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Place-based Land Policy and Spatial Misallocation: Theory and Evidence from China

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Abstract

Place-based land policies may create spatial misallocation. We investigate a major policy in China that aims to reduce regional development gaps by distributing more urban construction land quotas to underdeveloped inland regions. We first show causal evidence that this policy decreased firm-level TFP in more developed eastern regions relative to inland regions. We then build a spatial equilibrium model with migration, land constraints, and agglomeration. The model reveals that this policy led to substantial losses in national TFP and output. It shrinks regional output gap but lowers incomes of workers from underdeveloped regions by hindering their migration to developed regions.

Keywords: Place-based Policy; Land Policy; Spatial Misallocation; Regional Inequality; China;

JEL Classification Numbers: O18, R58, E24, J61, R52;

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1 Introduction

Most countries regulate land allocation using place-based policies. Many of these regulations, such as land supply quotas, target underdeveloped areas to promote balanced national development across regions (Neumark and Simpson, 2015). They commonly target on underdeveloped regions to promote balanced development across regions. However, promoting such balanced development may come at the cost of generating spatial misallocation.

In this paper, we study the consequences of a major place-based land allocation policy on both spatial misallocation and balanced development in China. We investigate a sudden shift of China's land supply policy in 2003 from demand-driven to development-promoting, which is typically known as the inland-favoring land policy.

Unlike most countries, the state owns and controls all urban land in China. The central government sets a strict cap on how much land can be used for construction in each city each year. Since the 1978 reforms, the Chinese government distributed construction land based on the demand of each city, which favored the rapidly developing eastern regions. However, the continuing divergence of economic development across regions became a major concern entering the 2000s, with the coastal eastern areas substantially outpacing the rest of the country. As a result, in 2003, the central government changed the demand-driven policy to a development-encouraging policy by reallocating land supply quota from developed regions to underdeveloped regions. This policy has since remained in place.

We find that this place-based policy generated severe spatial misallocation. It worsens property constraints in more productive developed regions, which increases housing costs and production floor space prices. Increased living costs and decreased labor demand then hinder migration into these more productive developed regions. Overall, national labor productivity is reduced for three reasons. First, less land is assigned to regions with higher productivity. Second, many workers stop migrating to places with high productivity. Third, the decline of migration further reduces agglomeration effects in places with high productivity.

But has China achieved the goal of promoting balanced development despite such spatial misallocation costs? Not really. Although the inland-favoring land supply policy shrinks the productivity and output gaps between developed eastern and underdeveloped inland regions, it lowers the incomes of workers from underdeveloped regions since they become less likely to migrate to developed regions with higher wages. The national overall welfare is largely reduced without a progress of utility of workers from poorer areas. Thus, this policy leads to a paradox of promoting geographically balanced development without helping people from underdeveloped regions.

By replacing the inland-favoring land supply policy with a direct regional transfer, China could increase national output as well as the incomes and welfare of workers from underdeveloped regions.

We analyze the consequences of this inland-favoring land supply policy in three steps. First, we combine Regression Discontinuity and Difference-in-Differences approaches (RD-DID) and show that this policy decreases relative firm-level TFP in eastern areas. Second, we develop a spatial equilibrium model to quantify the aggregate impact of the policy. We find that developed eastern cities have higher fundamental productivity and face more severe land supply constraints. Finally, by conducting a counterfactual exercise of eliminating this inland-favoring land supply policy, we find that total output and measured TFP would have been 2.3% and 6.4% higher in 2010. Although the output gap across geographical regions would have increased, the incomes of workers from underdeveloped cities would have increased. These results show that the inland-favoring policy creates spatial misallocation, which not only lowers overall productivity and output, but also lowers incomes of people from poorer areas.

In the first part of this study, we causally investigate the effect of the inland-favoring land supply policy adopted in 2003 on firm-level TFP in different regions. Firm-level TFP is calculated using data from the National Industrial Enterprise Database. A typical identification problem is that firms in the eastern region are usually very different from those in other regions, in terms of both observed and unobserved characteristics. To solve this endogeneity issue, we employ a method combining Border Regression Discontinuity Design (Black, 1999) and Difference-in-Differences approaches (RD-DID). The basic idea is that firms within a minimal bandwidth along the border are very similar, no matter if they are located on the eastern side or inland side. Thus, their prices and TFP should have similar time trends. This allows us to implement a DID strategy on these samples to identify the effect of the inland-favoring land policy.

We find that the inland-favoring policy lowers firm-level TFP in the eastern region by about 9%. The results are consistent across various regression robustness exercises. Further, there is no significant TFP improvement among inland firms. Thus, the empirical analysis shows that the inland-favoring land policy shrinks the productivity gap between eastern and inland firms by harming eastern firms without significantly helping inland firms.

In the second step, we construct a spatial general equilibrium model based on Ahlfeldt et al. (2015) to quantify the aggregate effects of China's land supply scheme. The model features substantial spatial heterogeneities (multi-city, multi-skill, and multi-sector), migration with costs, urban production with agglomeration, and floor space constraints in both housing and production. In the model, place-based land policy affects national TFP in three ways. First, reducing land supply in more developed cities directly reduces national TFP as productive firms in developed cities face tighter production floor space constraints. Second, it reduces migration into developed cities as workers face tighter residential floor space constraints (higher housing costs). Finally, it reduces agglomeration effects in more developed cities.

Using microdata from the Chinese Population Census, the City Statistical Yearbooks of 225 Chinese cities, and the Urban Statistical Yearbook of China in both 2005 and 2010, we solve and quantify the model. We then estimate the agglomeration parameter combining our empirical analysis of the natural experiment in the first part and the structural model using indirect inference in a novel way. We find that the agglomeration effect in China is larger than has been estimated for developed countries. Finally, we show in the quantitative results that in developed eastern cities measured TFP is much higher and the land constraint is much more severe.

In the final step, we implement two counterfactuals. In the first counterfactual, we examine what would happen if the pre-2003 land supply policy was maintained. Naturally, it increases land supply in eastern cities and decreases their floor space prices. It attracts more migrants to these cities and results in a 1.2% (1.2%) increase in total national output in 2005 (2010). We also find that the productivity loss due to the inland-favoring land supply policy is enormous. If we remove the policy, we estimate national TFP would increase by 4.8% in 2005 and by 6.4% in 2010 . The removal of the policy does reduce output and productivity in underdeveloped inland cities and causes a larger regional output gap. However, such downsides are effectively an illusion. Since workers in these underdeveloped inland cities now have better access to the developed cities their incomes are actually improving, and thus removing the inland-favoring policy can increase incomes for almost all workers. In sum, the inland-favoring land supply policy paradoxically helps poor regions but not people from poor regions.

In the second counterfactual, we propose a direct regional transfer as an alternative regional balancing policy to replace the place-based land supply policy. Instead of distributing more land to less developed regions, the central government could directly tax the additional benefits from more land in developed regions and transfer the proceeds to underdeveloped regions. Without loss of generality, we show that a simple direct transfer could truely increase the incomes and welfare of workers from underdeveloped regions with minimal spatial misallocation.

Literature Review Our study extends the current literature in four dimensions. First, it draws on evidence and theory for the effects of place-based policy. The literature has investigated various kinds of place-based policies in developed countries from different perspectives, including enterprise zones (Neumark and Kolko, 2010; Freedman, 2013; 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; Glaeser and Gottlieb, 2008; Becker, Egger, and Von Ehrlich, 2010), and community development (Eriksen and Rosenthal, 2010; Accetturo and De Blasio, 2012; Romero, 2009). This paper contributes to the literature as one of the first studies on national place-based land allocation policy. More specifically, we study a large scale place-based land policy in the largest developing country both empirically and theoretically. We are also one of the first to discuss a paradox of place-based policy where the region benefits but residents from the region do not.

Second, our study contributes to the large 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, 2020), farmland frictions (Fu, Xu, and Zhang, 2021; Yu, 2019), and combinations of some of the frictions above (Li, Ma, and Tang, 2021; Deng et al., 2020; Chen et al., 2019). Among these, the most related study is Yu (2019), who investigates the effect of the "Farmland Red Line Policy" on economic development in China. She finds that this restriction on converting rural farm land to urban construction land leads to severe spatial misallocation in land and labor, lowers GDP, and reduces welfare. Our paper contributes to the literature as one of the first to study the effects of place-based policy on spatial misallocation. More specifically, we investigate the combinations of migration frictions and land frictions in both production and residence on spatial misallocation. We are also the first to study the specific effects of this inland-favoring land policy on migration, productivity, and inequality in China.

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; Hao et al., 2019; Pi and Chen, 2019), international trade and labor mobility (Ma and Tang, 2020; Tian, 2018; Fan, 2019; Zi, 2020), housing constraints (Fang and Huang, 2022), air quality (Khanna et al., 2021), and local public services for migrants (Sieg, Yoon, and Zhang, 2021; Huang, 2020). This study contributes to the literature by connecting land misallocation and domestic migration to examine the effect of an important place-based policy on the Chinese economy in terms of both efficiency and equality.

Finally, we contribute to the literature on the estimation of the agglomeration effect, an intrinsically difficult parameter to pin down since population and density are endogenous (Combes and Gobillon, 2015). Previous studies address this issue using various strategies. The most popular method is to instrument current variables with lagged historical variables (Ciccone and Hall, 1996; Combes, Duranton, and Gobillon, 2008) or geological variables (Rosenthal and Strange, 2008; Combes et al., 2010). However, there has been no successful attempt to identify agglomeration in China due to data restrictions. Previous studies of China usually calibrate agglomeration parameters using values estimated from developed countries. Our paper uses a novel method similar to Ahlfeldt et al. (2015) to identify the agglomeration effect by exploiting the natural experiment of inland-favoring land supply policy in an indirect inference regression. This is the first study to causally estimate the agglomeration parameter in a spatial model in China.

Layout This paper is organized as follows. Section 2 provides the institutional background and describes the datasets. Section 3 provides empirical evidence that the inland-favoring land policy decreased firm-level TFP in more developed eastern regions relative to inland regions. Section 4 and 5 develop and estimate a spatial equilibrium model, and solves it using administrative microdata. Section Section 6 conducts a counterfactual analysis to eliminate the place-based land policy. Section 7 concludes.

2 Background and Data

2.1 Institutional Background

Land Ownership In China, there is no private land ownership. Agricultural land is owned collectively by the village, while urban land is state-owned. Agricultural land is transferred to the state through land expropriation before being used for urban construction. Then, construction companies need to buy the "use rights" from the local government. To ensure that there is enough agricultural land for the domestic food supply (Yu, 2019), the central government places strict controls on expanding urban areas. Each city is assigned a quota of construction land usage each year. Before 2003, the quota was mainly based on each city's demand.

The 2003 Reform The allocation of construction land quotas has been used as a place-based policy since 2003. Before 2003, developed areas with higher land demand were usually assigned more land quota. However, since 2003, the central government started to focus on balancing economic development by allocating more land to underdeveloped inland provinces.[1] In 2004, the central committee of the Chinese Communist Party made it clear that it is necessary to strengthen the role of land supply policy in macroeconomic management.[2] Additionally, the National Master Land Use Plan (2006–2020) issued in 2005 stated that construction land use in coastal areas will be strictly controlled, and land-use quotas in inland areas will be increased.[3]

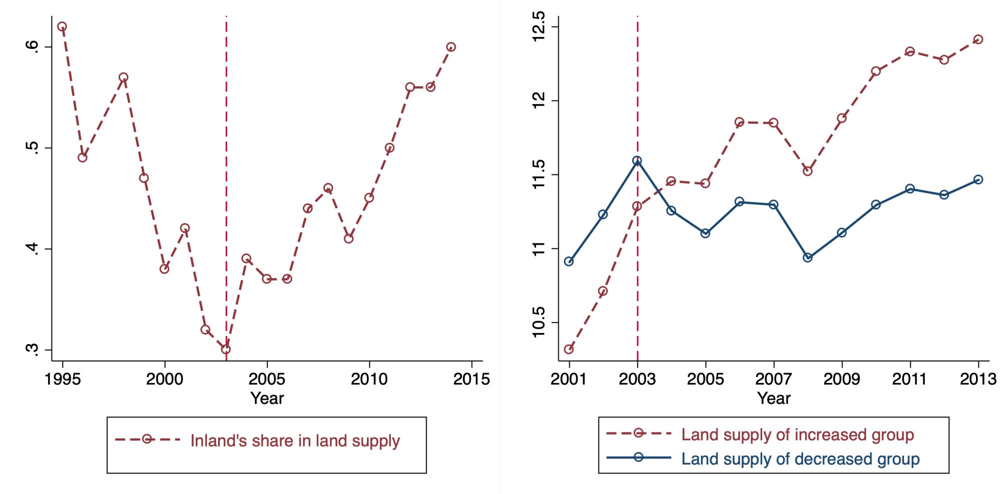
[1] Some studies have documented this significant change, see Lu and Xiang (2016), Han and Lu (2017), Liang, Lu, and Zhang (2016), or Fu, Xu, and Zhang (2021) for a reference.

[2] Decision of the State Council on deepening the reform of strict land management, issued on 12/21/2004 (link).

[3] The National Master Land Use Plan (2006–2020), published by Xinhua Press (link).

Figure 1:
The Inland-favoring Land Allocation Policy since 2003

(a) Inland Provinces' Share of Land Supply (b) Divergence between City Groups



Notes: Data sources are the National Bureau of Statistics of China, Statistical Yearbook of China's Land and Resources (2000–2016), and Yearbook of China's Land (1996–1999).

Another part of the policy is that, during 2003–2004, about 70% of existing development zones were closed. The planned urban construction land supply for these closed development zones was also cut. Most of these closed development zones were in the coastal region, and many newly opened development zones have since been established in inland areas to support local economic development (Lu and Xiang, 2016; Chen et al., 2019).

Figure 1 panel (a) shows that the inland provinces' share of the total land supply increased from less than 30% in 2003 to 60% in 2015. The turning point in 2003 is clear. The trend of using land-use quotas as an inland-favoring place-based policy became even more apparent at the city level. Figure 1 panel (b) divides Chinese cities into two groups: cities whose new land supply shares increased after 2003, and cities whose new land supply shares shrank after 2003. Land supply in the first group was lower before 2003, but it jumped and surpassed the second group after 2003, with the gap growing over time. Han and Lu (2017) also show that a city's land supply share was more likely to shrink after 2003 if it had a larger share of land supply before 2003. Most of these were developed eastern cities.

2.2 Data

2.2.1 Data for the Empirical Analysis

The main dataset we use in the empirical exercise is the National Industrial Enterprise Database, published by the National Bureau of Statistics. It covers all state- and non-state-owned enterprises that are "above scale" (main business revenue greater than 5 million RMB). This dataset accounts for more than 90% of all industrial production in China.[4] The dataset contains rich enterprise-level information, such as firm name, four-digit industry category, incorporation year, number of employees, total salary, and total fixed assets.[5] Table 1 shows the descriptive statistics of the enterprise data. Our main TFP calculation is based on the OP (Olley and Pakes, 1992) estimation method. We also calculate TFP using the LP (Levinsohn and Petrin, 2003) and the ACF (Ackerberg, Caves, and Frazer, 2015) methods. The results are similar, which are available in Appendix A.

Table 1:
Summary Statistics

Variable	Description	Observations	Mean	Std.dev.	Min	Max
Ln(tfp_op)	TFP(OP)	905,183	3.25	1.02	-0.038	5.63
Ln(tfp_lp)	TFP(LP)	905,183	6.37	1.10	3.08	9.02
Ln(tfp_acf)	TFP(ACF)	905,183	4.73	1.46	1.026	8.03
Ln(output)	Ln(1k yuan)	905,183	8.64	1.31	4.99	12.26
Ln(wage)	Ln(1k yuan)	903,922	2.40	0.64	0.087	4.12
Age	Year	905,183	9.70	9.26	1	48
Employee	Person	905,183	198.89	311.61	12	2150
East	Dummy	905,183	0.80	0.40	0	1
Firm Distance	Km	905,183	75.50	102.25	-199.99	200.00

Notes: East is a dummy variable set to 1 if the firm is in the eastern area. Firm distance is the distance from the firm's location to the east–inland provincial boundary, which is positive for eastern firms and negative for western firms. All chosen observations are within 200 km of the boundary.

2.2.2 Data for the Spatial Equilibrium Model

For the model part of this study, the main dataset we use is the Chinese Population Census. It is the most comprehensive household survey in China. Every ten years, the Chinese government carries out a thorough investigation of all households in the country, which is called the Census. All families must complete a short survey, which requires them to provide basic demographic

[4]Since there is a major missing data issue after 2007, we only use samples from 1998 to 2007.

[5]For unknown reasons, some companies provide missing or erroneous information. Therefore, we conducted a clean-up and applied a 1% censoring process to avoid abnormal observations.

information such as name, age, gender, education, and living address. Among all families, 10% of them must take a long survey. The long survey questionnaire includes additional information such as job and birth history. Between each decennial Census, there is a mini-Census. For each mini-Census, the National Bureau of Statistics randomly chooses 10% of the population to complete a survey similar to the long survey in the decennial Census. For simplicity, we call both the decennial Census and the mini-Census as Census data. In this study, we use Census data from 2005 and 2010. This gives us city-sector level migration flows and housing rents for individuals with different education levels. In total, we have 2,585,481 individuals in the year 2005, which covers 0.2% of the Chinese population. We have 4,803,589 observations in the year 2010, which covers 0.36% of the population.

Besides the Census, we also utilize the (manually collected) City Statistical Yearbooks of each city and the Urban Statistical Yearbook. The City Statistical Yearbooks are edited by local branches of the National Bureau of Statistics. Each city collects data on itself and publishes it annually. We use the city-industry level wage information in these books to impute city-skill level wages. The basic idea is as follows. We know each individual's industry and skill from the Census data. We also have average wages for each industry in each city from the City Statistical Yearbooks. We assign this average wage to each individual in the Census data based on their city and industry information as imputed individual wages. Then, we calculate the average wages in each city for each skill using these imputed wages. The detailed imputation method is identical to the one used in Fang and Huang (2022). We also derive city-level GDP growth and constructed land area data from the Urban Statistical Yearbook, which is a book summarizing key characteristics of all Chinese cities. We provide a complete list of cities with corresponding GDP, measured TFP, and land tightness which are used in our quantitative analysis in Appendix B1.

