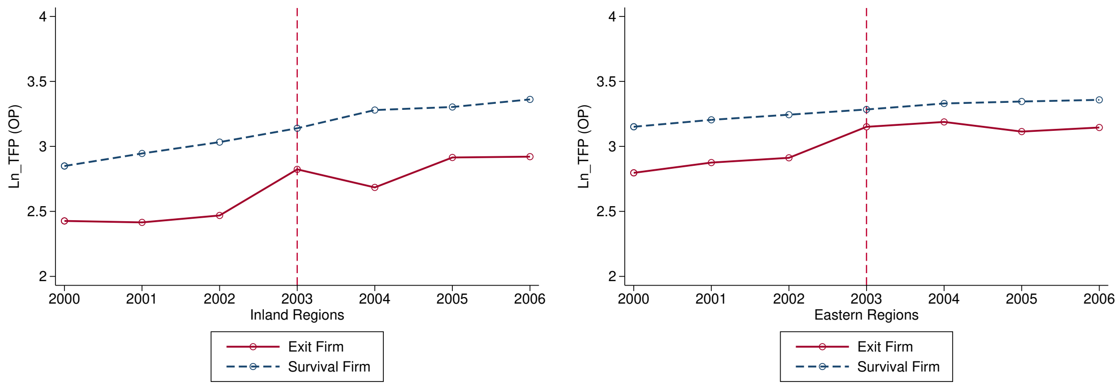


Notes: This figure shows the firm exit rate from the NIED Survey each year.

Figure 5: **TFP (OP) of Exiting and Surviving Firms by Region**

(a) Inland Firms' TFP

(b) Eastern Firms' TFP

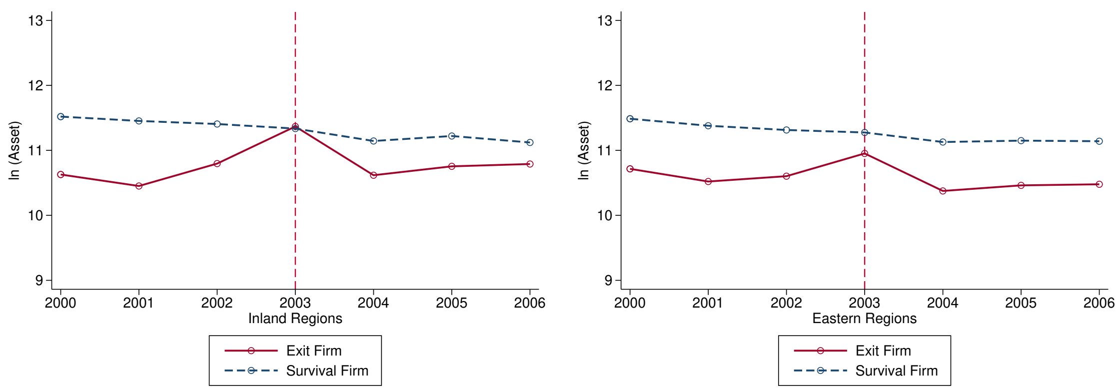


Notes: The data source is the National Industrial Enterprise Database. The blue dashed line represents surviving firms. The red solid line represents exiting firms. Subfigure (a) shows the TFP changes for inland firms. Subfigure (b) shows the TFP changes for eastern coastal firms.

Figure 6: **Total Assets of Exiting and Surviving Firms by Region**

(a) Inland Firms' Total Assets

(b) Eastern Firms' Total Assets



Notes: The data source is the National Industrial Enterprise Database. The blue dashed line represents surviving firms. The red solid line represents exiting firms. Subfigure (a) shows the changes in total assets for inland firms. Subfigure (b) shows the changes in total assets for eastern coastal firms.

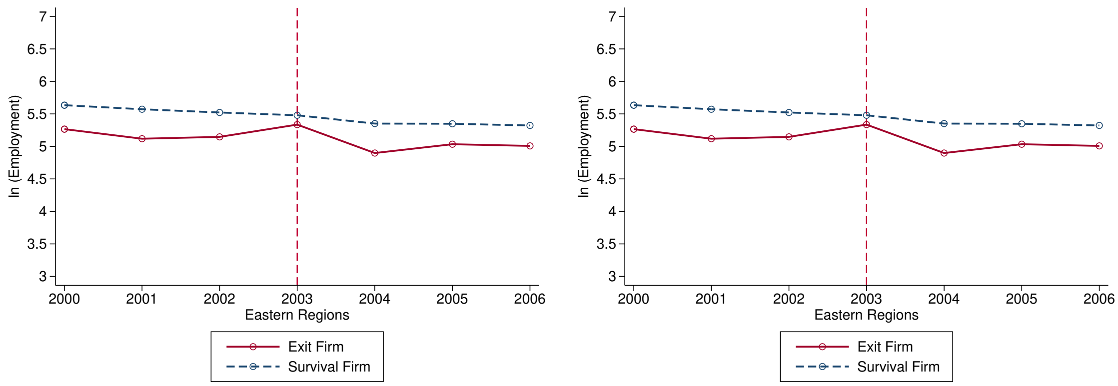
4.3 Heterogeneity

4.3.1 Land Demand Heterogeneity

We provide further evidence for our mechanism by investigating the heterogeneity of the policy effect. We investigate heterogeneous treatment effects across industries with varying land de-