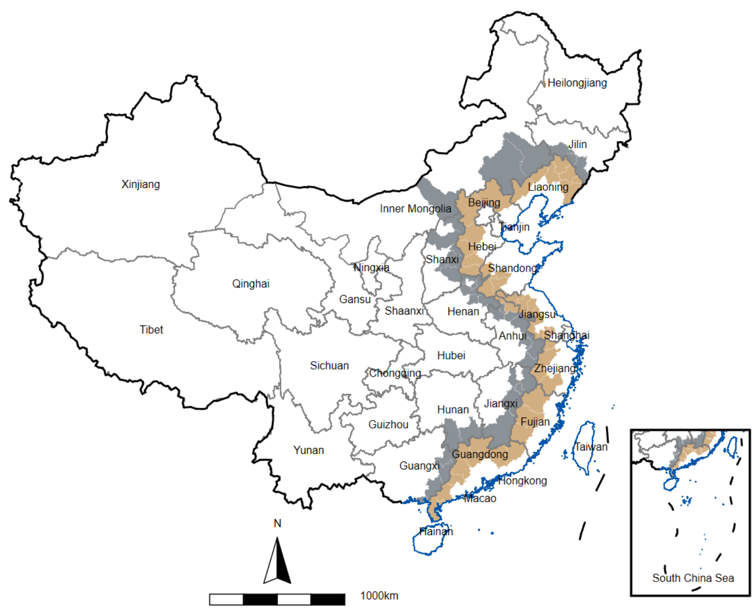
3 Empirical Analysis

In this section, we empirically analyze how the inland-favoring land supply policy in 2003 affected firms' TFP. We show causal evidence that this policy resulted in lower TFP for eastern firms relative to inland firms.

3.1 RD-DID Specification

The main empirical strategy we use is a combination of 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 time trend of TFP is similar in the neighborhood of the border, the DID design can identify the policy effect. Figure 2 shows the location of the boundary (at prefecture level) between the eastern and inland regions of China. We use the region definitions published by the National Bureau of Statistics of China.

Figure 2:
Boundary between Eastern and inland Region in China



Notes: 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:

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

where y_{ibct} is the TFP of firm i. $East_{ibt}$ is a dummy which equals 1 if the firm is located on the eastern side of the border. It has a subscript t since firms can change their locations across time. $f(Dist_{ibt})$ is a smooth function of the distance between the firm and the border, and $Post2003$ is a dummy which equals 1 if t is after 2003 (including 2003 itself).[6] X_{ct-1} is a set of lagged city-level

[6]We also run all regressions in a specification where 2003 is excluded from the treatment group. The results are

control variables, including the log of GDP, the log of population, the log of city area, and the value added of the service sector. ϕ_b is the border segment fixed effect. We divide the border into five segments of equal length and designate each firm to the nearest segment. γ_t is the year fixed effect. ψ_i is the firm fixed effect.[7]

This is a regression combining 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 regression with the running variable being the distance to the border. Using 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. We use three fitting functions in this study: local linear regression, linear regression, and quadratic regression.

Second, we add the interaction between the post 2003 dummy and all previous RD terms. Coefficient δ_1 then denotes the policy effect. It can be interpreted as the change in eastern region effects before and after the 2003 inland-favoring land allocation policy. Thus, this is a difference-in-differences estimation. The first difference is between the eastern and the inland regions (at the border, within the bandwidth). The second difference is between the before-policy (2003) period and the after-policy period. In general, this specification combines border regression discontinuity design with difference-in-differences.

3.2 Regression Assumptions Validation

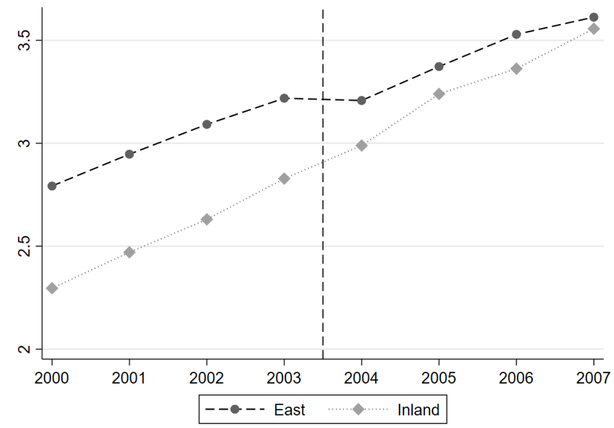
The main assumption of our regression specification is that firms on the eastern and inland sides of the border should have similar time trend. Figure 3 shows the time trends of the main outcome variable, firm-level TFP calculated using the Olley and Pakes (1992) method. The black line is the average outcome value in the developed eastern region and the grey line is the value in the inland region. The dashed vertical line is located just after 2003, the year in which the inland-favoring land policy was implemented. There is no evidence of different time trends before the policy. Another clear message we get from this figure is that although the 2003 policy aimed to help the inland region, the growth rate of TFP in the inland region did not increase. On the contrary, the policy suppressed the growth of the eastern region.

Furthermore, we implement a traditional event study regression to investigate the evolution of the eastern region effect across time. We take 2003 as the baseline year and then run the following

not qualitatively changed.

[7]We also investigate a simpler regression setting without firm fixed effect. The results are not qualitatively changed.

Figure 3:
Time Trends of TFP



Notes: This figure shows the time trends of firm-level TFP calculated using the Olley and Pakes (1992) method. The black line is the average outcome value in the developed eastern region and the grey line is the value in the inland region. The dashed vertical line indicates the implementation of the inland-favoring land policy. TFP is calculated using only firms within 40km of the border. It is clear that firm-level TFP followed similar trends before the policy.

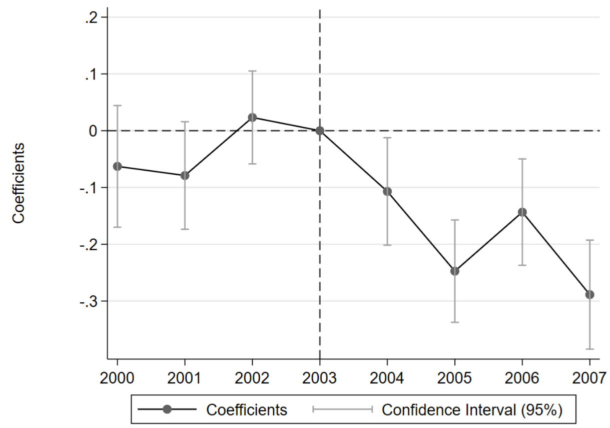
regression:

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

We plot the evolution of the coefficient δ_{1s} across time s in Figures 4, illustrating the changes of the eastern region effect across time, with 95% confidence intervals. We choose a linear smoothing function. We find that all the coefficients are very close to zero before 2003. They become statistically and economically distinguishable from zero only after the policy was implemented. The results from this event study confirm that there is no pre-trend in our data. These figures also give us a preview of the main results. After the central government imposed the inland-favoring land policy in 2003, there was a relative decrease in firm productivity in the eastern region.

Investigation of the before-and-after in each region makes it clear that this policy reduced firm-level TFP growth in the east while inland firm-level TFP growth remained roughly unchanged. Despite eastern firms starting with higher TFP than their inland peers, their average TFP fell below the original trend and converged to the average TFP of inland firms.

Figure 4:
Event Study - TFP (OP)



Notes: The dependent variable is firm-level TFP calculated using the Olley and Pakes (1992) method. The bandwidth is 40 km from the border. The corresponding confidence interval is 95%.

3.3 RD-DID Results

We show causal evidence that this policy resulted in lower TFP for eastern firms relative to inland firms. Table 2 shows the regression results when we use the log of firm-level TFP as the outcome variable. In the three columns, we use a local linear fit, linear fit, and quadratic fit for the smoothing function respectively. The optimal bandwidth we use for the local linear fit is based on Imbens and Kalyanaraman (2012). The bandwidth we use for the linear and the quadratic fit is 40 km.[8] We find that the reduction in land supply after 2003 reduced the measured TFP of eastern firms relative to inland firms by about 9%.

Robustness Checks We also implement five groups of robustness tests to address robustness concerns. The results are available in Appendix A. The first three groups address measurement concerns. The latter two address potential identification threats.

The first concern is with the robustness of our TFP estimates. We verify robustness by implementing the empirical analysis using firm-level TFP calculated through the Levinsohn and Petrin (2003) and the Ackerberg, Caves, and Frazer (2015) methods. Tables A1 and A2 show that the results are very similar to the main results. The second concern deals with the robustness of our bandwidth choice. We consequently vary the bandwidths for the linear and quadratic smoothing functions between 20 and 70 km in Tables A3 and A4. The results are very robust qualitatively. Third, we run all main regressions without city-level lagged control variables to address the po-

[8]We also try some other bandwidths, the results are similar. Please refer to the Empirical Appendix A for details.

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

	(1) Local Linear	(2) Poly RD (Poly=1)	(3) Poly RD (Poly=2)
Post2003×East	-0.093*	-0.097**	-0.093
	(0.055)	(0.039)	(0.057)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	47690	110794	110794
Adjusted R-squared	0.121	0.111	0.111

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1992) 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 cases is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

tential bad control issue. Tables A5 and A6 show that the resulting estimates are very similar to those with control variables.

We also address concerns relating to possible confounding place-based policies or events around 2003. First, we address the potential spatial effect of China 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 A7, A8, A9 and A10 show that the main conclusions are not changed. Second, we try to rule out the effects of some other subsidy and tax policies happening at this point which may distort our estimates. Tables A11, A12 and A13 show that the main results are maintained, where further detail on these concerns is also provided.

3.4 Remarks on the Empirical Analysis

In this empirical analysis, we show that the inland-favoring land policy decreased firm productivity in the developed eastern regions relative to firm productivity in the underdeveloped inland regions. This relative decrease is almost solely due to the reduction in the growth of firm productivity in the east rather than any acceleration of growth among inland firms.

These findings indicate that although government achieved the goal of shrinking the regional gap between the eastern and inland regions, it potentially came at a substantial cost of distorting the productivity of eastern firms rather than promoting inland firms. In other words, such regional convergence comes at the cost of spatial misallocation. Although these results are clean and causal, they are only local effects at the border. To better understand the national effect and the mechanism, we construct a spatial equilibrium model to conduct further quantitative and counterfactual analysis in the following sections.

4 The Model

The economy consists of a set of discrete locations, more specifically, **cities** (prefectures), which are indexed by $i = 1, ..., K$. Each city j consists of two sectors: urban u and rural r. The economy is populated by an exogenous measure of H workers, who are imperfectly mobile within the economy subject to migration costs. Each worker is either low skill $s = l$ or high skill $s = h$. Each location i has an effective supply of urban floor space S_i^u which is produced by a fixed amount of urban land supply L_i^u. In urban areas, floor space can be used for both production and residence, and we denote the endogenous fractions of floor space allocated to production and residential use by θ_i and $(1 - \theta_i)$, respectively. The housing market in rural areas is simplified such that the rent is proportional to the average rent in urban areas in the same city.[9]

Workers decide whether to move after observing idiosyncratic utility shocks between each possible pair of destinations and their original location. Firms produce a single final good, which is costlessly traded within the country, and is chosen as the numeraire. Locations differ in terms of their urban final goods productivity (A_i^u), rural final goods productivity (A_i^r), and supply of floor space in their urban region (S_i^u).

Finally, we introduce the agglomeration effect where city-level productivities in urban areas are positively related to their population density. Then we estimate the agglomeration parameters using our empirical findings above and our structural model with indirect inference.

4.1 Worker Preferences

The utility of worker o with skill s, originating from region i sector n, migrating to region j sector k, is a combination of final good consumption ($c_{in,jk}^o$), residential floor space consumption ($s_{in,jk}^o$),

[9]This model setting reflects the special land distribution system of rural China. All land in rural China is owned by the village collectively, but not by individual. There is no housing market in the rural area. The village council first distributes land to farmers (housing land, or in Chinese, *Zhaijidi*), then farmers build their houses by themselves. They cannot sell or buy any houses. Thus, the housing cost for them is basically building cost.

migration costs ($\tau^s_{in,jk}$), and an idiosyncratic shock ($z^o_{in,jk}$) in a Cobb-Douglas form:

$$U^o_{in,jk} = \frac{z^o_{in,jk}}{\tau^s_{in,jk}} \left(\frac{c^o_{in,jk}}{\beta}\right)^{\beta} \left(\frac{s^o_{in,jk}}{1-\beta}\right)^{1-\beta} \tag{3}$$

We model the heterogeneity in the utility that workers derive from working in different parts of the economy following Ahlfeldt et al. (2015). We also do not distinguish between urban residence and rural residence in the utility function, but allow rural workers to construct their own residential floor space by paying construction costs. For each worker o originating from region i sector n, migrating to region j sector k, the idiosyncratic component of utility ($z^o_{in,jk}$) is drawn from an independent Fréchet distribution:

$$F(z^o_{in,jk}) = e^{-{z^o_{in,jk}}^{-\epsilon}}, \ \epsilon > 1$$

where the shape parameter $\epsilon > 1$ controls the dispersion of idiosyncratic utility. We assume that the migration costs can be separated into two parts $\tau^s_{in,jk} = \bar{\tau}^s_{in} d_{in,jk}$ where $d_{in,jk}$ captures the physical distance and institutional costs due to the Hukou system[10] and other potential frictions in migrating from city i sector n to city j sector k, and $\bar{\tau}^s_{in}$ captures cost differences between individuals with different skills which may include skill-biased migration policies or differences in their preferences for specific types of amenities such as education for children, entertainments, or transportation.

After observing the realizations of idiosyncratic utility for each pair of origination and potential employment locations, each worker chooses their location and sector of employment to maximize utility, taking as given residential amenities, goods prices, factor prices, and the decisions of other workers and firms. Each worker is endowed with one unit of labor that is supplied inelastically with zero disutility. Combining our choice of the final good as numeraire with the first-order conditions for consumer equilibrium, we obtain the following demands for the final good and residential floor space for worker o with skill s from location i sector n who migrates to location j sector k:

$$c^o_{in,jk} = \beta v^s_{in,jk}, \quad s^o_{in,jk} = (1-\beta)\frac{v^s_{in,jk}}{Q_{jk}}$$

where $v^s_{in,jk}$ is the total income for a worker with skill s who stays in sector k and Q_{jk} is the rental cost of residential floor space in sector k in city j.

Floor space in city i sector n is not tradable and is owned in common by Hukou-registered work-

[10]Hukou system is a household registration system in China which restricts workers' mobility. For details, please refer to (Song, 2014).

ers originating from city i sector n. This assumption is broadly consistent with the institutional features of China and implies that migrant workers have no claim to this fixed factor income. Therefore, the income $v^s_{in,jk}$ is a combination of wage income which depends on skill s in city j sector k and equally-divided residential floor space rent income among all Hukou registrants in city i sector n:

$$v^s_{in,jk} = w^s_{jk} + \frac{Q_{in} S^R_{in}}{H^R_{in}} \tag{4}$$

where H^R_{in} denotes all Hukou registrants including those who migrated to work elsewhere.[11]

Substituting equilibrium consumption of the final good and residential land use into utility, we obtain the following expression for the indirect utility function:

$$U^o_{in,jk} = \frac{z^o_{in,jk} v^s_{in,jk} Q^{\beta-1}_{jk}}{\tau^s_{in,jk}} \tag{5}$$

4.2 Distribution of Migration Flows

Using the monotonic relationship between utility and the idiosyncratic shock, the distribution of utility for a worker migrating from city i sector n and move to city j sector k is also Fréchet distributed:

$$G^s_{in,jk}(u) = Pr[U \leq u] = F\Big(\frac{u \tau^s_{in,jk} Q^{1-\beta}_{jk}}{v^s_{in,jk}}\Big)$$

$$G^s_{in,jk}(u) = e^{-\Phi^s_{in,jk} u^{-\epsilon}}, \; \Phi^s_{in,jk} = (\tau^s_{in,jk} Q^{1-\beta}_{jk})^{-\epsilon} (v^s_{in,jk})^{\epsilon}$$

Since the maximum of a sequence of Fréchet distributed random variables is itself Fréchet distributed, the distribution of utility across all possible destinations is

$$1 - G^s_{in}(u) = 1 - \prod_{jk=11}^{JK} e^{-\Phi^s_{in,jk} u^{-\epsilon}}$$

[11] This assumption is unlike Tombe and Zhu (2019) which makes a stronger assumption that migrant workers have no claim to any fixed factor income from land of either their current working city or their Hukou city. In their model, whenever a worker migrates, she loses all fixed factor income from her previously owned local property in her Hukou city. Our mechanism in this paper would be even stronger with their assumption. However, we think our current assumption is closer to the institutional features of China.

Therefore we have

$$G^s_{in}(u) = e^{-\Phi^s_{in} u^{-\epsilon}}, \ \Phi^s_{in} = \sum_{jk=11}^{JK} \Phi^s_{in,jk}$$

Let $\pi^s_{in,jk}$ denote the share of workers with skill s registered in in who migrated to jk. The law of large numbers implies that the proportion of workers who migrate to sector-region jk is

$$\pi^s_{in,jk} = \frac{(\tau^s_{in,jk} Q_{jk}^{1-\beta})^{-\epsilon} (v^s_{in,jk})^{\epsilon}}{\sum_{j'k'=11}^{JK} ((\tau^s_{in,j'k'} Q_{j'k'}^{1-\beta})^{-\epsilon} (v^s_{in,j'k'})^{\epsilon})} = \frac{\Phi^s_{in,jk}}{\Phi^s_{in}} \tag{6}$$

This is a typical gravity equation in spatial equilibrium models.

4.3 Production

We assume that there is a single final good y that is costlessly traded within the economy. In urban regions, it is produced with constant returns to scale following a Cobb-Douglas form, using some efficient labor combination X_j, and production floor space S^M_j:

$$Y_{ju} = (X_{ju})^{\alpha} (S^M_{ju})^{1-\alpha}, \text{ where } X_{ju} = [(A^h_{ju} H^h_{ju})^{\frac{\sigma-1}{\sigma}} + (A^l_{ju} H^l_{ju})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{7}$$

where X_{ju} is a CES combination of high skill labor H^h_{ju} and low skill labor H^l_{ju} multiplied by their corresponding city-level efficiencies A^h_{ju} and A^l_{ju}. In rural regions, production is simply $Y_{jr} = A_{jr} H_{jr}$. Since we are not focusing on trade or substitution between agricultural goods and other goods, we simply assume that Y_r and Y_u are perfect substitutes. In equilibrium, A_{jr} equals the agricultural wage w_{jr} in city j rural sector r.[12]

Firm Optimization We assume that the goods market is perfectly competitive. Urban firms choose their inputs of workers and production floor space to maximize profits, taking as given final goods productivity ($\{A^h_{ju}, A^l_{ju}\}$), the distribution of idiosyncratic utility, factor prices, and decisions of other firms and workers. From the first-order conditions, we obtain:

$$w^l_{ju} = \alpha X_{ju}^{\alpha-1} S^{M\,1-\alpha}_{ju} A^{l\ \frac{\sigma-1}{\sigma}}_{ju} X_{ju}^{\frac{1}{\sigma}} H^{l\ -\frac{1}{\sigma}}_{ju} \tag{8}$$

$$w^h_{ju} = \alpha X_{ju}^{\alpha-1} S^{M\,1-\alpha}_{ju} A^{h\ \frac{\sigma-1}{\sigma}}_{ju} X_{ju}^{\frac{1}{\sigma}} H^{h\ -\frac{1}{\sigma}}_{ju} \tag{9}$$

$$S^M_{ju} = \left(\frac{1-\alpha}{q_{ju}}\right)^{\frac{1}{\alpha}} X_{ju} \tag{10}$$

[12] We make a simplification such that $w^h_{jr} = w^l_{jr} = w_{jr}$.

The zero profit property from the constant return to scale production function could determine the equilibrium production floor price q_j by

$$(X_{ju})^{\alpha}(S^M_{ju})^{1-\alpha} - W_{ju}X_{ju} - q_{ju}S^M_{ju} = 0$$

where $W_{ju}X_{ju} = w^l_{ju}H^l_{ju} + w^h_{ju}H^h_{ju}$. This together with profit maximization (10) yields the following expression for the equilibrium production floor price:

$$q_{ju} = (1-\alpha)\left(\frac{\alpha}{W_{ju}}\right)^{\frac{\alpha}{1-\alpha}} \tag{11}$$

Agglomeration We now introduce endogenous agglomeration forces as in Ahlfeldt et al. (2015) with slight modifications. We allow urban labor productivities for both skills to depend on production fundamentals (a^h_{ju} and a^l_{ju}) and production externalities (D_j). Production externalities impose structure on how the productivity of a given region is affected by the density of workers with the region,[13]

$$A^s_{ju} = a^s_{ju} \times (D_{ju})^{\gamma}, \quad D_{ju} = \frac{H^h_{ju} + H^l_{ju}}{\bar{L}_j} \tag{12}$$

where $(H^h_{ju} + H^l_{ju})/\bar{L}_j$ is the working population density per unit of administration land area and γ controls its relative importance in determining overall productivity. We use the 2003 land policy natural experiment to infer the agglomeration coefficient in the following sections.

4.4 Land Market Clearing

Urban Areas Urban land market equilibrium requires a no-arbitrage condition between production and residential land usage after taking into account the land use regulations between production and housing

$$q_{ju} = \eta_j Q_{ju}$$

where η_j captures the land use regulations that restrict the price of production land relative to the price of residential land. Let θ_i be the proportion of floor space allocated to production use. We assume that $\theta_i \in (0,1)$. Because production requires both production land and labor, and there is no commuting to work across cities, a city cannot have 100% production or 100% residential land.

Production land market clearing requires that the demand for production floor space equals the supply of floor space allocated to production use in each location: $\theta_j S_{ju}$. Using the first-order

[13] Considering administrative zones are fixed, the changes in density are identical to changes in population.

conditions for profit maximization, this production land market clearing condition is:

$$S^M_{ju} = \left(\frac{(1-\alpha)}{q_{ju}}\right)^{\frac{1}{\alpha}} X_{ju} = \theta_j S_{ju} \tag{13}$$

Residential land market clearing implies that the demand for residential floor space equals the supply of floor space allocated to residential use in each location: $(1-\theta_j)S_j$. Using utility maximization for each worker and taking expectations over the distribution for idiosyncratic utility, this residential land market clearing condition can be expressed as:

$$S^R_{ju} = E[s_{ju}]H_{ju} = (1-\beta)\frac{E[v_{ju}]H_j}{Q_{ju}} = (1-\theta_j)S_{ju} \tag{14}$$

We assume that floor space S is supplied by a highly-regulated construction sector that uses geographic land L and a regulated density of development ϕ_j (the ratio of floor space to land) to produce $S_{ju} = \phi_j L^u_j$.

Rural Areas Rural housing markets are simpler as there is no production land. We assume that rural housing costs are a fixed fraction of the urban cost $Q_{jr} = \tau Q_{ju}$. Therefore, the price Q_{jr} is the cost of building a unit of floor space on rural land. Given the cost, rural residents choose the optimal amount of floor space to build.

4.5 Definition of Spatial General Equilibrium

We now define and characterize the properties of a spatial general equilibrium given the model's fixed parameters $\{\beta, \epsilon, \alpha, \sigma, \mu, \gamma\}$.

A ***Spatial General Equilibrium*** *for this economy is defined by a set of exogenous economic conditions* $\{\tau^s_{in,jk}, A^s_j, \eta_j, \phi_j, L_j, H^s_{in}\}$, *a list of endogenous prices* $\{Q_{ju}, q_{ju}, w^s_{jk}\}$, *quantities* $\{v^s_{in,jk}, Y_{jk}, H^s_{jk}, S_{ju}\}$, *and proportions* $\{\pi^s_{in,jk}, \theta_j\}$ *that solve the firms' problem, workers' problem, floor space producers' problem, and market clearing such that:*

*(i).**[Worker Optimization]** Taking the exogenous economic conditions* $\{\tau^s_{in,jk}, A^s_{jk}\}$ *and the aggregate prices* $\{Q_{ju}, w^s_{jk}\}$ *as given, workers' optimal migration choices pin down the equilibrium labor supply in each city* H^s_{jk} *and the migration flow between each city pair* $\pi^s_{in,jk}$.

*(ii).**[Firm Optimization]** Taking the exogenous economic conditions* $\{A^s_{jk}\}$ *and the aggregate prices* $\{q_{ju}, w^s_{jk}\}$ *as given, firms' optimal production choices pin down the equilibrium labor demand* H^s_j *and equilibrium production floor space demand* $\theta_j S_{ju}$ *in each city.*

*(iv).[**Market Clearing**] For all cities, labor supply equals labor demand and floor space supply equals floor space demand. This pins down the equilibrium aggregate prices $\{Q_{ju}, q_{ju}, w^s_{jk}\}$, equilibrium floor space S_{ju}, and equilibrium output Y_{ju}.*

5 Quantitative Analysis

In this section, we first solve the model for the unobserved fundamentals of the economy using the Census data in 2005 and 2010. We then estimate the agglomeration parameters using the indirect inference method (Gourieroux, Monfort, and Renault, 1993) which combines our firm-level data from the empirical analysis and the solved unobserved fundamentals of the economy in 2005. Finally, we quantitatively analyze the spatial distributions of measured productivity and land tightness across regions with different levels of development.

5.1 Calibration of the Fixed Parameters

We fix a set of parameters to match data moments. Table 3 gives a short summary table of our calibrated parameters. Our calibration relies on our various data sources and the estimates from Fang and Huang (2022) for the city pair migration elasticity (ϵ).

Table 3:
Parameters

Parameter	Description	Value
β	share of consumption in utility	0.77
α	share of labor in production	0.88
η_j	relative cost of production to residential land	city-specific
σ	elasticity of substitution between H/L-skills	1.4
ϵ	migration elasticity	1.9
τ	relative cost of rural housing	0.34

Notes: This table displays a summary of calibrated parameters.

We match $(1-\beta)$ to the cost share of residential floor space in consumer expenditure, $(1-\alpha)$ to the cost share of production floor space in firm costs, and $(\eta - 1)$ to ratio of production land cost to residential land cost. To match $(1 - \beta)$, we use the average accommodation expenditure share of total consumption from the Urban Household Survey of China (UHS). The survey is conducted by the National Bureau of Statistics of China with a change in measurement approach starting in 2012. We believe the new measurement standard is more realistic, which gives us an average share of roughly 23% from 2013 to 2017.[14] Hence, we choose β to be 0.77. Second, to match $(1-\alpha)$, we use average production floor space cost per unit of output. Unfortunately, there is no direct measure of floor space costs available, therefore, we rely on the Enterprise Surveys of Chinese manufacturing firms conducted by the World Bank in 2005. Firms report tax payments based on land usage through which we can infer the costs of production land. The mean across all firms and cities is 12% of output. Therefore, we choose the labor share of production (α) to be 0.88. Finally, to match $(\eta - 1)$, we need to compare the land use costs of production to residential land costs. Different city governments may have different incentives to promote residential or production construction through tax or development motivations. Therefore, we use land price differences to match η_j for each city j. The land price differences in each city come from land transaction data via the China Land Market Website (`http://www.landchina.com/`). We define land used for both industrial and service firms as production land.

The elasticity of substitution between high and low skill (σ) is calibrated to be 1.4 as in Katz and Murphy (1992), which has been widely used in previous literature. The city pair migration elasticity (ϵ) is calibrated to be 1.9. Tombe and Zhu (2019) estimates this elasticity at the province-sector pair level and end up with a value of 1.5. Fang and Huang (2022) show that the city pair migration elasticity is around 1.9. We choose the latter value since it is estimated in an almost identical model context to this study. Finally, the relative cost of rural housing (τ) is calculated using average rent paid by rural sector workers over average rent paid by urban sector workers in each city in both Census 2005 and Census 2010. This gives us a value of 0.34.

5.2 Solving for Unobservables

Based on the data we have on the observed equilibrium allocations and prices $\{H^s_{jk}, \pi^s_{in,jk}, w^s_{jk}, Q_{jk}, q_{jk}\}$, we can calculate all unobserved variables except the agglomeration parameters: productivities $\{A^l_{jk}, A^h_{jk}\}$, migration costs $(\tau^s_{in,jk})$, floor spaces $\{S^M_{ju}, S^R_{ju}, S^R_{jr}\}$, and construction density (ϕ_i) in both 2005 and 2010 as follows. We then estimate the agglomeration parameters.

Productivities First, from profit maximization and zero profits, we can infer productivity from the data on employment and wages. First, we solve for productivity A^h_j as a function of A^l_j using the first order conditions $A^h_{ju} = A^l_{ju}\left(\frac{H^h_{ju}}{H^l_{ju}}\right)^{\frac{1}{\sigma-1}}\left(\frac{w^h_{ju}}{w^l_{ju}}\right)^{\frac{\sigma}{\sigma-1}}$. Plugging A^h_{ju} into the definition of X_{ju}, we

[14] According to the old statistical standard, the average housing expenditure share ranges from 11.7% in 2012 to 14.3% in 2002, which is very low because they did not include imputed rent costs of self-owned houses and apartments. From 2013, the imputed rent costs of self-owned houses and apartments were added to housing costs which resulted in a range from 22.7% in 2017 to 23.3% in 2013. Within each of these measurement regimes, we find that the average expenditure share is very stable across time.

have

$$X_{ju} = A^l_{ju} H^l_{ju} \left[\frac{w^h_{ju} H^h_{ju} + w^l_{ju} H^l_{ju}}{w^l_{ju} H^l_{ju}} \right]^{\frac{\sigma}{\sigma-1}} \equiv A^l_{ju} H^l_{ju} (\Xi^l_{ju})^{-\frac{\sigma}{\sigma-1}}$$

where $\Xi^l_{ju} = \frac{w^l_{ju} H^l_{ju}}{w^h_{ju} H^h_{ju} + w^l_{ju} H^l_{ju}}$ is the share of labor income distributed to low skill workers. We also assume that agricultural productivity equals agricultural wages $A^s_{jr} = w_{jr}, \quad \textit{for both } s = \{h, l\}$. Combining the previous equation with the definition of W_{ju}, we have $W_{ju} = \frac{w^h_{ju} H^h_{ju} + w^l_{ju} H u^l_{ju}}{X_{ju}} = \frac{w^l_{ju}}{A^l_{ju}} (\Xi^l_{ju})^{\frac{1}{\sigma-1}}$. Plugging W_j into the price function of q_j, we can solve

$$A^l_{ju} = \frac{q_{ju}^{\frac{1-\alpha}{\alpha}} w^l_{ju} (\Xi^l_{ju})^{\frac{1}{\sigma-1}}}{\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}}, \quad A^h_{ju} = \frac{q_{ju}^{\frac{1-\alpha}{\alpha}} w^h_{ju} (\Xi^h_{ju})^{\frac{1}{\sigma-1}}}{\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}} \tag{15}$$

where $\Xi^h_{ju} = 1 - \Xi^l_{ju}$. Intuitively, higher production floor prices, higher wages, and a higher share of skill s in total payroll all require higher skill s productivity at equilibrium.

Land Market Clearing Second, from workers' first order conditions for residential floor space, the summation over all workers residing in each city j (residential demand), and the firms' first order conditions for production floor space, we can calculate both urban and rural floor space:

$$S^R_{ju} = \frac{1-\beta}{\beta Q_{ju}} \left[w^l_{ju} H^l_{ju} + w^h_{ju} H^h_{ju} \right], \quad S^M_{ju} = \left(\frac{(1-\alpha)}{q_{ju}} \right)^{\frac{1}{\alpha}} X_{ju}, \quad S^R_{jr} = \frac{1-\beta}{\beta Q_{jr}} \left[w_{jr} H_{jr} \right]$$

We are then able to calculate the total amount of urban floor space $S_{ju} = S^R_{ju} + S^M_{ju}$ and finally back out the implied construction intensity $\phi_j = S_{ju}/L_j$.

Migration Costs To compute migration costs, we need to first compute the city-level equally-divided rent income for local residents $\frac{Q_i S^R_i}{H_i}$ from the residential floor space S^R_i calculated above, which we can add to observed wages to determine incomes of workers of skill s and sector n moving from i to j: $v^s_{in,jk} = w^s_{jk} + \frac{Q_{jn} S^R_{jn}}{H^R_{in}}$. Then from the gravity equations, we can calculate all migration costs between all city pairs. We assume that the iceberg migration cost for staying in one's original city is one, that is $\tau^s_{in,in} = 1$. With Q_{in}, $v^s_{in,jk}$ and $\pi^s_{in,jk}$ in hand, along with the gravity equation, we have:

$$\Phi^s_{in} = \sum_{jk=11}^{JK} (\tau^s_{in,jk} Q^{1-\beta}_{jk})^{-\epsilon} (v^s_{in,jk})^{\epsilon} = \frac{(Q^{1-\beta}_{jk})^{-\epsilon} (v^s_{in,in})^{\epsilon}}{\pi^s_{in,in}}$$

by inserting Φ^s_i into the original gravity equation, we have:

$$\tau^s_{in,jk} = \frac{v^s_{in,jk}}{Q^{1-\beta}_{jk} (\pi^s_{in,jk} \Phi^s_{in})^{1/\epsilon}} \text{ , for } i \neq j \tag{16}$$

and for city-sector pairs with zero migration flow, we assign a migration probability $\pi^s_{in,jk} \sim 0$, resulting in a prohibitive migration cost approaching infinity.

5.3 Estimation of the Agglomeration Parameters

The estimation of the agglomeration parameters is not an easy task. A simple but naive way to identify these parameters is to log-linearize the agglomeration equation (12) and run a regression:

$$log(A^s_j) = \gamma log(D_j) + a^s_j$$

However, the above regression suffers from a severe endogeneity issue. Fundamental productivity a^s_j is absolutely correlated with D_j since locations with higher fundamental productivity will naturally attract more workers. Usually, people choose instruments such as long population lags or soil fertility to estimate this regression (Ciccone and Hall, 1996; Rosenthal and Strange, 2008; Combes et al., 2010). Nevertheless, there has been almost no successful attempt to estimate city-level agglomeration effect in China due to data limitation.

Fortunately, in our model, we are able to pin down these parameters using the indirect inference method. The basic idea is to simulate the effect of the 2003 inland-favoring land policy from the model and match it with the empirical analysis. We first run a city-level difference-in-differences regression to obtain the effect of the inland-favoring policy on observed city-level TFP in the real world. We then simulate the model to investigate the responses of city-level TFP if we remove the land supply policy. Using these simulated data, we run the same city-level regression and match the simulated regression coefficients with the corresponding ones in the empirical regression.

To estimate the agglomeration parameters in this way, we need a consistent comparison between urban TFP in the model and in the empirical analysis . We need to calculate our own measured TFP in the model. There are two reasons. First, the labor productivities A^s_{ju} are not the consistent with TFP used in our empirical analysis. Our measurements of TFP in the empirical analysis follows Olley and Pakes (1992), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015), which do not consider land as one of the production inputs. Second, data on land input costs at the firm-level is not available, nor are the fundamental skill-augmented labor productivities A^h_{ju} and A^l_{ju} distinguishable in the data. We calculate measured urban TFP in the model as output net of measured labor inputs:

$$ln(\widetilde{TFP}_{ju}) = ln\left(\frac{Y_{ju}}{(H^h_{ju} + H^l_{ju})^\alpha}\right) \tag{17}$$

With the measured TFP for each city $ln(\widetilde{TFP}_{ju})$, we are able to estimate the agglomeration parameters in the model: production fundamentals (a^h_{ju} and a^l_{ju}) and agglomeration elasticity (γ).

Method We now delve into the details. In the first step, we run a traditional difference-in-differences regression using our data from the empirical analysis as follows:

$$ln(\overline{TFP}_{ju}) = \alpha + \delta_1 Post2003 \times East_{ju} + \phi_{ju} + \gamma_t + \epsilon_{jut} \tag{18}$$

where $\overline{TFP}_{ju}$ is city-level average urban TFP calculated from our firm-level data in the emprical analysis. The coefficient δ_1 is the effect of the 2003 inland-favoring policy on city-level average TFP. We can estimate δ_1 by running this regression using data from the our empirical analysis and have the real world estimation of $\hat{\delta_1}^*$.