Figure 7: **Employment of Exiting and Surviving Firms by Region**

(a) Inland Firms' Employment (b) Eastern Firms' Employment



Notes: The data source is the National Industrial Enterprise Database. The blue dashed line represents surviving firms. The red solid line represents exiting firms. Subfigure (a) shows the average changes in employment for inland firms. Subfigure (b) shows the average changes in employment for eastern coastal firms.

Table 7: **DDD TFP Selection Results**

	(1) OP	(2) LP
Exit×Post2003×East	-0.0153	-0.0134
	(0.0183)	(0.0185)
Double Interactions	Y	Y
Exiting Dummy	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	805,880	805,880
R-squared	0.7061	0.7449

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) and the Levinsohn and Petrin (2003) methods. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

mands. If the mechanism we propose holds, we should expect firms in land-intensive industries to suffer more from an inland-favoring land policy, since they are more sensitive to land price changes.

To investigate this issue, we calculate land demand intensity using data from the Chinese Enterprise Tax Survey. This report shows land taxes paid by each firm, from which we can infer

Table 8: **Land Intensity Heterogeneity Analysis on TFP**

	Across Industry		
	(1) Not Land Intensive	(2) Land Intensive	(3) Pooled
Post2003×East	-0.0457	-0.0989**	-0.0617*
	(0.0524)	(0.0499)	(0.0362)
Land Intensive×Post2003×East			-0.0378**
			(0.0159)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	59,612	59,312	119,633
R-squared	0.7402	0.7425	0.7386

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. In this table, we use local linear regression as the smoothing function. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 9: **Land Intensity Heterogeneity Analysis on R&D**

	Across Industry		
	(1) Not Land Intensive	(2) Land Intensive	(3) Pooled
Post2003×East	-0.0777	-0.0998*	-0.0926**
	(0.0590)	(0.0593)	(0.0414)
Land Intensive×Post2003×East			-0.0181
			(0.0177)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	16,433	15,495	32,246
R-squared	0.6454	0.6657	0.6508

Notes: The dependent variables is the dummy of whether R&D expenditure is larger than zero. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the service-sector scale. In this table, we use local linear regression as the smoothing function. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

their land usage. Using this firm-level data, we calculate the average land use for each industry and define land-intensive industries as those with land use above the median. We discuss the definition of the land intensity in more detail in Appendix Section C. Table 8 shows the results. Columns (1) and (2) run the regression separately for land-intensive and non-intensive industries. Column (3) pools them together and adds an interaction term with the land-intensive industry indicator. We find that the impact of the inland-favoring land policy is much more significant for firms in land-intensive industries, both statistically and economically. This confirms that our proposed mechanism is true. Firms in land-intensive industries suffered more from the policy because they are more sensitive to changes in land prices. In Table 9, we also investigate the heterogeneous impact on firm R&D and find that firms in land-intensive industries experienced larger R&D reduction.

Table 10: **SOE vs Non-SOE Analysis on TFP**

	By Ownership Type		
	(1) SOE	(2) Non-SOE	(3) Private
Post2003×East	-0.0390	-0.0850*	-0.1249**
	(0.1190)	(0.0471)	(0.0625)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	7,355	82,785	59,133
R-squared	0.8082	0.7065	0.7043

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the service-sector scale. In this table, we use local linear regression as the smoothing function. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. TFP is calculated using only firms within 40km of the border. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.3.2 SOE and Non-SOE

We further investigate the heterogeneity of the effects across firms with different ownership types in Table 10. We run our main regression separately for state-owned enterprises (SOEs), non-SOEs, and private enterprises in columns (1), (2), and (3), respectively. Specifically, the category of non-SOEs is broader than that of private enterprises, as it also includes foreign-owned and collective firms. The regression results show that the effect is primarily driven by non-SOEs, particularly private firms. For SOEs, we find no evidence that the inland-favoring land policy reduces productivity. This can be attributed to most SOEs enjoying preferential access to credit and land allocation, which makes them less constrained by land supply. We also investigate the heterogeneous impact on firm R&D and find that non-SOEs experienced larger R&D reduction.