In the second step, we construct a counterfactual 2005 equilibrium by guessing the agglomeration parameter γ^0 (and correspondingly, $a^{s,0}_j$). Given all the variables and parameters we have derived so far, we can solve for the 2005 equilibrium, except γ and a^s_j, which we obtain through iteration. For an initial guess γ^0, we can simulate the counterfactual case with no inland-favoring policy. We get this counterfactual equilibrium using the algorithm described in Appendix B.2 with the counterfactual labor productivity $A^{s,0}_j$. Second, given the counterfactual labor productivity A^{s0*}_j, we calculate the counterfactual measured TFP $\widetilde{TFP}^0_{ju}$ using equation (20).

In the third step, we run the same regression (18) using the simulated data from both the original equilibrium $ln(\widetilde{TFP}_{ju})$ and the counterfactual equilibrium $ln(\widetilde{TFP}_{ju})$ as follows:

$$ln(\widetilde{TFP}^0_{ju}) = \alpha + \delta_1 Post2003 \times East_{ju} + \phi_{ju} + \gamma_t + \epsilon_{jut} \tag{19}$$

where $Post2003 = 1$ indicates the original equilibrium and $Post2003 = 0$ indicates the counterfactual equilibrium without inland-favoring land policy. We get an estimated coefficient $\hat{\delta}^0_1$.

In the fourth step, we calculate the absolute distance between $\hat{\delta}^0_1$ and the real world estimation $\hat{\delta}^*_1$. We then repeat this process until we find the γ^* that minimizes this distance between the simulated regression coefficient $\hat{\delta}_1$ and the real world regression coefficient $\hat{\delta}^*_1$.

Results Table 4 shows the city-level regression estimate from the real world data. We use three different methods to measure firm TFP (OP, LP, and ACF) and then calculate the average firm TFP in each city, weighted by total firm assets.[15] We find that the 2003 inland-favoring policy leads to a 5-6% decrease in the city average TFP in the eastern region. Quantitative Appendix B.3 shows the event study plots of this regression. We do not find any significant differences in pre-

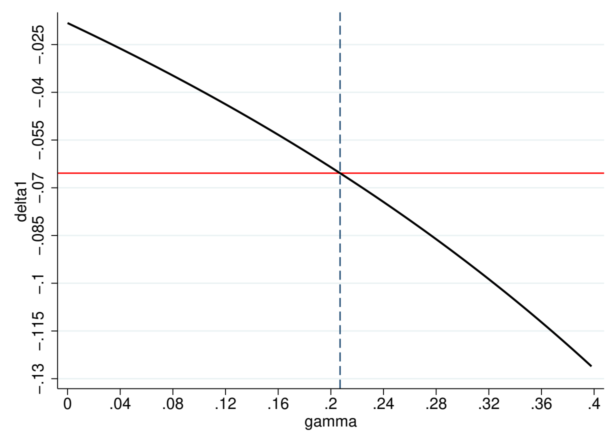
[15]We also investigate the results by different weighting schemes, including by value-added, by total production, and by number of employees. The results are very similar. They are available upon request.

Table 4:
City-level DID Results on TFP

	(1) OP	(2) LP	(3) ACF
Post2003×East	-0.0654***	-0.0517*	-0.0515
	(0.0240)	(0.0305)	(0.0366)
City Lagged Controls	Y	Y	Y
Year FE	Y	Y	Y
City FE	Y	Y	Y
Observations	2,061	2,061	2,061
Adjusted R-squared	0.8833	0.8615	0.8946

Notes: The dependent variable is city average firm-level TFP measured by the OP, LP, and ACF 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 also control for lagged city level firm characteristics, including average firm size, average leverage, average firm age, average number of employees, average profit rate, proportion of state-owned enterprises, average capital/labor ratio, and average sales. The standard errors are clustered at city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure 5:
Relationship between γ and $\hat{\delta}_1$



Notes: This figure shows the regression result using the data simulated by the model from both the original equilibrium $ln(\widetilde{TFP}_{ju})$ and the counterfactual equilibrium $ln(\widetilde{TFP}_{ju})$ as follows $ln(\widetilde{TFP}^{0}_{ju}) = \alpha + \delta_1 Post2003 \times East_{ju} + \phi_{ju} + \gamma_t + \epsilon_{jut}$, where $Post2003 = 1$ indicates the original equilibrium and $Post2003 = 0$ indicates the counterfactual equilibrium without inland-favoring land policy. We get an estimated coefficient $\hat{\delta}^0_1$.

trends between the treated eastern area and the untreated inland area before 2003. We choose $\hat{\delta}^*_1 = -0.0654$.

Figure 5 shows the relationship between the value of the agglomeration parameter γ and the regression estimate of $\hat{\delta}_1$ from the model simulated data. We find a monotonic negative relationship: the stronger the agglomeration effect is, the larger the loss generated by the inland-favoring land policy. Matching $\hat{\delta}_1^* = -0.0654$ would give us an estimate of $\gamma = 0.207$. This is larger than the estimates of 0.05 in developed countries (Combes and Gobillon, 2015). There are two explanations. First, China has much higher regional trade costs and migration costs than developed countries (Fan, 2019; Tombe and Zhu, 2019), which makes supply chain integration much more profitable. Second, it is very hard for inland regions to benefit from technology progress in developed areas when China is still relatively not developed. Thus, knowledge spillover effects are strong within Chinese cities or regions relative to across regions. Our result is also in line with other studies of China (Glaeser and Lu, 2018; Khanna et al., 2021). Although these studies consider a different kind of externality, namely human capital externalities in Chinese cities, they also find that the effect of city-level average education on wages is much larger in China than in developed countries (Moretti, 2004). We check the robustness of our results across a wide range of values for γ and there are no qualitative changes.

5.4 The Spatial Distribution of TFP and Land Tightness

We now quantify the spatial distribution of TFP and land tightness in our model. The complete list of cities with TFP and land abundance is provided in Appendix B1; here we show only key moments. We first show how TFP differs across regions with different levels of development and which component of TFP contributes most to these differences. We then show similar patterns for land tightness. Finally, we examine the spatial correlation of TFP and land abundance in equilibrium.

Spatial Distribution of Productivity To start, we first decompose measured TFP into three components:

$$\begin{aligned}
ln(\widetilde{TFP}_{ju}) =& ln\left(\frac{Y_{ju}}{(H^h_{ju}+H^l_{ju})^{\alpha}}\right) \\
=& \alpha ln\left(\frac{[(A^h_{ju}H^h_{ju})^{\frac{\sigma-1}{\sigma}}+(A^l_{ju}H^l_{ju})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}}{H^h_{ju}+H^l_{ju}}\right)+(1-\alpha)ln(S^M_{ju}) \\
=& \underbrace{\frac{\alpha\sigma}{\sigma-1}ln(A^l_{ju})}_{\text{fundamental}}+\underbrace{\frac{\alpha\sigma}{\sigma-1}ln\left((\frac{A^h_{ju}}{A^l_{ju}}\Gamma^h_{ju})^{\frac{\sigma-1}{\sigma}}+(\Gamma^l_{ju})^{\frac{\sigma-1}{\sigma}}\right)}_{\text{skill premium}}+\underbrace{(1-\alpha)ln(S^M_{ju})}_{\text{land scale premium}}
\end{aligned} \tag{20}$$

where $\Gamma^h_{ju} = \frac{H^h_{ju}}{H^h_{ju}+H^l_{ju}}$ and $\Gamma^l_{ju} = 1-\Gamma^h_{ju} = \frac{H^l_{ju}}{H^h_{ju}+H^l_{ju}}$ are the corresponding high-skill and low-skill labor shares. The decomposition shows that $ln(\widetilde{TFP}_{ju})$, measured urban TFP in city j, can be decomposed into three components: fundamental low-skill labor productivity, a skill premium from higher share of high-skill workers (relative high-skill productivity), and a land scale premium from more construction land.

Table 5:
Spatial Distribution of Measured TFP

Regions (loc., dev.)	No. of Cities	2005 Total	2005 Fund	2005 SP	2005 LSP	2010 Total	2010 Fund	2010 SP	2010 LSP
National	225	38.17	35.31	0.66	2.19	40.44	37.52	0.70	2.22
(east, high)	21	39.73	36.73	0.75	2.25	41.50	38.44	0.77	2.29
(east, mid)	51	38.15	35.34	0.56	2.25	40.32	37.42	0.65	2.24
(east, low)	25	36.78	34.08	0.57	2.13	39.31	36.68	0.57	2.06
(inland, high)	2	38.00	35.27	0.67	2.06	39.74	36.72	0.88	2.13
(inland, mid)	50	37.18	34.30	0.78	2.11	39.87	36.91	0.78	2.17
(inland, low)	76	36.65	33.92	0.63	2.09	39.61	36.87	0.59	2.14

Notes: This table displays a summary of measured TFP $ln(\widetilde{TFP}_{ju})$ in the model by group (weighted by population) in 2005 and 2010, as well as its decomposition: Fund stands for fundamental, SP stands for skill premium, and LSP stands for land scale premium. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, as in the data. For the level of development, we divide all cities into three categories {high, mid, and low} to capture {10%, 45%, 45%} of the distribution of GDP per capita. Each region consists of the same cities in both 2005 and 2010 for consistent comparisons over time.

Using this decomposition, we calculate each component of measured TFP for each city. To better display the spatial patterns, we display the results by summarizing across six regions classified by city location (eastern or inland) and level of development (GDP per capita) in 2005, for which we divide all cities into three categories {high, mid, and low} to capture {10%, 45%, 45%} of the distribution of GDP per capita. We also examined a number of other alternate summary presentations, but the results are consistently robust to classification. Each region consists of the same cities in both 2005 and 2010 for consistent comparisons over time.

Table 5 shows a summary of measured TFP and its decomposition following equation (20) across regions. There are four observations. First, the major difference in measured TFP across regions is in the fundamentals. The more developed eastern cities have much higher fundamental productivity than inland or less developed cities. Second, growth in measured TFP is mainly from growth in fundamental productivity rather than the premiums. Third, eastern and more developed cities have higher land scale premiums due to their relatively large size, in terms of both population and land. Fourth, however, eastern and more developed cities do not necessarily have higher skill premiums.

Table 6:
Spatial Distribution of Land Abundance

Regions (loc., dev.)	No. of Cities	Worker/Land 2005	Worker/Land 2010
National	225	0.093	0.083
(east, high)	21	0.077	0.068
(east, mid)	51	0.084	0.082
(east, low)	25	0.080	0.108
(inland, high)	2	0.127	0.130
(inland, mid)	50	0.140	0.101
(inland, low)	76	0.104	0.086

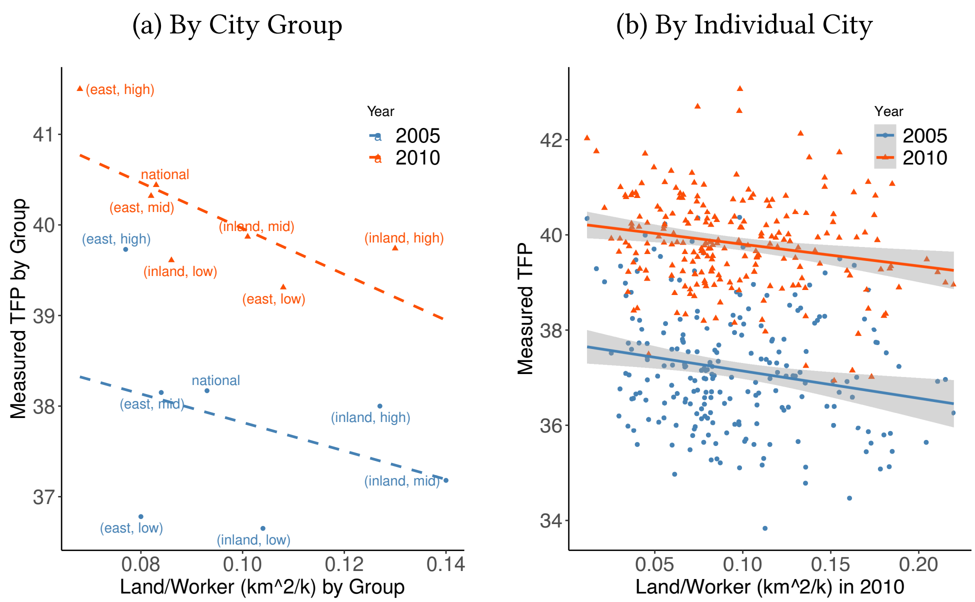
Notes: This table displays a summary of the tightness of total urban land supply data by group (weighted by urban population) in 2005 and 2010 (unit: thousand workers/km^2). Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, as in Table 5.

We calculate national-level TFP as the weighted average of city-level TFP, with the number of workers as the weights. Using our decomposition, we can investigate the changes in national-level weighted TFP by moving a low-skill worker from a small city to a big city. First, the fundamental term will increase as this worker migrates to a big city with higher low-skill productivity. Second, the change in the land scale premium is negative. This term is a concave function of S which means the marginal increment in big cities is smaller than the marginal loss in small cities when one worker migrates to a big city. However, the fundamental term dominates the two premia in terms of magnitude, making it clear that having more workers in big cities increases national weighted TFP.

Spatial Distribution of Land Abundance As discussed in the empirical section, the inland-favoring land allocation policy potentially constrains land supply in eastern and more developed cities. Now, we examine the spatial distribution of land abundance. We measure across-city differences in land abundance using land per thousand workers.

Table 6 shows a summary of land abundance across regions. The across-city differences in land abundance show that eastern and more developed cities have much lower and decreasing land abundance, which matches the trend in Figure 1. Compared to inland and less developed cities, eastern and more developed cities have on average 30% to 50% less land per worker. More importantly, the total construction land supply is actually growing nationally, from 22,268 km^2 to 28,336 km^2 (as shown in Table 7 below). This means many land quota increments are being distributed to cities with net outmigration so the population weighted national average land abundance is worsening even though total land supply is increasing considerably faster than the Chinese population.

Figure 6:
Correlation between Productivity and Land Abundance



Notes: This figure plot the correlation between productivity and land abundance in the model. Plot (a) shows the correlation by city group as in the tables above. Plot (b) shows the correlation by individual city. Plot (b) excludes 6 extreme values for visual clarity; for the plot with whole sample, please refer to Figure B2 in the Quantitative Appendix. The correlation is stronger including the extreme values.

Correlation Between Productivity and Land Abundance We further show the correlation between productivity and land abundance in Figure 6. Plot (a) shows the correlation by city group as in the tables above. Plot (b) shows the correlation by individual city, from which the city group plot is created. We have two observations. First, there is a strong negative correlation between productivity and land abundance. More developed eastern cities are much more productive but much more land constrained. Second, land abundance is increasingly severe even though productivity is generally improving. Both patterns show the existence of substantial spatial misallocation of land and workers in the presence of place-based land policy.

5.5 Spatial Distribution of Economic Development and Income

We provide additional results on the quantitative analysis in Appendix B.5. These additional results examine the spatial distribution of economic development and income in depth, containing three key observations that are consistent with our findings above. First, more developed eastern cities have much higher output, especially urban output. Second, these cities are much more populated with higher floor space prices. Third, workers in these cities earn higher incomes (higher wages for all workers and higher non-wage incomes for Hukou workers). These findings supplement our results above on the spatial misallocation created by place-based land policy.

5.6 Remarks on the Quantitative Analysis

These patterns in measured TFP and the spatial distribution of land tightness indicate that there are potential losses in both productivity and equality due to the place-based land policy that reallocates land from eastern and more developed cities to inland and less developed cities. Since eastern and more developed cities have much higher fundamental productivity and tighter land constraints, this land reallocation mitigates migration to these developed cities and generates much lower national average productivity.

6 Eliminating the Inland-favoring Land Policy

In this section, we simulate a counterfactual land allocation policy to alleviate the land supply distortions. In this counterfactual world, we assume that the inland-favoring land supply policy was not implemented and the pre-2003 land allocation rule was maintained. Then, we investigate the effect of removing the inland-favoring policy on worker migration, land markets, TFP, and worker income in different regions. Since the model features non-linear interactions between skills and contains multiple housing markets, the classical hat algebra is not feasible here. Therefore, we develop a multi-layer iteration algorithm (global solution) to compute the counterfactuals. The algorithm clears all markets across cities and sectors simultaneously. The details are in the Quantitative Appendix B.2.

6.1 Constructing the Counterfactual Policy

Land Supply We investigate what would have happened if the 2003 inland-favoring land supply policy was not implemented. To do so, we preserve the total new land quota increments from 2003 to 2005 and 2010, but redistribute the total new land supply based on the land supply growth rate from 2000 to 2003.[16] The following equation shows the details of the new supply rule:

$$\widehat{L_j(t)} = L_j(2003) + \underbrace{\sum_j [L_j(t) - L_j(2003)]}_{\text{actual total increment of land}} \times \underbrace{\frac{L_j(2003)(1+g_{L_j})^{t-2003}}{\sum_j L_j(2003)(1+g_{L_j})^{t-2003}}}_{\text{city j's share if no inland-favoring}} \tag{21}$$

where the first component $L_j(2003)$ is city j's urban land stock in 2003 just before the structural change happened. The second component is a multiplication of the actual total increment of land $\sum_j [L_j(t) - L_j(2003)]$ across the whole nation and city j's share of land supply if total land supply followed the pre-2003 growth rate. We consider this constrained counterfactual policy since it still fulfills the central government's strict goal of controlling total urban land supply.

Such a counterfactual policy is feasible. Two important concerns are if enough land exists in developed regions to satisfy these allocations and whether this land would actually be developed if designated for urban space. We argue that neither is a concern. First, according to the satellite data, in 2005, only 23% of the land was developed in tier-1 cities (the most developed), and only 9.3% of the land was developed in tier-2 cities (Wu and You, 2020). Second, much land in developed regions is still farmland due to the farmland redline policy (Yu, 2019).

Table 7:
Removing the Inland-favoring Policy:
Total Land Supply (km^2)

Regions (loc., dev.)	No. of Cities	Reality 2005	Reality 2010	Counterfactual $\widehat{2005}$	Counterfactual $\widehat{2010}$
National	225	22268	28336	22268	28336
(east, high)	21	5838	7272	6597	10958
(east, mid)	51	5875	7832	5734	6551
(east, low)	25	1418	1681	1472	1596
(inland, high)	2	169	206	169	169
(inland, mid)	50	5131	6578	4537	4819
(inland, low)	76	3837	4767	3760	4244

Notes: This table displays a summary of total urban land supply data by city group (summations within group) in 2005 and 2010, as well as the counterfactual migration-based land supply in 2010 (unit: 2). Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, as in Table 5.

Policy Summary The counterfactual land allocation policy is summarized in Table 7. Columns 3-4 show the realized land supply under the policy, and Columns 5-6 show the counterfactual land supply according to the allocation rule in equation (21). In general, we find that if land

[16]We choose the 2000-2003 growth rate because pre-1999 land supply data at the city level is mostly unavailable.

supply policy had not changed in 2003, more developed cities would have gained more land. For instance, the land quota for eastern highly developed cities would have been 10958 km^2 in 2010 if there was no inland-favoring policy, compared with the observed 7272 km^2. On the contrary, the land quota for inland low development cities would have been 4244 km^2 in 2010 if there was no inland-favoring policy, compared with the observed 4767 km^2. We show the detailed changes in land supply in Counterfactual Appendix C.1.

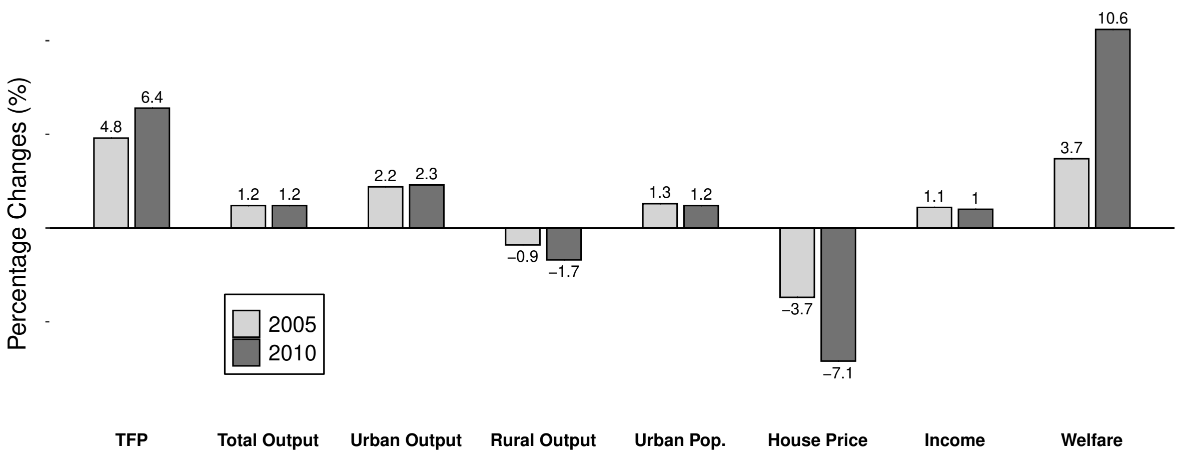
6.2 Aggregate Effects

We first show the aggregate effects of removing the inland-favoring land policy on national TFP, output, urban output, rural output, urban population, and national average income and welfare (the welfare calculation method is in Counterfactual Appendix C.2). The results are plotted in Figure 7. We find that removing the place-based land policy leads to significant gains in TFP, urban output, average income, and welfare in both 2005 and 2010. The national gain in TFP is 4.8% in 2005 and 6.4% in 2010, and total output is increased by 1.2% in both years. Removal of the policy also increases the urban population by lowering the price of residential floor space in the urban areas of developed cities. On the contrary, rural output is decreased due to workers' emigration. The gains in welfare (3.7% in 2005 and 10.6% in 2010) are significantly higher than the gains in income (1.1% in 2005 and 1.0% in 2010) since the most housing-constrained workers now have much better access to floor space (housing prices drop by 3.7% in 2005 and 7.1% in 2010). The huge housing price reduction results in real incomes rising by more than nominal incomes.

6.3 Spatial Effects on Economic Development

We further show the spatial effects of removing the inland-favoring policy on economic development. Table 8 shows the changes of TFP, urban output, rural output, urban population, and housing prices across different regions. There are three main conclusions. First, after removing the inland-favoring land policy, housing prices fall substantially in developed eastern cities but increase in other cities. Second, more workers migrate to developed eastern cities and the urban population in 2010 rises by 13.1%. Third, both productivity and output increase in eastern developed cities and decrease in other cities. Specifically, measured TFP increases by 6.7% and urban output increases by 14.4% in 2010 under our counterfactual. The decreases of TFP and output in other cities are smaller in magnitude. We show more results in Counterfactual Appendix C.3 including a TFP decomposition and changes in the urban population by skill type. We find that most of the increases in national TFP are from increases in fundamental productivity

Figure 7:
Aggregate Effects of Removing the Inland-Favoring Policy



Notes: This figure shows the aggregate effects of removing the inland-favoring policy on the Chinese economy in 2005 and 2010. Black columns represent changes in 2010. Grey columns represent changes in 2005. We find substantial national gains in TFP, total output, urban output, urban population, income, and welfare in both years.

via two channels. First, the reform encourages more workers to migrate to developed regions with higher TFP, which raises national TFP. Second, the inflows of migrant workers amplify the agglomeration effect on local productivity in developed regions.

In general, we find that removing the inland-favoring policy widens the regional development gap and attracts more migrations to developed areas. Thus, the inland-favoring land policy does achieve its original goal to balance the development of eastern and inland regions. However, when we witness this geographic convergence, does it necessarily mean that workers from underdeveloped regions benefit from this policy? The answer is no.

6.4 Spatial Effects on Income and Welfare

The first four columns in Table 9 show the income and welfare (utility) changes of workers from different regions when we remove the inland-favoring policy. After removing the policy, the incomes of workers from all regions increase. The incomes of workers from inland (eastern) cities with low development level increase by 1.7% (0.9%) in 2005 and by 1.1% (1.1%) in 2010. This illustrates a paradox that the inland-favoring land policy shrinks the regional output gap but lowers the incomes of workers from poor regions. The reason is that this policy reduces

Table 8:
Removing the Inland-Favoring Policy:
Spatial Effects on Economic Development

Regions (loc., dev.)	No. of Cities	Δ TFP		Δ Urban Output		Δ Rural Output		Δ Urban Pop.		Δ House Price	
		$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$
National	225	4.8%	6.4%	2.2%	2.3%	-0.9%	-1.7%	1.3%	1.2%	-3.7%	-7.1%
(east, high)	21	2.9%	6.7%	6.3%	14.4%	0.0%	4.0%	6.2%	13.1%	-18.7%	-34.5%
(east, mid)	51	0.0%	-1.2%	-0.7%	-3.8%	-0.5%	-0.9%	-0.4%	-2.6%	1.5%	12.4%
(east, low)	25	-0.3%	-1.7%	-0.4%	-3.9%	-1.4%	-3.5%	-0.6%	-2.6%	-3.1%	3.6%
(inland, high)	2	-0.2%	-2.2%	0.0%	-3.1%	0.0%	2.1%	0.1%	-0.9%	1.7%	18.8%
(inland, mid)	50	0.0%	-5.2%	-2.1%	-10.0%	-1.5%	-2.9%	-1.6%	-6.6%	1.9%	11.3%
(inland, low)	76	0.2%	-3.2%	-1.3%	-5.5%	-1.7%	-3.2%	-1.4%	-4.2%	-3.5%	-0.6%

Notes: This table displays a summary of changes in core economic development variables by city group (weighted by population) in 2005 and 2010. All numbers are relative changes from the observed data to the counterfactual results without the inland-favoring policy. For each variable, we show the changes in 2005 and 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, as in Table 5.

land supply in developed areas, which leads to increases in housing costs and decreases in labor demand. Thus, many workers from underdeveloped regions who would have migrated are now locked in their hometowns with lower wages.

How about welfare? Is it possible that workers from poorer regions are better off because they can find jobs in their hometowns thanks to the inland-favoring policy? The answer is not necessarily. We find that the changes in utility for workers from underdeveloped cities are mixed. By removing the inland-favoring policy, the average utility of workers from eastern low development cities is reduced by 1.7% in 2005, but the average utility of workers from inland low development cities is increased by 2.3%. The situation is reversed in 2010. Overall, we find no evidence that the inland-favoring land supply policy increases the welfare of workers in poorer regions. This policy significantly decreases national welfare without helping workers from poor regions.

6.5 Direct Regional Transfers

As we show above, the inland-favoring land supply policy leads to severe spatial misallocation and reductions in national output and productivity. It generates an illusionary regional convergence by shrinking the geographic output gap without helping workers from poor regions. In this section, we design a second counterfactual which creates less spatial misallocation and meaningfully helps people from poor regions. The idea is that, instead of implementing the place-based land policy, the central government chooses to redistribute the additional land income generated

Table 9:
Removing the Inland-Favoring Policy:
Spatial Effects on Income and Welfare

Regions	No. of	Without Transfer				Regional Transfer			
		Δ Income		Δ Welfare		Δ Income		Δ Welfare	
(loc., dev.)	Cities	2005	2010	2005	2010	2005	2010	2005	2010
National	225	1.1%	1.0%	3.7%	10.6%	0.5%	1.1%	2.8%	4.1%
(east, high)	21	2.1%	5.7%	9.8%	17.9%	-7.0%	-14.5%	3.9%	4.1%
(east, mid)	51	0.2%	-0.3%	-0.2%	-3.9%	-2.2%	1.3%	0.5%	0.3%
(east, low)	25	0.9%	1.1%	-1.7%	0.8%	-1.1%	5.2%	0.8%	6.6%
(inland, high)	2	0.0%	-1.6%	-0.5%	-5.1%	-1.3%	-2.2%	-1.2%	-3.6%
(inland, mid)	50	0.7%	-1.1%	-0.3%	-5.5%	11.2%	6.6%	3.1%	5.0%
(inland, low)	76	1.7%	1.1%	2.3%	-3.7%	2.8%	6.0%	2.6%	7.6%

Notes: This table displays a summary of total urban land supply data by group (summations within group) in 2005 and 2010, as well as the counterfactual migration-based land supply in 2010 (unit: km^2). Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, as in Table 5. Each row represents all workers whose hometowns are in the relevant cities. Columns 1-4 show the changes when we remove the inland-favoring land policy. Columns 5-8 show the changes when we replace the inland-favoring land policy with a direct regional transfer.

from the counterfactual land allocations to developed cities to underdeveloped cities. The only difference between this *Regional Transfers* and the *Removing the Inland-Favoring Policy counterfactual* is that the former adopts a feasible direct regional transfer on top of the latter. Please refer to Counterfactual Appendix C.5 for a detailed discussion of the transfer rule and tuning parameters, and Counterfactual Appendix C.6 for additional results of the regional transfer on economic development and income.

Columns 5-8 in Table 9 show the income and welfare (utility) changes of workers from different regions when we replace the inland-favoring land supply policy with the direct regional transfer. There are two main findings. First, with the direct regional transfer, we effectively shrink the income gaps between workers from developed regions and workers from underdeveloped regions. Incomes of workers from inland cities with low (middle) development levels increase by 2.8% (11.2%) in 2005 and 6.0% (6.6%) in 2010. Incomes of workers from eastern and developed regions are reduced. Second, national welfare still increases after the regional transfer. Workers from almost all regions benefit from the direct transfer in terms of utility. Specifically, the utility of those from eastern high development cities rises by 4.1% in 2010, and by 7.6% for eastern low development cities. Workers from underdeveloped regions migrate to developed cities for higher wages and workers from developed regions benefit from much lower housing costs.

6.6 Remarks on the Counterfactual Analysis

Our counterfactual results show that the inland-favoring land supply policy resulted in a severe misallocation of both land and labor. It increased the price of residential and production floor space and discouraged workers in underdeveloped cities from migrating to developed cities. This led to a loss in national output and TFP.

The observed regional convergence is just an illusion. It seems that regional output and productivity gaps were reduced, which was precisely the government's original goal. However, workers from both developed and underdeveloped regions suffered income losses. The income gap was reduced not because the income of people from poor areas increased, but because everyone's income decreased and people from rich areas were hurt more. Similarly, the 2003 reform also reduced national welfare largely without promoting the welfare of workers from poor regions. Thus, this place-based land policy helped poor regions but did not help people from those poor regions. We finally show that a direct regional transfer policy is a superior alternative to the inland-favoring land policy, reducing inequalities by substantially helping workers from poorer regions instead of causing substantial spatial misallocation of land and labor.

7 Conclusion

This paper studies how place-based land allocation policy creates spatial misallocation. We focus on a major policy change favoring less-developed inland regions in China, which was intended to balance regional growth and reduce spatial inequality. Causal evidence shows that this policy change decreased firm-level TFP in developed eastern regions relative to underdeveloped inland regions. A spatial equilibrium model shows that spatial misallocation resulted because developed eastern regions have higher productivity and the reduced land supply also reduced migration to these high productivity areas. Counterfactual simulations of eliminating this inland-favoring policy suggest resolving this spatial misallocation would increase national productivity and output.

Despite sacrificing national productivity and output, the inland-favoring policy did not benefit workers from underdeveloped regions. By eliminating this policy change, the incomes of workers from underdeveloped regions would increase through more migration to developed regions. Even though the inland-favoring policy reduced regional output gaps, it caused TFP and output losses, and hurt workers from underdeveloped regions by hindering their migration opportunities to higher-wages developed regions. We suggest, instead of the inland-favoring land supply policy, a direct regional transfer could promote regional convergence by increasing income and welfare for workers from underdeveloped regions with minimal efficiency losses due to spatial misallocation.

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Appendix

A Robustness Checks of the Empirical Analysis

In this section, we implement five groups of robustness checks for our empirical analysis.

TFP Estimation Method First, we implement the empirical analysis using firm-level TFP calculated through the LP and the ACF methods. Table A1 and A2 shows the results of the main regression. All results are very similar to the results when we calculate TFP using the OP method.

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

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.088*	-0.114***	-0.087
	(0.049)	(0.041)	(0.059)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	73622	110794	110794
Adjusted R-squared	0.140	0.143	0.143

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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A2: RD-DID Results on TFP (ACF)

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.198***	-0.082*	-0.103*
	(0.069)	(0.043)	(0.061)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	35517	110813	110813
Adjusted R-squared	0.123	0.116	0.117

Notes: The dependent variable is firm-level TFP measured by the Ackerberg, Caves, and Frazer (2015) method. The regression specifications are identical to Table 2. The standard errors are clustered at firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Bandwidth Choices Second, we change the bandwidth for the linear and the quadratic smoothing functions. We show results from choices between 20 km to 70 km in Tables A4 and A3. The results are qualitatively very robust, though when we shrink the bandwidth we lose observations and our estimation precision is decreased.

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

bandwidth	20km (1)	30km (2)	40km (3)	50km (4)	60km (5)	70km (6)
Post2003×east	-0.096*	-0.070	-0.097**	-0.090***	-0.061*	-0.029
	(0.055)	(0.045)	(0.039)	(0.034)	(0.031)	(0.029)
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	49526	93228	110794	137327	163473	196591
Adjusted R-squared	0.118	0.106	0.111	0.115	0.117	0.113

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1992) 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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A4: Robustness: TFP Regressions with Different Bandwidth Choices (LP)

bandwidth	20km (1)	30km (2)	40km (3)	50km (4)	60km (5)	70km (6)
Post2003×east	-0.085	-0.070	-0.114***	-0.104***	-0.074**	-0.040
	(0.057)	(0.045)	(0.041)	(0.035)	(0.032)	(0.030)
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	49526	93228	110794	137327	163473	196591
Adjusted R-squared	0.150	0.106	0.143	0.147	0.150	0.146

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 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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Without City-level Controls Third, we run all main regressions without city-level lagged control variables. There are two reasons to do this. First, although we use lagged city characteristics, there is still serial correlation with current period values, which may lead to bad control issues. Second, this can also serve as a balance check. If dropping controls does not change the point estimates much, it means that the possibility of omitted variable bias (in this case, location-period level unobserved variables) is slim (Oster, 2019). Tables A6 and A5 show that the resulting estimates are very similar to those of the regressions with control variables. The point estimates are almost unaffected. The implies that adding city characteristics does not affect the regression results, which further validates the assumption that the cities at the border have similar trends.

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

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.102*	-0.095**	-0.103*
	(0.056)	(0.039)	(0.057)
City Lagged Controls	N	N	N
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	47690	110794	110794
Adjusted R-squared	0.116	0.106	0.107

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1992) method. The regression specifications are identical to Table 2, except we drop all city-level lagged controls. The standard errors are clustered at firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A6: Robustness: TFP Regressions without City-level Controls (LP)

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.082*	-0.111***	-0.095
	(0.049)	(0.041)	(0.059)
City Lagged Controls	N	N	N
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	73622	110794	110794
Adjusted R-squared	0.135	0.138	0.139

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

The WTO Effect Fourth, China entered the WTO at the end of 2001, which dramatically changed China's economic structure. Although this is about two years before the inland-favoring land supply policy, we are still concerned about possible confounding from this reduction in trade barriers, which may have affected eastern and inland firms differently. To address this issue, we run the TFP regression keeping only firms with zero exports. These firms should be the ones that least affected by any WTO effects. We also run the main regression controlling for firm-level exporting to eliminate any WTO effect. The regression results are shown in Tables A7, A8, A9 and A10. The main conclusions are sustained. We also find that firm exporting is positively related to its productivity, which is aligned with predictions in the trade literature as in Bernard et al. (2007) and Bernard et al. (2018).