5 Conclusion

In this note, we provide direct causal evidence on how China's 2003 inland-favoring land policy affected firm-level productivity by examining firms along the border between the eastern and inland regions. The main results are consistent with Fang et al. (Forthcoming). The mechanism analysis shows that the decrease in eastern firm productivity can be attributed to reduced R&D expenditure. This policy also deterred new-firm entry in the eastern region, thereby shrinking agglomeration effects. These findings indicate that although the government may have achieved the goal of narrowing the regional gap, it did so at the cost of market distortion, reduced productivity among eastern firms, and lower overall economic efficiency.

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A Robustness Checks

In this section, we implement nine groups of robustness checks for our empirical analysis. We also examine the policy's effect on other outcome variables.

A.1 Robustness Checks for TFP Estimation Method

First, we implement the empirical analysis using firm-level TFP calculated using the method proposed by Levinsohn and Petrin (2003). Table A1 shows the results of the primary regression using this productivity measure instead of the OP method, and all results remain very similar.

Table A1: **Robustness: RD-DID Results on TFP (LP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0978***	-0.0927**
	(0.0367)	(0.0439)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7619	0.7598

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. The regression specifications are identical to Table 2. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.2 Robustness Checks for Bandwidth Choices

Second, we adjust the bandwidth for the linear and quadratic smoothing functions. We present results for bandwidth choices ranging from 20 km to 70 km in Tables A2 and A3. The results remain qualitatively robust, although reducing the bandwidth results in fewer observations and decreased estimation precision.

Table A2: **Robustness: TFP Regressions with Different Bandwidth Choices (OP)**

bandwidth	(1) 20km	(2) 30km	(3) 40km	(4) 50km	(5) 60km	(6) 70km
Post2003×east	-0.0235	-0.0079	-0.0766*	-0.0825**	-0.0574*	-0.0271
	(0.0682)	(0.0512)	(0.0426)	(0.0363)	(0.0330)	(0.0298)
City Lagged Controls	Y	Y	Y	Y	Y	Y
Border FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	35,302	65,391	90,742	114,963	138,582	168,202
R-squared	0.7540	0.7380	0.7384	0.7385	0.7380	0.7359

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the scale of the service sector. We use a linear fit as the smoothing function. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A3: **Robustness: TFP Regressions with Different Bandwidth Choices (LP)**

bandwidth	(1) 20km	(2) 30km	(3) 40km	(4) 50km	(5) 60km	(6) 70km
Post2003×east	-0.0056	-0.0046	-0.0927**	-0.0947**	-0.0688**	-0.0376
	(0.0695)	(0.0527)	(0.0439)	(0.0373)	(0.0341)	(0.0309)
City Lagged Controls	Y	Y	Y	Y	Y	Y
Border FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	35,302	65,391	90,742	114,963	138,582	168,202
R-squared	0.7763	0.7608	0.7598	0.7618	0.7605	0.7595

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. We use a linear fit as the smoothing function. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.3 Robustness Checks for No City-level Controls

Third, we run all main regressions without city-level lagged control variables for two reasons. First, although we use lagged city characteristics, there may still be serial correlation in current-period values, potentially leading to control issues. Second, this can also serve as a balance check. If dropping controls does not significantly change the point estimates, this suggests that the likelihood of omitted variable bias (in this case, location-period-level unobserved variables) is low. Tables A4 and A5 demonstrate that the resulting estimates are similar to those in the regressions with control variables. The point estimates remain virtually unchanged. This implies that adding city-level characteristics does not affect the regression results, further validating the assumption that cities on the border exhibit similar trends.

Table A4: **Robustness: TFP Regressions without City-level Controls (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0833**	-0.0705*
	(0.0355)	(0.0425)
City Lagged Controls	N	N
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7372	0.7335

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The regression specifications are identical to those in Table 2, except that we drop all city-level lagged controls. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A5: **Robustness: TFP Regressions without City-level Controls (LP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.1000***	-0.0872**
	(0.0366)	(0.0438)
City Lagged Controls	N	N
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7604	0.7584

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. The regression specifications are identical to those in Table 2, except that we drop all city-level lagged controls. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.4 Keeping Slopes Unchanged at the Boundary

Fourth, we make the regression specification more parsimonious by keeping the slopes unchanged at the boundary. That is, we drop the fourth and the seventh terms in the main regression to have:

$$
\begin{aligned}
ln(y_{ibct}) = \alpha + \beta_1 East_{ibt} + \beta_2 f(Dist_{ibt}) + Post2003 \times [\delta_1 East_{ibt} + \delta_2 f(Dist_{ibt})] \\
+ \beta_4 X_{ct-1} + \phi_b + \gamma_t + \psi_i + \epsilon_{ibct} \qquad (5)
\end{aligned}
$$

Table A6 shows that this does not change our results. Our conclusion is not sensitive to the choice of the regression discontinuity functional form.