Table A7: Robustness: TFP Regressions without Exporting Firms (OP)

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.107 (0.068)	-0.115** (0.046)	-0.099 (0.069)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	39174	87149	87149
Adjusted R-squared	0.121	0.116	0.116

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1992) method. The regression specifications are identical to Table 2. We drop all firms with positive exports. The standard errors are clustered at firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A8: Robustness: TFP Regressions without Exporting Firms (LP)

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.152*** (0.049)	-0.157*** (0.048)	-0.114 (0.072)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	83531	87149	87149
Adjusted R-squared	0.145	0.148	0.148

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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A9: Robustness: TFP Regressions Controlling for Exporting (OP)

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.092*	-0.091**	-0.091
	(0.055)	(0.039)	(0.057)
log(Export)	0.014***	0.016***	0.016***
	(0.002)	(0.001)	(0.001)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	47690	110794	110794
Adjusted R-squared	0.123	0.113	0.113

Notes: We additionally control for firm-level export in this regression. The dependent variable is firm-level TFP measured by the Olley and Pakes (1992) method. The regression specifications are otherwise identical to Table 2. The standard errors are clustered at firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A10: Robustness: TFP Regressions Controlling for Exporting (LP)

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	-0.081*	-0.104**	-0.083
	(0.049)	(0.040)	(0.058)
log(Export)	0.026***	0.025***	0.025***
	(0.002)	(0.001)	(0.001)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	73622	110794	110794
Adjusted R-squared	0.145	0.148	0.148

Notes: We additionally control for firm-level export 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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Subsidy and Tax Policies Fifth, we try to rule any effects of other subsidy and tax policies potentially happening concurrently to the land reform. This is because, beyond the land supply policy, the Chinese government also implemented other inland-favoring policies to promote inland economic growth, such as manufacturing subsidies. We run the main regression with firm-level government subsidies as the outcome variable. This regression aims to check whether relative subsidies changed for firms at the border during the same year the inland-favoring land policy was implemented. Table A11 shows that firms on either side of the border received similar government subsidies both before and after 2003. We then run the firm-level TFP regressions with additional controls including city-level central government subsidies per capita, firm subsidies from government, and firm-level taxes paid to government. Table A12 and A13 show that the main results are unchanged in all regression settings.

Table A11: RD-DID Results on Firm-level Subsidies

	Local Linear (1)	Poly RD (Poly=1) (2)	Poly RD (Poly=2) (3)
Post2003×East	0.001	-0.010	-0.033
	(0.013)	(0.016)	(0.021)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	150777	107307	107307
Adjusted R-squared	0.000	0.000	0.001

Notes: The dependent variable is firm-level subsidies. The set of lagged city-level control variables includes the log of GDP, the log of population, the log of city area, and the value added 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 for the Polynomial RD cases is restricted to be within a bandwidth of 40 km around the raw boundary. The standard errors are clustered at firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A12: RD-DID Results with Firm-level Subsidy and Tax Controls (OP)

	Local Linear	Poly RD (Poly=1)	Poly RD (Poly=2)
	(1)	(2)	(3)
Post2003×East	-0.126**	-0.115***	-0.124**
	(0.056)	(0.040)	(0.058)
Tax	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Subsidy	-0.037**	-0.014	-0.014
	(0.016)	(0.010)	(0.010)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	46202	107307	107307
Adjusted R-squared	0.123	0.113	0.113

Notes: The dependent variable is firm-level TFP measured by the Olley and Pakes (1992) 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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A13: RD-DID Results with Firm-level Subsidy and Tax Controls (LP)

	Local Linear	Poly RD (Poly=1)	Poly RD (Poly=2)
	(1)	(2)	(3)
Post2003×East	-0.109**	-0.129***	-0.115*
	(0.050)	(0.041)	(0.060)
Tax	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Subsidy	-0.013	-0.002	-0.002
	(0.013)	(0.010)	(0.010)
City Lagged Controls	Y	Y	Y
Border FE	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	71271	107307	107307
Adjusted R-squared	0.143	0.147	0.147

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 firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

B Supplements to the Quantitative Analysis

B.1 List of Cities by Productivity and Land Tightness

Table B1: List of Cities

City Name	GDP Per Capita (RMB)	Group	TFP 05	TFP 10	Land Abundance 2005	Land Abundance 2010
Beijing	38315	East, High	38.96	40.85	0.13	0.11
Tianjin	34170	East, Middle	38.95	41.63	0.03	0.14
Shijiazhuang	31850	East, Middle	36.53	39.25	0.12	0.04
Tangshan	27995	East, Middle	38.40	40.81	0.18	0.07
Qinhuangdao	39214	East, High	35.29	39.82	0.25	0.09
Handan	19687	East, Middle	36.95	40.24	0.14	0.05
Xingtai	18043	East, Middle	37.72	40.16	0.11	0.04
Baoding	23312	East, Middle	37.06	39.76	0.07	0.04
Zhangjiakou	24225	East, Middle	36.59	40.02	0.18	0.06
Chengde	20145	East, Middle	37.23	38.90	0.14	0.19
Taiyuan	20622	Non-east, Middle	37.54	40.04	0.10	0.12
Datong	16655	Non-east, Middle	37.03	40.82	0.08	0.12
Yangquan	16700	Non-east, Middle	38.45	40.95	0.06	0.10
Changzhi	20807	Non-east, Middle	37.74	40.84	0.04	0.07
Jincheng	20974	Non-east, Middle	38.14	40.37	0.03	0.06
Shuozhou	13665	Non-east, Low	36.58	40.20	0.07	0.08
Jinzhong	9873	Non-east, Low	36.57	39.42	0.02	0.04
Yuncheng	7584	Non-east, Low	36.67	38.36	0.03	0.06
Xinzhou	4795	Non-east, Low	36.13	37.49	0.02	0.05
Linfen	10588	Non-east, Low	37.72	39.22	0.03	0.03
Hohhot	31585	Non-east, Middle	35.87	38.45	0.27	0.17
Baotou	39561	Non-east, High	38.23	40.04	0.20	0.17
Wuhai	20081	Non-east, Middle	37.16	40.21	0.11	0.24
Chifeng	7547	Non-east, Low	36.56	39.00	0.19	0.09
Tongliao	13789	Non-east, Low	35.66	38.95	0.15	0.13
Ordos	35380	Non-east, Middle	38.46	42.13	0.05	0.13
Hulunbeir	13785	Non-east, Low	37.38	39.64	0.06	0.05
Shenyang	34345	East, Middle	37.80	39.89	0.18	0.12
Dalian	54183	East, High	38.29	41.01	0.18	0.15
Anshan	43816	East, High	38.41	39.73	0.21	0.13
Fushun	19635	East, Middle	37.73	39.89	0.24	0.18
Dandong	15440	East, Low	36.49	38.92	0.11	0.07
Fuxin	11242	East, Low	35.80	38.30	0.19	0.18
Tieling	11041	East, Low	36.14	39.66	0.12	0.08
Chaoyang	10781	East, Low	36.98	39.56	0.07	0.08
Changchun	37003	East, Middle	36.92	39.22	0.14	0.21
Jilin	23046	East, Middle	37.01	39.94	0.15	0.16
Siping	14560	East, Low	35.11	39.04	0.08	0.10
Liaoyuan	12097	East, Low	36.96	39.00	0.17	0.21
Tonghua	14717	East, Low	37.28	39.48	0.06	0.07
White City	9091	East, Low	33.83	37.96	0.06	0.11
Harbin	30534	East, Middle	37.11	39.33	0.19	0.13
Qiqihar	13431	East, Low	36.40	36.94	0.15	0.15
Jixi	8480	East, Low	36.59	37.15	0.18	0.16
Hegang	8432	East, Low	37.03	39.52	0.16	0.13
Shuangyashan	12678	East, Low	37.52	38.34	0.32	0.18
Yichun	8546	East, Low	35.63	39.11	0.66	0.53
Jiamusi	14080	East, Low	35.08	39.27	0.14	0.18
Shanghai	57423	East, High	40.22	41.11	0.04	0.06

Table B2: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Group	TFP 05	TFP 10	Land Abundance 2005	Land Abundance 2010
Nanjing	35464	East, Middle	39.36	40.89	0.32	0.16
Wuxi	58976	East, High	39.07	41.34	0.12	0.06
Xuzhou	31592	East, Middle	37.94	40.37	0.13	0.10
Changzhou	36335	East, Middle	39.05	40.78	0.08	0.06
Suzhou	60326	East, High	39.99	41.71	0.08	0.04
Nantong	35059	East, Middle	38.01	41.08	0.04	0.04
Lianyungang	29298	East, Middle	36.46	39.71	0.20	0.09
Huaian	11557	East, Low	36.99	41.05	0.17	0.08
Yancheng	15929	East, Middle	36.56	40.16	0.08	0.04
Zhenjiang	34988	East, Middle	39.62	40.62	0.13	0.08
Hangzhou	49055	East, High	39.86	41.30	0.16	0.07
Ningbo	60381	East, High	39.70	41.42	0.06	0.05
Wenzhou	45795	East, High	38.72	40.79	0.07	0.03
Jiaxing	30988	East, Middle	39.34	41.00	0.08	0.03
Huzhou	26260	East, Middle	39.55	40.52	0.14	0.05
Shaoxing	35753	East, Middle	39.24	40.82	0.08	0.04
Jinhua	19113	East, Middle	39.02	40.57	0.06	0.02
Zhoushan	21215	East, Middle	38.80	41.26	0.17	0.10
Taizhou	30647	East, Middle	39.47	40.88	0.09	0.04
Yeosu	17653	East, Middle	37.03	40.59	0.07	0.05
Hefei	29058	Non-east, Middle	39.50	41.73	0.29	0.15
Wuhu	33544	Non-east, Middle	38.00	40.41	0.22	0.17
Bengbu	15456	Non-east, Low	35.64	39.48	0.29	0.20
Huainan	9784	Non-east, Low	37.74	40.82	0.23	0.18
Ma'anshan	29536	Non-east, Middle	38.84	41.11	0.24	0.17
Huaibei	15007	Non-east, Low	36.00	40.43	0.23	0.15
Anqing	19917	Non-east, Middle	35.27	39.24	0.11	0.08
Chuzhou	17353	Non-east, Middle	36.06	39.78	0.07	0.08
Fuyang	4229	Non-east, Low	35.92	38.71	0.26	0.07
Suzhou	4900	Non-east, Low	35.21	38.58	0.10	0.09
Lu'an	3039	Non-east, Low	36.15	39.55	0.18	0.08
Bozhou	6314	Non-east, Low	35.66	39.55	0.14	0.10
Chizhou	7290	Non-east, Low	37.11	39.74	0.10	0.12
Xuancheng	8989	Non-east, Low	37.80	40.78	0.11	0.07
Fuzhou	43600	East, High	38.27	40.70	0.12	0.07
Xiamen	40146	East, High	38.74	43.06	0.15	0.10
Sanming	25396	East, Middle	37.59	40.23	0.05	0.04
Quanzhou	28010	East, Middle	38.79	40.83	0.02	0.04
Zhangzhou	29056	East, Middle	38.24	40.88	0.05	0.04
Nanping	16169	East, Middle	37.09	39.83	0.04	0.03
Longyan	24690	East, Middle	38.21	40.37	0.07	0.04
Ningde	12408	East, Low	37.51	39.92	0.03	0.03
Nanchang	28388	Non-east, Middle	37.39	39.96	0.15	0.11
Jingdezhen	19486	Non-east, Middle	35.95	37.91	0.23	0.17
Pingxiang	13828	Non-east, Low	36.99	40.47	0.21	0.07
Jiujiang	29840	Non-east, Middle	35.78	39.43	0.07	0.07
Xinyu City	12046	Non-east, Low	36.69	39.94	0.24	0.15
Yingtan	11379	Non-east, Low	36.98	39.81	0.14	0.12
Ganzhou	12262	Non-east, Low	36.66	39.61	0.05	0.04
Ji'an	14198	Non-east, Low	35.89	38.41	0.06	0.04
Yichun	4600	Non-east, Low	36.68	39.29	0.05	0.04
Shangrao	12052	Non-east, Low	36.20	39.64	0.04	0.03
Jinan	36697	East, Middle	38.28	39.39	0.18	0.14
Qingdao	43327	East, High	39.24	41.10	0.10	0.07
Zibo	37104	East, Middle	38.15	39.66	0.19	0.14
Zaozhuang	13923	East, Low	36.38	38.87	0.18	0.12
Dongying	86523	East, High	39.20	41.20	0.26	0.15
Yantai	35583	East, Middle	38.74	40.47	0.13	0.13
Weifang	24267	East, Middle	37.26	40.44	0.09	0.06
Jining	18548	East, Middle	37.25	40.17	0.05	0.06
Tai'an	16938	East, Middle	37.15	39.71	0.14	0.08
Weihai	48100	East, High	38.20	39.94	0.15	0.14
Rizhao	16930	East, Middle	36.40	40.02	0.16	0.15
Laiwu	18042	East, Middle	37.55	40.45	0.32	0.14

Table B3: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Group	TFP 05	TFP 10	Land Abundance 2005	Land Abundance 2010
Linyi	17479	East, Middle	36.98	40.25	0.13	0.08
Dezhou	24777	East, Middle	36.27	39.71	0.09	0.08
Liaocheng	8844	East, Low	36.58	39.03	0.13	0.08
Binzhou	19158	East, Middle	37.30	40.27	0.11	0.12
Zhengzhou	27261	Non-east, Middle	36.71	39.77	0.26	0.10
Kaifeng	11976	Non-east, Low	35.44	38.85	0.39	0.17
Luoyang	26555	Non-east, Middle	36.73	39.93	0.22	0.12
Pingdingshan	18337	Non-east, Middle	37.15	39.82	0.17	0.08
Anyang	19362	Non-east, Middle	36.74	39.54	0.18	0.07
Hebi	14703	Non-east, Low	34.47	39.15	0.39	0.16
Xuchang	14306	Non-east, Low	36.63	39.65	0.16	0.11
Luohe	23156	Non-east, Middle	35.12	38.29	0.53	0.14
Sanmenxia	15414	Non-east, Low	36.35	39.21	0.17	0.08
Nanyang	25615	Non-east, Middle	35.64	38.19	0.23	0.08
Shangqiu	14764	Non-east, Low	35.49	38.86	0.16	0.07
Zhoukou	13144	Non-east, Low	33.75	38.60	0.15	0.39
Wuhan	24963	Non-east, Middle	37.38	40.19	0.12	0.11
Shiyan	35874	Non-east, Middle	36.70	38.93	0.14	0.08
Yichang	26548	Non-east, Middle	36.03	38.15	0.09	0.10
Xiangfan	12493	Non-east, Low	36.02	38.84	0.15	0.10
Ezhou	13519	Non-east, Low	35.45	41.07	0.23	0.18
Jingmen	19907	Non-east, Middle	35.62	38.24	0.12	0.08
Xiaogan	6977	Non-east, Low	35.99	38.80	0.08	0.03
Jingzhou	10007	Non-east, Low	35.58	39.36	0.09	0.06
Huanggang	10270	Non-east, Low	34.97	38.78	0.05	0.06
Xianning	8278	Non-east, Low	35.60	38.93	0.08	0.12
Suizhou	8350	Non-east, Low	35.30	38.61	0.54	0.11
Changsha	34131	Non-east, Middle	37.89	40.15	0.10	0.10
Zhuzhou	24835	Non-east, Middle	38.31	40.75	0.12	0.09
Xiangtan	26112	Non-east, Middle	37.51	40.77	0.12	0.10
Hengyang	15457	Non-east, Low	37.17	40.47	0.15	0.08
Shaoyang	8988	Non-east, Low	36.07	39.96	0.07	0.05
Yueyang	28512	Non-east, Middle	37.32	39.85	0.12	0.08
Changde	18270	Non-east, Middle	37.19	39.62	0.10	0.08
Zhangjiajie	6514	Non-east, Low	38.52	39.86	0.19	0.13
Yiyang	8840	Non-east, Low	37.23	39.30	0.11	0.08
Chenzhou	14959	Non-east, Low	37.54	40.34	0.06	0.07
Yongzhou	8503	Non-east, Low	37.52	40.30	0.13	0.09
Huaihua	15795	Non-east, Middle	37.24	40.29	0.09	0.07
Guangzhou	63819	East, High	40.36	42.60	0.08	0.10
Shaoguan	19590	East, Middle	37.25	40.38	0.03	0.12
Shenzhen	59271	East, High	40.35	42.69	0.08	0.07
Zhuhai	64960	East, High	39.74	40.72	0.06	0.10
Shantou	12456	East, Low	36.43	39.54	0.06	0.11
Foshan	47500	East, High	38.99	40.83	0.03	0.03
Jiangmen	30791	East, Middle	37.57	40.37	0.04	0.08
Zhangjiang	24248	East, Middle	37.68	39.15	0.04	0.09
Maoming	20541	East, Middle	38.26	40.15	0.03	0.10
Zhaoqing	25943	East, Middle	38.09	40.02	0.03	0.11
Huizhou	37681	East, Middle	38.73	40.72	0.04	0.11
Meizhou	10984	East, Low	37.54	40.23	0.02	0.07
Shanwei	10193	East, Low	36.76	39.91	0.01	0.03
Heyuan	11453	East, Low	37.76	39.24	0.01	0.07
Yangjiang	18778	East, Middle	37.01	38.88	0.04	0.09
Qingyuan	12004	East, Low	38.13	40.27	0.03	0.10
Dongguan	71997	East, High	40.34	42.03	0.01	0.01
Zhongshan	44005	East, High	39.29	41.76	0.02	0.02
Yunfu	12543	East, Low	36.84	39.14	0.02	0.06