Table A6: **Robustness: RD-DID Results with No Slope Change (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0859**	-0.0766*
	(0.0345)	(0.0416)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7386	0.7348

Notes: We keep the slopes unchanged around the boundary in this setting. The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.5 Thick Border

Fifth, following Michalopoulos and Papaioannou (2014)'s recommendation, we use a thick border in our regression analysis. Provincial borders are often defined by geographical features such as mountains or rivers, and firms at these boundaries may differ significantly from those elsewhere. To address this, we exclude firms within 10 km of either side of the original provincial borders and extend our bandwidth by 10 km on the far side of each border to preserve the total bandwidth. This approach mitigates the potential impact of these unique geographic characteristics on our results. Table A7 presents the results using a thick border, and there are no significant changes compared with our baseline setting.

Table A7: **Robustness: RD-DID Results with Thick Border (OP)**

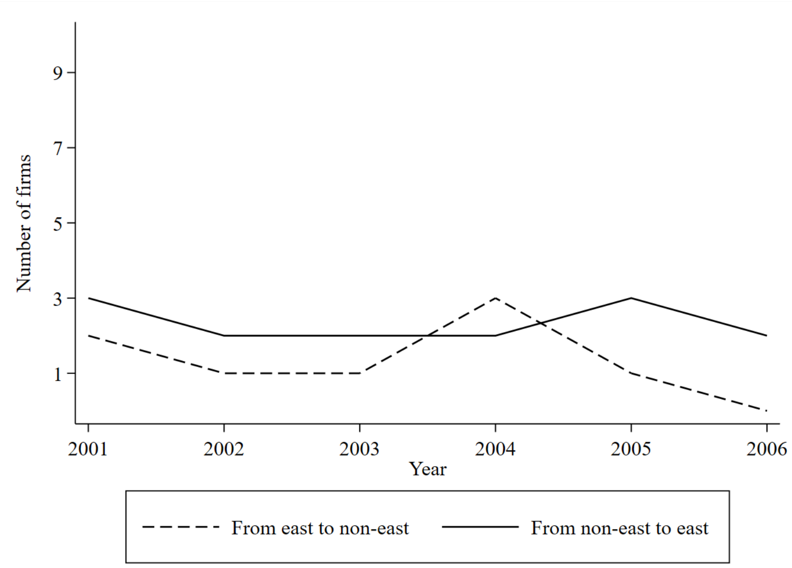
	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0942	-0.0962*
	(0.0707)	(0.0509)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	71,845	101,257
R-squared	0.7372	0.7397

Notes: We drop all firms within 10 km of the boundary and create a thick border. The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.6 Relocating Firms

Sixth, our empirical analysis is based on the National Industrial Enterprise Database, a panel dataset that tracks firm movements. However, a potential concern is that these relocation decisions may not be exogenous and could be influenced by the inland-favoring land policy. For instance, firms on the eastern side of the border may move to the other side of the boundary to take advantage of cheaper land. If the policy's effect on the local productivity gap is solely a result of this relocation, it may not have a meaningful impact on the economy as a whole.

Figure A1: **Number of Movers from 2001 to 2007**



Notes: This figure shows the number of firms relocating from eastern to inland regions and from inland to eastern regions in each year between 2001 and 2007.

Figure A1 illustrates the yearly count of companies relocating from eastern to inland regions and vice versa between 2001 and 2007 in our dataset. Generally, the number of relocating firms is minimal. For instance, only 3 out of 10,000 firms in our data moved from the east to inland in 2004. Additionally, we do not find any sudden change around the policy year 2003. Table A8 presents the main regression results after dropping all movers. There is no significant change.

Table A8: **Robustness: RD-DID Results without Movers (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0861**	-0.0755*
	(0.0355)	(0.0427)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	120261	90,666
R-squared	0.7386	0.7350

Notes: We drop all firms changing location. The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.7 Placebo Test

In this section, we address the spatial spillover issue using two placebo tests. In the first placebo test, we move the boundary west and east to create alternate imaginary boundaries. Then, we compare firms on opposite sides of these imaginary boundaries using the main regression. If there are obvious spatial spillovers, that is, if inland firms near the border were also negatively impacted by the policy, we should detect negative policy effects when we move the imaginary boundary to the west. Table A9 shows no evidence for this.