Table B4: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Group	TFP 05	TFP 10	Land Abundance 2005	Land Abundance 2010
Nanning	24296	Non-east, Middle	35.60	39.23	0.19	0.11
Liuzhou	23042	Non-east, Middle	37.31	40.60	0.21	0.12
Guilin	22192	Non-east, Middle	37.60	39.84	0.10	0.06
Beihai	18530	Non-east, Middle	36.92	39.25	0.23	0.16
Yulin	8573	Non-east, Low	37.22	39.63	0.10	0.07
Baise	12227	Non-east, Low	36.71	39.63	0.08	0.07
Hechi	9114	Non-east, Low	35.60	38.46	0.07	0.04
Laibin	5947	Non-east, Low	36.90	39.37	0.15	0.11
Chongzuo	6633	Non-east, Low	35.84	39.38	0.04	0.09
Haikou	17928	East, Middle	36.89	38.89	0.08	0.14
Sanya	9538	East, Low	37.76	39.96	0.10	0.12
Chongqing	13342	Non-east, Low	37.80	40.73	0.10	0.12
Chengdu	29463	Non-east, Middle	37.89	39.83	0.24	0.07
Zigong	14452	Non-east, Low	35.83	39.34	0.22	0.18
Panzhihua	20725	Non-east, Middle	36.92	40.26	0.42	0.15
Luzhou	10166	Non-east, Low	37.04	38.94	0.25	0.13
Deyang	15421	Non-east, Low	38.23	40.87	0.07	0.06
Mianyang	18200	Non-east, Middle	36.08	39.87	0.16	0.10
Guangyuan	6323	Non-east, Low	35.79	39.71	0.34	0.08
Suining	5207	Non-east, Low	36.71	39.23	0.25	0.08
Leshan	9887	Non-east, Low	36.45	38.76	0.19	0.07
Nanchong	6373	Non-east, Low	35.98	39.17	0.19	0.07
Meishan	8575	Non-east, Low	37.34	39.89	0.20	0.09
Yibin	16042	Non-east, Middle	36.45	39.78	0.09	0.08
Guang'an	4584	Non-east, Low	36.55	38.33	0.24	0.07
Ziyang	7540	Non-east, Low	36.70	39.07	0.10	0.09
Guiyang	18874	Non-east, Middle	36.68	39.57	0.16	0.11
Liupanshui	13504	Non-east, Low	38.03	40.34	0.16	0.08
Zunyi City	15180	Non-east, Low	37.43	39.81	0.08	0.05
Anshun	4921	Non-east, Low	36.04	39.52	0.14	0.11
Kunming	31780	Non-east, Middle	38.12	40.26	0.11	0.09
Qujing	17659	Non-east, Middle	37.59	39.80	0.23	0.06
Yuxi	52230	Non-east, High	37.71	39.08	0.03	0.05
Baoshan	4656	Non-east, Low	36.94	39.18	0.05	0.07
Zhaotong	6819	Non-east, Low	37.94	40.12	0.04	0.05
Lijiang	11223	Non-east, Low	35.71	39.13	0.12	0.10
Xi'an	17528	Non-east, Middle	37.07	39.49	0.09	0.08
Tongchuan	8160	Non-east, Low	35.13	39.29	0.12	0.18
Baoji	24210	Non-east, Middle	36.38	40.01	0.06	0.13
Xianyang	18391	Non-east, Middle	36.25	38.96	0.42	0.07
Weinan	5411	Non-east, Low	36.16	39.83	0.05	0.06
Yan'an	10092	Non-east, Low	36.47	40.21	0.03	0.06
Yulin	5932	Non-east, Low	36.01	40.99	0.12	0.06
Lan'Zhou	22470	Non-east, Middle	36.60	39.09	0.14	0.13
Jiayuguan	25206	Non-east, Middle	38.51	40.05	0.31	0.44
Jinchang	31236	Non-east, Middle	36.19	40.31	0.12	0.28
Baiyin	17406	Non-east, Middle	36.26	38.96	0.13	0.22
Tianshui	6311	Non-east, Low	35.16	38.21	0.10	0.11
Wuwei	7307	Non-east, Low	34.78	37.24	0.10	0.14
Zhangye	8654	Non-east, Low	35.62	37.02	0.05	0.17
Pingliang	7591	Non-east, Low	36.20	38.99	0.11	0.08
Xining	11160	Non-east, Low	37.04	38.95	0.05	0.08
Yinchuan	13956	Non-east, Low	36.32	39.50	0.10	0.12
Shizuishan	15503	Non-east, Low	36.39	40.43	0.16	0.31

Notes: This table displays the complete list of cities used in the quantitative model. The second column gives GDP per capita in 2005. The third column shows the category of the city according to their location and GDP per capita. We divide cities into three levels of development by their GDP per capita. The fourth and fifth columns show TFP in 2005 and 2010, as calculated in the quantitative model. The sixth and the seventh columns show the land tightness in 2005 and 2010, as calculated in the quantitative model.

B.2 Computational Method of Solving the Model

Given the exogenous variables and parameters, we need to calculate the responses of endogenous variables resulting from model policy changes. As mentioned, we select the equilibrium that is the closest to the one observed in the real world. Thus, the initial values of the variables are set equal to the data in 2005 and 2010. Since we have a within-city land market between residential and production uses, we adopt a double-loop variation of the method in Fang and Huang (2022).

We first specify the exogenous variables and the model equation system. The exogenous variables are $\{H_i^s, \epsilon_j^s, \tau_{ij}^s, L_j, \phi_j, \eta_j\}$ where i indexes Hukou city, j indexes destination city, and s indexes skill. The equation system consists of three blocks: 1). Migration Block: worker income equations, and gravity equations; 2). Production Block: production equations, wage equations, and production floor space price equations; 3). Housing Block: construction equations and market clearing equations.

To calculate the counterfactuals following policy changes, we start with the block in which the changes happen, and then iterate block by block to update the endogenous variables until all endogenous variables converge within certain small thresholds. We present the process of calculating a counterfactual following an increase in land supply as an example below.

Suppose a land reallocation policy is $\hat{L_j} = \Delta_j \times L_j$ for every city j. We have the following process of updating variables $\{\hat{x_{jk}}\}^{OI}$, which indicates the t^{th} iteration of variable x. Start with the housing block to initiate the process (there is no need to update $\{\hat{S}_j\}^*$ again):

Outer Loop: In the outer loop we update the floor space distribution between residential and production uses according to the inner loop equilibrium unit prices of residential and production floor space. The outer loop converges when the prices satisfy the equilibrium price equation between both markets.

Step 1: Initiation (ensuring non-zero floor space supply)

$$\{\hat{S_{ju}}\}^* = \phi_j \hat{L_j} \tag{22}$$

$$\{\hat{S_{ju}^R}\}^1 = S_{ju}^R \times (\{\hat{S_{ju}}\}^* / S_{ju}) \tag{23}$$

$$\{\hat{S_{ju}^M}\}^1 = S_{ju}^M \times (\{\hat{S_{ju}}\}^* / S_{ju}) \tag{24}$$

Step 2: **Inner Loop** (feedback prices to Outer Loop, x^{1*} means Inner Loop for x converges)

$$\{\hat{Q_{ju}}\}^{\mathbf{1}^*} = \frac{1-\beta}{\beta}\frac{\{w^l_{ju}H^l_{ju} + w^h_{ju}H^h_{ju}\}^{\mathbf{1}^*}}{\{\hat{S^R_{ju}}\}^1} \tag{25}$$

$$\{\hat{q}_{ju}\}^{\mathbf{1}^*} = (1-\alpha)\left(\frac{\alpha}{\{\hat{W_{ju}}\}^{\mathbf{1}^*}}\right)^{\frac{\alpha}{1-\alpha}} \tag{26}$$

Step 3: Compare floor space prices and generate excess demand for residential space. The core idea is that if $\{\hat{Q_{ju}}\}^{\mathbf{1}^*} > \frac{\{\hat{q_{ju}}\}^{\mathbf{1}^*}}{\eta_j}$, residential floor space is smaller than equilibrium and production floor space is larger than equilibrium, so we need to redistribute more residential floor space to production floor space, until $\{\hat{Q_{ju}}\}^{\mathbf{1}^*} = \frac{\{\hat{q_{ju}}\}^{\mathbf{1}^*}}{\eta_j}$. We update partially with step size γ.

$$\{ED^R_j\}^1 = \gamma\left(\frac{\{\hat{Q_{ju}}\}^{\mathbf{1}^*} - \frac{\{\hat{q_{ju}}\}^{\mathbf{1}^*}}{\eta_j}}{\{\hat{Q_{ju}}\}^{\mathbf{1}^*} + \frac{\{\hat{q_{ju}}\}^{\mathbf{1}^*}}{\eta_j}}\right) \times \{\hat{S^R_{ju}}\}^1 \tag{27}$$

Step 4: Update floor space

$$\{\hat{S^R_{ju}}\}^2 = \{\hat{S^R_{ju}}\}^1 + \{ED^R_j\}^1 \tag{28}$$

$$\{\hat{S^M_{ju}}\}^2 = \{\hat{S^M_{ju}}\}^1 - \{ED^R_j\}^1 \tag{29}$$

Finally, we repeat Step 2 to Step 4 until the market clearing condition holds: $\{\hat{Q_{ju}}\}^{**} = \frac{\{\hat{q_{ju}}\}^{**}}{\eta_j}$.

Inner Loop: In the Inner Loop we update the migration and production decisions given the residential and production floor space. This Inner Loop is almost identical to Fang and Huang (2022)'s method. Notation: for variable x^{OI}, O denotes the step in the Outer Loop and I denotes the step in the Inner Loop. Here we demonstrate with $O = 1$.

Step 2-1: Update the housing block

$$\{\hat{Q_{ju}}\}^{11} = \frac{1-\beta}{\beta}\frac{w^l_{ju}H^l_{ju} + w^h_{ju}H^h_{ju}}{\{\hat{S^R_{ju}}\}^1} \tag{30}$$

$$\{\hat{Q_{jr}}\}^{11} = \tau\{\hat{Q_{ju}}\}^{11} \tag{31}$$

$$\{S^R_{jr}\}^{11} = \frac{1-\beta}{\beta}\frac{w_{jr}H_{jr}}{\{\hat{Q_{jr}}\}^{11}} \tag{32}$$

Step 2-2: Update the migration block

$$\{\hat{v^s_{in,jk}}\}^{11} = w^s_{jk} + \frac{\{\hat{Q_{in}}\}^{11}\{\hat{S^R_{in}}\}^{11}}{H^R_{in}} \quad \text{from eq.(4)} \tag{33}$$

$$\{\hat{\pi^s_{in,jk}}\}^{11} = \frac{(\tau^s_{in,jk}\{\hat{Q_{jk}}\}^{11^{1-\beta}})^{-\epsilon}(\{\hat{v^s_{in,jk}}\}^{11})^{\epsilon}}{\sum_{j'k'=11}^{JK}(\tau^s_{in,jk}\{\hat{Q_{j'k'}}\}^{11^{1-\beta}})^{-\epsilon}(\{\hat{v^s_{in,j'k'}}\}^{11})^{\epsilon}} \text{ from eq.(6)} \tag{34}$$

Then, combining $\{\hat{\pi^s_{in,jk}}\}^{11}$ with $\{H^s_{in}\}$, we are able to calculate $\{\hat{H^s_{jk}}\}^{11}$.

Step 2-3: Update the production block

$$\{\hat{X_{ju}}\}^{11} = [(\{A^h_{ju}\}^{11}\{\hat{H^h_{ju}}\}^{11})^{\frac{\sigma-1}{\sigma}} + (\{A^l_{ju}\}^{11}\{\hat{H^l_{ju}}\}^{11})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \text{ from eq.(7)} \tag{35}$$

$$\{\hat{w^l_{ju}}\}^{11} = \alpha(\{\hat{X_{ju}}\}^{11})^{\alpha-1}(\{\hat{S^M_{ju}}\}^1)^{1-\alpha}(\{A^l_{ju}\}^{11})^{\frac{\sigma-1}{\sigma}}(\{\hat{X_{ju}}\}^{11})^{\frac{1}{\sigma}}(\{\hat{H^l_{ju}}\}^{11})^{-\frac{1}{\sigma}} \text{ from eq.(8)} \tag{36}$$

$$\{\hat{w^h_{ju}}\}^{11} = \alpha(\{\hat{X_{ju}}\}^{11})^{\alpha-1}(\{\hat{S^M_{ju}}\}^1)^{1-\alpha}(\{A^h_{ju}\}^{11})^{\frac{\sigma-1}{\sigma}}(\{\hat{X_{ju}}\}^{11})^{\frac{1}{\sigma}}(\{\hat{H^h_{ju}}\}^{11})^{-\frac{1}{\sigma}} \text{ from eq.(9)} \tag{37}$$

Step 2-4: Update prices

$$\{\hat{Q_{ju}}\}^{12} = \frac{1-\beta}{\beta}\frac{\{w^l_{ju}H^l_{ju} + w^h_{ju}H^h_{ju}\}^{11}}{\{\hat{S^R_{ju}}\}^1} \tag{38}$$

We repeat Step 2-1 to Step 2-4 until residential floor space prices $\{\hat{Q_{ju}}\}^{1t}$ converge to $\{\hat{Q_{ju}}\}^{1*}$. We then output $\{\hat{Q_{ju}}\}^{1*}$ and $\{\hat{q}_{ju}\}^{1*}$ for the use in outer loop.

$$\{\hat{Q_{ju}}\}^{1*} = \frac{1-\beta}{\beta}\frac{\{w^l_{ju}H^l_{ju} + w^h_{ju}H^h_{ju}\}^{1*}}{\{\hat{S^R_{ju}}\}^1} \tag{39}$$

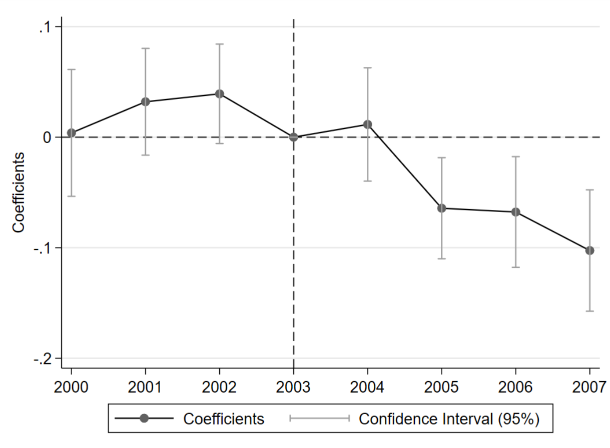
$$\{\hat{W_{ju}}\}^{11} = \frac{\{\hat{w^h_{ju}}\}^{11}\{\hat{H^h_{ju}}\}^{11} + \{\hat{w^l_{ju}}\}^{11}\{\hat{H^l_{ju}}\}^{11}}{\{\hat{X_{ju}}\}^{11}} \tag{40}$$

$$\{\hat{q}_{ju}\}^{1*} = (1-\alpha)\left(\frac{\alpha}{\{\hat{W_{ju}}\}^{1*}}\right)^{\frac{\alpha}{1-\alpha}} \tag{41}$$

B.3 Estimation of the Agglomeration Parameters: Event Study

Figure B1 provides city-level event study plots for our city-level regression (18) in the main paper. The dependent variable is TFP measured using the Olley and Pakes (1992) method. The result shows no difference in pre-trend before 2003. City-level average TFP consequently fell in the eastern region after the implementation of the policy.

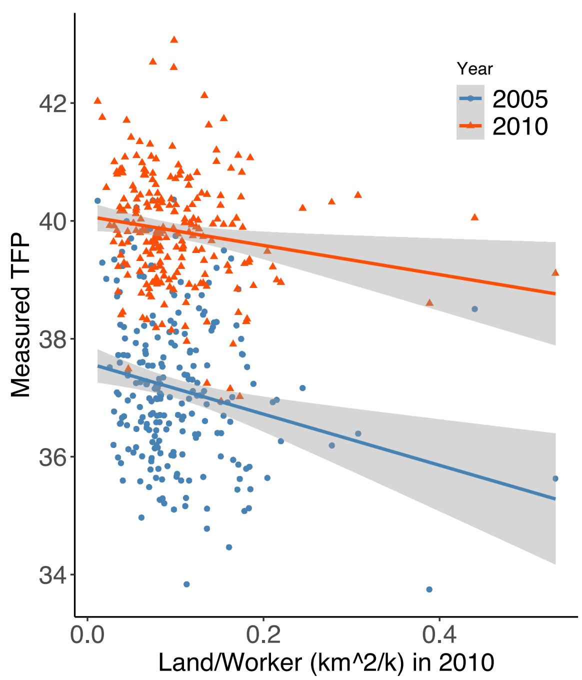
Figure B1: City-level Event Study Results (OP)



Notes: This is the event study plot from the city-level regression. TFP is measured using the Olley and Pakes (1992) method. All the specifications are the same as for the city-level DID regression.

B.4 Correlation between Productivity and Land Abundance

Figure B2: Correlation between Productivity and Land Abundance
By Individual City Including Extreme Values



Notes: This figure plots the correlation between productivity and land abundance in the model at the individual city level, including the extreme values omitted in the main paper.

Figure B2 plots the correlation between productivity and land tightness in the model at the individual city level, including the extreme values omitted in the main paper. We still observe a strong negative correlation between productivity and land tightness with the extreme values included.

B.5 Additional Results of the Quantitative Analysis

In this section, we show additional results of the quantitative analysis on the spatial distribution of economic development and income. Table B5 shows the spatial distributions of total output, urban output, rural output, and urban population in 2005. Table B6 shows the spatial distributions of both urban and rural workers by skill and the floor space price in 2005. Table B7 and B8 show the above contents in 2010. Table B9 shows the spatial distribution of total income, wage income, and non-wage income for Hukou workers.

Across these five tables, we have three observations that are consistent with our findings above. First, more developed eastern cities have much higher output, especially urban output. Second, these cities are much more populated with higher floor space prices. Third, workers in these cities earn higher incomes (higher wages for all workers and higher non-wage incomes for Hukou workers). These findings supplement our main findings on the spatial misallocation created by China's place-based land policy.

Table B5:
Quantitative Analysis: Year 2005
Spatial Distribution of Economic Development I

Regions (loc., dev.)	No. of Cities	Total Output	Urban Output	Rural Output	Urban Pop.
		Units are Chinese Yuan and Person			
National	225	7.28E+12	5.08E+12	2.20E+12	2.38E+08
(east, high)	21	2.38E+12	2.23E+12	1.52E+11	7.59E+07
(east, mid)	51	1.95E+12	1.38E+12	5.67E+11	6.97E+07
(east, low)	25	4.62E+11	2.51E+11	2.11E+11	1.76E+07
(inland, high)	2	6.01E+10	2.67E+10	3.34E+10	1.33E+06
(inland, mid)	50	1.13E+12	6.55E+11	4.72E+11	3.68E+07
(inland, low)	76	1.31E+12	5.39E+11	7.68E+11	3.70E+07

Notes: This table displays a summary of economic development variables by city group (weighted by population) in 2005. Regions are classified by location of city (east or inland) and level of development (GDP per capita) in 2005, as in Table 5.