Table A9: **Robustness: Moving Boundary Placebo Test (OP)**

	(1) West 50km	(2) West 100km	(3) East 50km	(4) East 100km
Post2003×East	-0.0209	-0.0062	-0.0215	0.0139
	(0.0421)	(0.0316)	(0.0186)	(0.0142)
City Lagged Controls	Y	Y	Y	Y
Border FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	51,068	67,418	192,240	272,109
R-squared	0.7411	0.7363	0.7153	0.6968

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. In columns (1) and (2), we move the boundary westward by 50 and 100 kilometers, respectively. In columns (3) and (4), we move the boundary eastward by 50 and 100 kilometers, respectively. We use a linear fit as the smoothing function, with a bandwidth of 40 km. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.8 Clustering Standard Errors

In the main regression, we cluster the standard errors at the firm level, which is the cross-sectional unit of our panel data. This is recommended by Angrist and Pischke (2009) and Abadie et al. (2023). A potential concern is that firms located close to each other may be exposed to common shocks, which can result in spatial correlation of error terms. To capture this correlation, we cluster the standard errors at the province level. We estimate this regression after dropping all firms that changed location during the sampling period (movers) due to technical issues. Table A10 shows that we still have significant (or marginally significant) estimates. These estimates correspond to those in Table A8. We claim that this is a very conservative estimation of our standard errors because we have a dataset of all above-scale enterprises in China. If we do not account for our non-negligible sample size relative to the population, the standard errors are likely to be overestimated (Abadie et al., 2020). Clustering at too high a level is not recommended by Abadie et al. (2023). Therefore, we cluster the standard errors at the firm level in our main regression.

Table A10: **RD-DID Results on TFP (Clustering at Province-level)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0861	-0.0755*
	(0.0505)	(0.0405)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	120,261	90,666
R-squared	0.7386	0.7350

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD cases is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.9 Dropping Liaoning from the Sample

Ninth, we drop Liaoning Province from our sample. Since northeastern China also enjoyed certain other favorable policies for regional development, Liaoning was not restricted by the land supply policy after 2003. It is not accurate to categorize this province as either the treated or the control group. Table A11 shows that our results are robust to this change.

Table A11: **RD-DID Results on TFP without Liaoning**

	(1) OP	(2) LP
Post2003×East	-0.0749*	-0.0928**
	(0.0431)	(0.0444)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	87,643	87,643
R-squared	0.7349	0.7606

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) and the Levinsohn and Petrin (2003) methods. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. We use a linear smoothing function with a bandwidth of 40km around the raw boundary in this regression. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.10 Robustness Checks for The WTO Effect

Tenth, China joined the WTO at the end of 2001, leading to significant changes in the country's economic structure. Despite the policy occurring two years earlier, we remain concerned about the potential confounding effects of the reduction in trade barriers, which may have influenced eastern and inland firms differently. To address this issue, we run the TFP regression using only firms with zero exports, as they should be the least affected by WTO effects. Additionally, we run the main regression while controlling for firm-level exporting to eliminate any WTO-related influence. The regression results are displayed in Tables A12, A13, A14, and A15. Our main conclusions remain. We also find that a firm's exporting activity positively relates to its productivity, which aligns with predictions in the trade literature (Bernard et al., 2007, 2018).

Table A12: **Robustness: TFP Regressions without Exporting Firms (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0895**	-0.1079**
	(0.0406)	(0.0487)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	93,247	70,435
R-squared	0.7432	0.7391

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The regression specifications are identical to Table 2. We drop all firms with positive exports. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A13: **Robustness: TFP Regressions without Exporting Firms (LP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.1126***	-0.1395***
	(0.0419)	(0.0502)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	93,247	70,435
R-squared	0.7595	0.7575

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. The regression specifications are identical to Table 2. We drop all firms with positive exports. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A14: **Robustness: TFP Regressions Controlling for Exporting (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0720**	-0.0666
	(0.0355)	(0.0425)
log(Export)	0.0157***	0.0160***
	(0.0013)	(0.0015)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7391	0.7354

Notes: We additionally control for firm-level exports in this regression. The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The regression specifications are otherwise identical to Table 2. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A15: **Robustness: TFP Regressions Controlling for Exporting (LP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0855**	-0.0766*
	(0.0365)	(0.0436)
log(Export)	0.0245***	0.0256***
	(0.0013)	(0.0015)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7631	0.7611

Notes: We additionally control for firm-level exports in this regression. The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. The regression specifications are otherwise identical to Table 2. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.11 Robustness Checks for Subsidy and Tax Policies

Eleventh, we attempt to rule out the effects of other concurrent subsidy and tax policies that may have been implemented alongside the land reform. Apart from the land supply policy, the Chinese government also enacted other inland-favoring measures to promote inland economic growth, such as manufacturing subsidies. We conduct the primary regression using firm-level government subsidies as the outcome variable to check whether relative subsidies changed for firms at the border during the same year the inland-favoring land policy was introduced. Table A16 indicates that firms on either side of the border received similar government subsidies before and after 2003. We then estimate the firm-level TFP regressions with additional controls, including city-level central government subsidies per capita, firm subsidies from the government, and firm-level taxes paid to the government. Tables A17 and A18 demonstrate that the main results remain consistent across all regression settings.

Table A16: **Robustness: RD-DID Results on Firm-level Subsidies**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0010	-0.0015
	(0.0016)	(0.0019)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.6061	0.6028

Notes: The dependent variable is firm-level subsidies. The set of lagged city-level control variables includes the logs of GDP, population, and city area, and the value added in the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample for the polynomial RD case is restricted to be within a bandwidth of 40 km around the original boundary. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A17: **RD-DID Results with Firm-level Subsidy and Tax Controls (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0730**	-0.0658
	(0.0339)	(0.0404)
Tax	-1.7400***	-1.7556***
	(0.0213)	(0.0244)
Subsidy	-0.9290***	-0.9819***
	(0.0934)	(0.1062)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7783	0.7760

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. We additionally control for firm-level subsidies and firm-level taxes in these regressions. The regression specifications are identical to Table 2. We drop city-level lagged controls. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A18: **RD-DID Results with Firm-level Subsidy and Tax Controls (LP)**

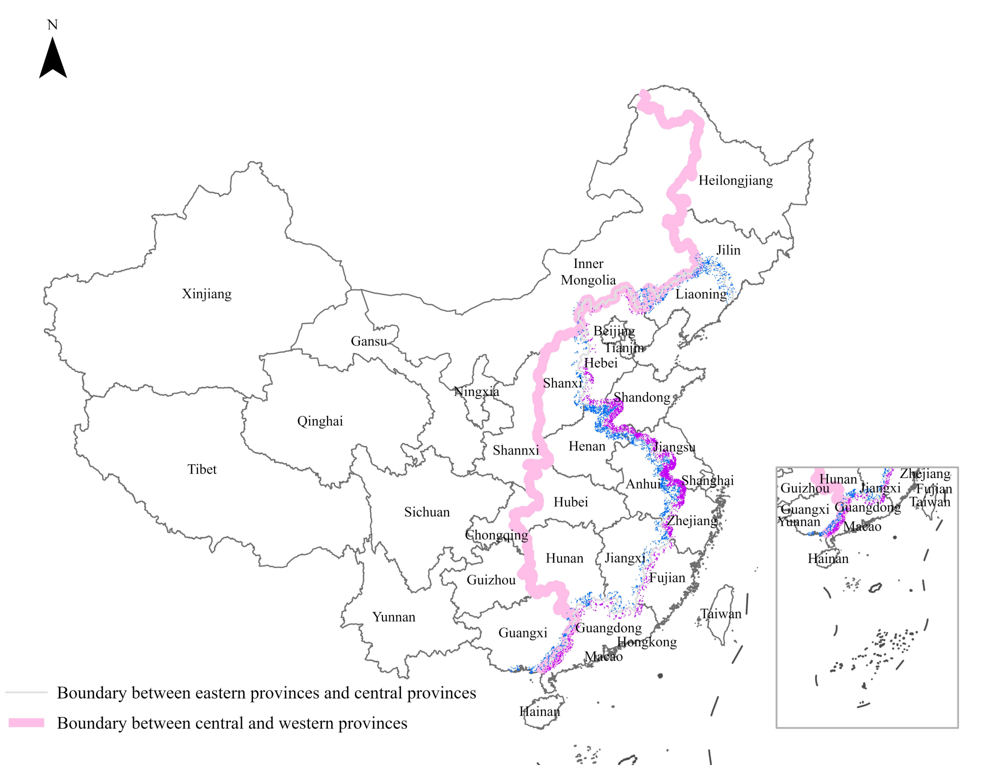
	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0908***	-0.0816*
	(0.0349)	(0.0416)
Tax	-1.7510***	-1.7640***
	(0.0218)	(0.0250)
Subsidy	-0.8810***	-0.9218***
	(0.0974)	(0.1110)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7985	0.7972

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. We additionally control for firm-level subsidies and firm-level taxes in these regressions. The regression specifications are identical to Table 2. We drop city-level lagged controls. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.12 Robustness Checks for Great Western Development Program

Another potential confounding policy is the Great Western Development Program (GWDP), which was initiated in 2000 by the central government of China to accelerate economic growth in 12 western provinces (Jia et al., 2020). We argue that this policy does not confound our results for two reasons. First, this policy started in 2000. However, we do not find any change in the firm productivity gap before 2003. Second, our study focuses on the boundary between eastern and inland (western + middle) provinces, which differs from the boundary between non-western and western provinces. As shown in Figure A2, these two boundaries diverge significantly. Third, in Tables A19 and A20, we exclude regions overlapping with the GWDP boundary and find that our results remain unchanged.

Figure A2: **China's Western Province Boundary**



Notes: The boundary is between eastern provinces and their inland neighbors. Purple dots represent firms on the eastern side of the boundary. Blue dots represent firms on the inland side of the boundary (to avoid confusion, the black dots on the eastern coastline are just islands and are not part of our firm sample). The pink line is the boundary between Western and non-Western provinces. The data source is the National Bureau of Statistics of China.

Table A19: **RD-DID Results on TFP without GWDP (OP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0854*	-0.0944**
	(0.0480)	(0.0484)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	79,009	78,134
R-squared	0.7257	0.7255

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the scale of the service sector. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A20: **RD-DID Results on TFP without GWDP (LP)**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.1135**	-0.1241**
	(0.0503)	(0.0508)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	79,009	78,134
R-squared	0.7572	0.7568

Notes: The dependent variable is firm-level TFP measured by the Levinsohn and Petrin (2003) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the service-sector scale. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

A.13 Robustness Checks for Granular Border Segment

In the main context, we divide the border into five segments. In this section, we further divide it into a more granular level with fifteen segments and control this set of fixed effects. Table A21 shows that our main results are not changed.

Table A21: **RD-DID Results on TFP with Fifteen Border Segments**

	(1) Local Linear	(2) Poly RD (Poly=1)
Post2003×East	-0.0795**	-0.0768*
	(0.0356)	(0.0426)
City Lagged Controls	Y	Y
Border FE	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
Observations	119,633	90,742
R-squared	0.7386	0.7350

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1996) method. The set of lagged city-level control variables includes the logs of GDP, population, and city area, as well as the service-sector scale. The sample in the local linear regression specification is restricted to be within an optimal bandwidth using a constant kernel. The sample in the polynomial RD case is restricted to be within a bandwidth of 40 km. The standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

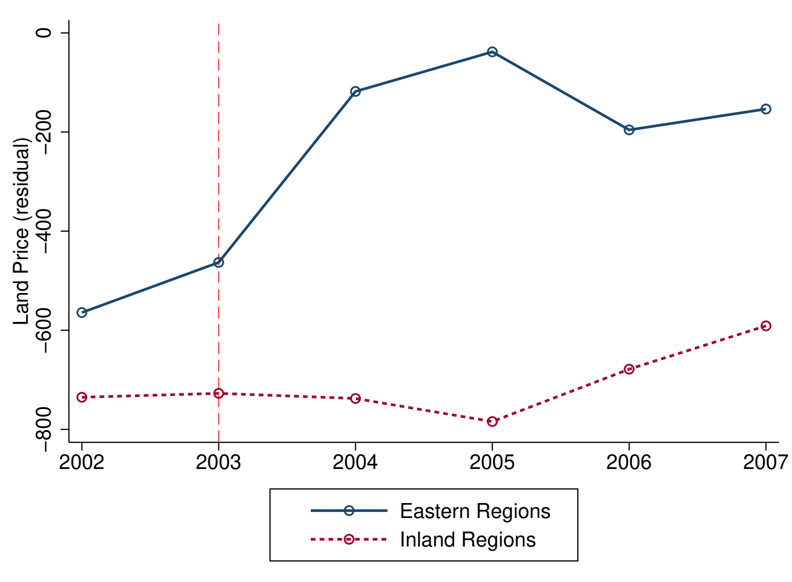
B Policy Effects on Land Prices

Our empirical strategy for analyzing land prices employs a DID regression at the land parcel level. Local land administration departments were required to publish information on the transfer of state-owned land-use rights only after the enactment of *The Regulations on the Disposition of State-Owned Land Use Rights for Auctions and Biddings* in 2007. Consequently, transaction data before 2007 is incomplete. The sample size became sufficient only after 2002; therefore, we conducted the regression using data from 2002 to 2007. Figures B1 illustrate the time trends for land prices. A significant increase in the land price gap between eastern and inland regions is observed after 2003. For land parcel i in prefecture j in year t, we estimate the following regression:

$$ln(P_{ijt}) = \alpha + \delta_1 Post2003_t \times East_i + \phi_j + \gamma_t + \epsilon_{jt} \tag{6}$$

$ln(P_{ijt})$ is the log land price. $East_i$ indicates whether this land parcel is located in the eastern region. ϕ_j and γ_t are prefecture and year fixed effects, respectively. We further control for linear time trends in different provinces and prefectures with different initial periods (2001) characteristics, including GDP per capita and industry composition. Table B1 presents the DID regression results. Our findings indicate that the inland-favoring land policy widened the land price gap between eastern and inland regions by 50 percentage points.

Figure B1: **Land Price Time Trends**



Notes: This figure shows land parcel price time trends. The black line is the average outcome value in the developed eastern region, and the grey line is the average outcome value inland. The dashed vertical line indicates the implementation of the inland-favoring land policy.

Table B1: **DID Results on Land Prices**

	(1)
Post2003×East	0.513**
	(0.220)
GDP Per Capita × Time Trend	Y
Industry Share × Time Trend	Y
Year FE	Y
Prefecture FE	Y
Observations	189,619
R-squared	0.502

Notes: The dependent variable is land parcel prices. We also control for land parcel-level selling categories. The standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

C The Construction of the Land Intensity Variable

In this section, we describe the method used to construct land demand intensity in our study. We calculate land demand intensity using data from the *Chinese Enterprise Tax Survey* for the period 2008–2014. This dataset reports the "urban land use tax" paid by each firm, from which we can infer their land usage. Using this firm-level information, we calculate the average land usage for each industry and define land-intensive industries as those with land usage above the median.

The database is a comprehensive, accurate, random-survey dataset. Each year, it includes samples of over 700,000 enterprises, covering all 16 tax types related to firm operations. The data collection is jointly organized and administered by the Ministry of Finance and the State Taxation Administration. We observe 262,630 firm-year observations over the period 2008–2014, holding urban land stock (others may lease land, or hold rural construction land stock), accounting for about 13.5% of the total number of manufacturing firms in the original database. This paper focuses on the entries related to the "urban land use tax." Starting from 2011, the database began reporting both the "urban land use tax" and the corresponding "total taxable land area." Before 2011, however, only the "urban land use tax" was available. According to the formula for the urban land use tax:

$$\text{Urban land use tax} = \text{Total taxable land area} \times \text{Applicable unit tax amount}.$$

We use the "applicable unit tax amount" of firms calculated for 2011 to impute the missing indicator and estimate the "total taxable land area" of firms for the period 2008–2010.

Table C1 presents the average land usage per firm across industries. Industries are ranked in descending order. This table intuitively displays the proportion of industrial land held by each industry and reflects the respective land demand intensity of each industry. The average land usage of firms in the *ferrous metal smelting and rolling processing industry* is significantly higher than that of firms in other industries, reaching 169,493 square meters. In contrast, the average land area of firms in the *textile, clothing, footwear, and headgear manufacturing industry* is much smaller, at only 18,878 square meters. These findings indicate substantial heterogeneity in land intensity across industries.

Table C1: **Descriptive Statistics of Land Usage by Industry**

Industry Name	Average Area (sq. m)
Ferrous Metal Smelting and Rolling Processing Industry	169,493
Chemical Fiber Manufacturing Industry	90,583
Non-ferrous Metal Smelting and Rolling Processing Industry	86,510
Beverage Manufacturing Industry	84,653
Chemical Raw Materials and Chemical Products Manufacturing Industry	67,077
Non-metallic Mineral Products Industry	61,049
Transportation Equipment Manufacturing Industry	60,828
Papermaking and Paper Products Industry	56,940
Pharmaceutical Manufacturing Industry	53,829
Rubber Products Industry	49,713
Food Manufacturing Industry	45,879
Agricultural and Sideline Food Processing Industry	43,549
Communication Equipment, Computers, and Other Electronic Equipment Manufacturing Industry	43,395
Waste Resources and Waste Materials Recycling and Processing Industry	42,675
Furniture Manufacturing Industry	42,544
Electrical Machinery and Equipment Manufacturing Industry	42,160
Specialized Equipment Manufacturing Industry	42,023
Textile Industry	39,723
Wood Processing and Wood, Bamboo, Rattan, Palm, and Grass Products Industry	38,826
General Equipment Manufacturing Industry	34,060
Metal Products Industry	33,864
Handicrafts and Other Manufacturing Industries	28,733
Plastic Products Industry	26,782
Cultural, Educational, and Sports Goods Manufacturing Industry	25,199
Leather, Fur, Feather (Down), and Related Products Industry	24,934
Printing and Reproduction of Recording Media Industry	22,094
Instrumentation, Cultural, and Office Machinery Manufacturing Industry	20,435
Textile, Clothing, Footwear, and Headgear Manufacturing Industry	18,878