Table B6:
Quantitative Analysis: Year 2005
Spatial Distribution of Economic Development II

Regions (loc., dev.)	No. of Cities	Urban Pop. High-skill	Urban Pop. Low-skill	Rural Pop. High-skill	Rural Pop. Low-skill	Floor Space Price
National	225	4.24E+07	1.96E+08	5.85E+05	2.19E+08	6.24E+01
(east, high)	21	1.41E+07	6.18E+07	6.38E+04	8.83E+06	1.21E+02
(east, mid)	51	1.07E+07	5.90E+07	1.35E+05	5.32E+07	4.78E+01
(east, low)	25	2.54E+06	1.51E+07	8.77E+04	2.40E+07	4.37E+01
(inland, high)	2	2.56E+05	1.07E+06	6.24E+03	1.96E+06	5.21E+01
(inland, mid)	50	8.06E+06	2.87E+07	1.25E+05	4.65E+07	4.71E+01
(inland, low)	76	6.71E+06	3.03E+07	1.67E+05	8.48E+07	3.83E+01

Notes: This table displays a summary of economic development variables by group (weighted by population) in 2005. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table B7:
Quantitative Analysis: Year 2010
Spatial Distribution of Economic Development I

Regions (loc., dev.)	No. of Cities	Total Output	Urban Output	Rural Output	Urban Pop.
		Units are Chinese Yuan and Person			
National	225	1.64E+13	1.28E+13	3.62E+12	3.40E+08
(east, high)	21	5.33E+12	5.08E+12	2.47E+11	1.07E+08
(east, mid)	51	4.50E+12	3.41E+12	1.09E+12	9.53E+07
(east, low)	25	6.44E+11	4.14E+11	2.30E+11	1.55E+07
(inland, high)	2	8.24E+10	5.84E+10	2.39E+10	1.59E+06
(inland, mid)	50	2.99E+12	2.20E+12	7.82E+11	6.51E+07
(inland, low)	76	2.89E+12	1.63E+12	1.25E+12	5.53E+07

Notes: This table displays a summary of economic development variables by city group (weighted by population) in 2005. Regions are classified by location of city (east or inland) and level of development (GDP per capita) in 2005, as in 5.

Table B8:
Quantitative Analysis: Year 2010
Spatial Distribution of Economic Development II

Regions (loc., dev.)	No. of Cities	Urban Pop. High-skill	Urban Pop. Low-skill	Rural Pop. High-skill	Rural Pop. Low-skill	Floor Space Price
National	225	6.20E+07	2.78E+08	1.45E+06	1.83E+08	1.15E+02
(east, high)	21	1.96E+07	8.78E+07	1.32E+05	8.05E+06	1.75E+02
(east, mid)	51	1.62E+07	7.91E+07	4.44E+05	5.26E+07	9.64E+01
(east, low)	25	2.29E+06	1.33E+07	1.01E+05	1.36E+07	7.37E+01
(inland, high)	2	3.60E+05	1.23E+06	9.31E+03	9.25E+05	1.03E+02
(inland, mid)	50	1.42E+07	5.10E+07	3.47E+05	3.91E+07	1.08E+02
(inland, low)	76	9.29E+06	4.60E+07	4.17E+05	6.85E+07	7.88E+01

Notes: This table displays a summary of economic development variables by group (weighted by population) in 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table B9:
Quantitative Analysis:
Spatial Distribution of Hukou-based Income

Regions (loc., dev.)	No. of Cities	Total Income		Wage Income		Non-Wage Income	
		2005	2010	2005	2010	2005	2010
National	225	1.90E+04	3.69E+04	1.46E+04	2.85E+04	4.35E+03	8.48E+03
(east, high)	21	3.73E+04	7.00E+04	2.46E+04	4.10E+04	1.27E+04	2.90E+04
(east, mid)	51	1.94E+04	3.71E+04	1.51E+04	2.89E+04	4.30E+03	8.26E+03
(east, low)	25	1.47E+04	2.93E+04	1.18E+04	2.42E+04	2.86E+03	5.07E+03
(inland, high)	2	2.26E+04	4.01E+04	1.74E+04	3.04E+04	5.21E+03	9.71E+03
(inland, mid)	50	1.72E+04	3.49E+04	1.37E+04	2.76E+04	3.45E+03	7.34E+03
(inland, low)	76	1.47E+04	3.05E+04	1.22E+04	2.60E+04	2.55E+03	4.46E+03

Notes: This table displays a summary of income variables by group (weighted by population) in 2005 and 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

C Supplements to the Counterfactual Analysis

C.1 Constructing the Counterfactual Policy

Table D1, D2, and D3 provide additional summary statistics of the counterfactual land allocation policy when we redistribute the land quota according to equation (21). In general, we find that if we maintain the pre-2003 land policy instead of adopting the inland-favoring policy, we would distribute more urban land to more developed cities and increase their land per worker, compared with the data. This lowers the land tightness in more developed cities.

Table D1:
Removing the Inland-favoring Policy:
Spatial Distribution of Land Tightness

Regions (loc., dev.)	No. of Cities	Reality 2005	Reality 2010	Counterfactual $\widehat{2005}$	Counterfactual $\widehat{2010}$
National	225	0.093	0.083	0.092	0.082
(east, high)	21	0.077	0.068	0.082	0.090
(east, mid)	51	0.084	0.082	0.083	0.071
(east, low)	25	0.080	0.108	0.084	0.106
(inland, high)	2	0.127	0.130	0.127	0.107
(inland, mid)	50	0.140	0.101	0.126	0.079
(inland, low)	76	0.104	0.086	0.103	0.080

Notes: This table displays a summary of urban land supply relative to workers by city group (weighted by urban population) as well as the counterfactual migration-based land supply in 2005 and 2010 (unit: km^2/k). Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

C.2 Calculation of Welfare

In this section, we briefly discuss the welfare (utility) changes of workers. We relegate this discussion to the appendix since we believe the results are only suggestive. First, utility is fundamentally ordinal. Thus, the aggregation of utilities across people with different characteristics from different regions is not innocuous. We do not know how to assign weights to different people. Second, the aggregation results depend heavily on the functional form of utility. As a result, we emphasize the income changes in the main paper. Due to these limitations, this section can only provide suggestive implications for the policy effect on worker welfare.

To calculate welfare, we can calculate the ex-ante expected utility of workers based on the

Table D2: **Removing the Inland-favoring Policy: Changes in Total Land Supply**

Regions (loc., dev.)	No. of Cities	Changes 2005	Changes 2010
National	225	0%	0%
(east, high)	21	13%	51%
(east, mid)	51	-2%	-16%
(east, low)	25	4%	-5%
(inland, high)	2	0%	-18%
(inland, mid)	50	-12%	-27%
(inland, low)	76	-2%	-11%

Notes: This table displays changes in counterfactual total urban land supply by group (summations within group) in 2005 and 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D3: **Removing the Inland-favoring Policy: Changes in Land Tightness**

Regions (loc., dev.)	No. of Cities	Changes 2005	Changes 2010
National	225	-1%	-1%
(east, high)	21	6%	34%
(east, mid)	51	-2%	-14%
(east, low)	25	4%	-2%
(inland, high)	2	0%	-17%
(inland, mid)	50	-10%	-21%
(inland, low)	76	-1%	-7%

Notes: This table displays changes in counterfactual urban land per thousand workers by group (summations within group) in 2005 and 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

properties of a Fréchet distribution. The cumulative distribution function of the utility of workers originating from city i sector n with skill s is

$$G_{in}^{s}(u) = e^{-\Phi_{in}^{s} u^{-\epsilon}}, \ \Phi_{in}^{s} = \sum_{j'k'=11}^{JK} (\tau_{in,j'k'}^{s} Q_{j'k'}^{1-\beta})^{-\epsilon} (v_{in,j'k'}^{s})^{\epsilon}$$

with their expected utility as:

$$\mathbf{E}_{in}^{s}[u] = \Gamma\left(1 - \frac{1}{\epsilon}\right) \times \Phi_{in}^{s\ \frac{1}{\epsilon}}$$

where the Gamma function $\Gamma\left(1 - \frac{1}{\epsilon}\right)$ is a constant number and Φ_{in}^{s} reflects the expected utility from accesses to all alternative cities and sectors. This choice set value is positively correlated with potential income $v^s_{in,j'k'}$ and is negatively correlated with migration and housing costs. We then calculate the changes in ex-ante expected utility as:

$$\Delta \mathbf{E}^s_{in}[u] = \frac{\hat{\mathbf{E}^s_{in}[u]}}{\mathbf{E}^s_{in}[u]} - 1 \tag{42}$$

To aggregate to national or regional welfare, we assign equal weights to each worker and simply sum across all groups.

C.3 Additional Results on Spatial Economic Development

Measured TFP Table D4 shows the effects of changing the land supply policy on the spatial distribution of measured TFP. We see that by keeping the pre-2003 land allocation rule and distributing more land to developed regions, we can increase national TFP substantially by 4.8% in 2005 and 6.4% in 2010. The decomposition also shows that most of the national TFP gains are driven by the increase in the fundamental productivity term. The reform encourages more workers to migrate to developed regions with higher TFP, which raises the weighted national TFP. The inflow of migrant workers also amplifies the agglomeration effect on local productivity in developed regions.

The TFP changes are uneven across regions. In 2005, TFP in eastern cities with high productivity increases by 2.9%, but there is almost no change in TFP in other cities. In 2010, although we find a larger TFP increase of 6.7% in developed cities, there is also a significant TFP decrease in underdeveloped cities due to the land losses. For instance, TFP in inland cities with medium and low productivity declines by 5.2% and 3.2%, respectively. This result shows that although national TFP and output would be higher with the pre-2003 land allocation policy, regional productivity gaps will also increase.

Table D4:
Removing the Inland-Favoring Policy:
Spatial Effects on Measured TFP

Regions (location, development)	No. of Cities	2005				2010			
		Total	Fund	SP	LSP	Total	Fund	SP	LSP
National	225	4.8%	4.7%	-0.8%	0.8%	6.4%	6.6%	-0.6%	0.3%
(east, high)	21	2.9%	3.2%	-2.9%	2.8%	6.7%	4.9%	-2.7%	4.5%
(east, mid)	51	0.0%	0.2%	0.1%	-0.3%	-1.2%	0.5%	0.4%	-2.1%
(east, low)	25	-0.3%	-0.8%	0.1%	0.4%	-1.7%	-0.6%	-0.1%	-1.0%
(inland, high)	2	-0.2%	0.0%	0.0%	-0.2%	-2.2%	0.2%	0.0%	-2.4%
(inland, mid)	50	0.0%	0.9%	0.0%	-1.0%	-5.2%	-1.4%	-0.3%	-3.6%
(inland, low)	76	0.2%	0.4%	0.1%	-0.3%	-3.2%	-1.4%	0.2%	-2.1%

Notes: This table displays a summary of changes in measured TFP $ln(\widetilde{TFP}_{ju})$ by group (weighted by population) in 2005 and 2010 as well as its decomposition: Fund stands for fundamental, SP stands for skill premium, and LSP stands for land scale premium. Regions are classified by location of the city (east or inland) and level of development (GDP per capita) in 2005 according to the data. For the level of development, we divide all cities into three categories {high, mid, and low} to capture {10%, 45%, 45%} of the distribution of GDP per capita. Each region consists of the same cities in both 2005 and 2010 for consistent comparisons over time.

Migration Tables D5 and D6 illustrates the counterfactual changes in migration compared with the real world. More workers migrate to urban areas in developed cities when more land is allocated to developed regions. Specifically, the urban low-skill (high-skill) population in eastern cities with high productivity increases by 7.1% (2.1%) in 2005 and by 13.9% (8.7%) in 2010. Conversely, less developed cities lose population. The urban low-skill (high-skill) population in inland cities with low productivity declines by 1.7% (1.0%) in 2005 and by 4.6% (2.8%) in 2010.

Table D5:
Removing the Inland-Favoring Policy:
Spatial Effects on Migration in 2005

Regions (loc., dev.)	No. of Cities	Urban Pop. High-skill	Urban Pop. Low-skill	Rural Pop. High-skill	Rural Pop. Low-skill
National	225	0.0%	1.5%	-1.3%	-1.4%
(east, high)	21	2.1%	7.1%	-0.3%	0.0%
(east, mid)	51	-0.9%	-0.5%	-1.5%	-0.6%
(east, low)	25	-0.5%	-0.7%	-2.3%	-1.3%
(inland, high)	2	-0.1%	0.1%	-0.2%	0.1%
(inland, mid)	50	-1.5%	-1.7%	-1.4%	-1.7%
(inland, low)	76	-1.0%	-1.7%	-0.8%	-1.9%

Notes: This table displays a summary of economic development variables by city group (weighted by population) in 2005. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D6:
Removing the Inland-Favoring Policy:
Spatial Effects on Migration in 2010

Regions (loc., dev.)	No. of Cities	Urban Pop. High-skill	Urban Pop. Low-skill	Rural Pop. High-skill	Rural Pop. Low-skill
National	225	0.0%	1.4%	-1.4%	-2.2%
(east, high)	21	8.7%	13.9%	5.8%	3.2%
(east, mid)	51	-2.5%	-2.7%	-1.9%	-0.8%
(east, low)	25	-3.3%	-3.0%	-0.7%	-2.2%
(inland, high)	2	-1.0%	-0.9%	3.2%	1.8%
(inland, mid)	50	-6.3%	-6.9%	-2.5%	-3.1%
(inland, low)	76	-2.8%	-4.6%	-2.4%	-3.5%

Notes: This table displays a summary of economic development variables by city group (weighted by population) in 2005. Regions are classified by location of city (east or inland) and level of development (GDP per capita) in 2005, as in Table 5.

C.4 Additional Results on Spatial Income and Welfare

Spatial Effects on Income Table D7 shows the decomposition of the spatial effects on income into two components: wage incomes and non-wage incomes (including housing asset income and potential regional transfers). We show that the changes of non-wage income play the essential role in shaping the spatial distribution of total income.

Table D7:
Removing the Inland-Favoring Policy:
Decomposition of Spatial Effects on Income

Regions	No. of	Without Transfer				Regional Transfer			
		Δ Wage Income		Δ Non-wage Income		Δ Wage Income		Δ Non-wage Income	
(loc., dev.)	Cities	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$
National	225	1.1%	1.0%	1.1%	1.1%	1.0%	0.5%	-1.1%	3.1%
(east, high)	21	0.1%	0.0%	6.0%	13.7%	0.2%	0.2%	-21.1%	-35.3%
(east, mid)	51	0.4%	0.4%	-0.5%	-2.9%	0.4%	-0.1%	-11.3%	6.1%
(east, low)	25	1.3%	2.1%	-1.1%	-3.8%	1.5%	1.8%	-11.7%	21.4%
(inland, high)	2	0.0%	-1.6%	0.0%	-1.6%	0.0%	-1.6%	-5.9%	-4.2%
(inland, mid)	50	1.3%	0.7%	-1.9%	-8.1%	0.9%	-0.1%	52.0%	31.9%
(inland, low)	76	2.4%	2.1%	-1.6%	-4.6%	2.0%	1.4%	6.7%	33.1%

Notes: This table displays a summary of income by city group (summations within group) in 2005 and 2010. Regions are classified by location of city (east or inland) and level of development (GDP per capita) in 2005, as in Table 5.

Spatial Effects on Welfare Tables D8, D9, D10, and D11 show the decomposition of the spatial effects on welfare into four sector-skill groups: (urban, high), (urban, low), (rural, high), (rural, low). We first show that without a regional transfer, workers in developed eastern cities benefit more from removing the inland-favoring policy. When the regional transfer is implemented on top of removing the inland-favoring policy, workers in underdeveloped cities, especially in the rural sector, benefit significantly from the counterfactual policy.

Table D8:
Removing the Inland-Favoring Policy:
Decomposition of Spatial Effects on Welfare

Regions	No. of	Without Transfer (Year 2005)				
(loc., dev.)	Cities	Welfare	(Urban, High)	(Urban, Low)	(Rural, High)	(Rural, Low)
National	225	3.7%	1.9%	1.4%	4.7%	1.2%
(east, high)	21	9.8%	6.3%	5.8%	14.3%	3.0%
(east, mid)	51	-0.2%	-0.7%	-0.7%	-0.2%	-0.4%
(east, low)	25	-1.7%	0.8%	0.8%	-2.5%	1.6%
(inland, high)	2	-0.5%	-0.3%	-0.3%	0.3%	-1.0%
(inland, mid)	50	-0.3%	-2.2%	-1.3%	0.4%	-2.5%
(inland, low)	76	2.3%	0.0%	0.0%	3.1%	0.5%

Notes: This table displays a summary of welfare by city group (summations within group) in 2005. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D9:
Removing the Inland-Favoring Policy:
Decomposition of Spatial Effects on Welfare

Regions (loc., dev.)	No. of Cities	Without Transfer (Year 2010) Welfare	(Urban, High)	(Urban, Low)	(Rural, High)	(Rural, Low)
National	225	10.6%	2.8%	-0.6%	9.2%	12.4%
(east, high)	21	17.9%	16.1%	13.6%	19.3%	17.5%
(east, mid)	51	-3.9%	-4.5%	-5.4%	-3.3%	-3.5%
(east, low)	25	0.8%	-2.5%	-2.9%	6.3%	0.8%
(inland, high)	2	-5.1%	-5.7%	-6.7%	-4.9%	-4.9%
(inland, mid)	50	-5.5%	-9.4%	-8.7%	-4.5%	-3.3%
(inland, low)	76	-3.7%	-4.7%	-3.8%	-9.2%	-0.9%

Notes: This table displays a summary of welfare by city group (summations within group) in 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D10:
Removing the Inland-Favoring Policy:
Decomposition of Spatial Effects on Welfare

Regions (loc., dev.)	No. of Cities	Regional Transfer (Year 2005) Welfare	(Urban, High)	(Urban, Low)	(Rural, High)	(Rural, Low)
National	225	2.8%	-8.8%	-8.9%	4.0%	1.0%
(east, high)	21	3.9%	-12.1%	-12.3%	9.7%	-2.6%
(east, mid)	51	0.5%	-8.0%	-8.6%	1.4%	1.7%
(east, low)	25	0.8%	-5.6%	-6.9%	1.6%	1.6%
(inland, high)	2	-1.2%	-7.4%	-7.9%	1.0%	0.7%
(inland, mid)	50	3.1%	-5.4%	-6.0%	2.2%	11.9%
(inland, low)	76	2.6%	-5.6%	-6.6%	2.8%	3.4%

Notes: This table displays a summary of welfare by city group (summations within group) in 2005. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D11:
Removing the Inland-Favoring Policy:
Decomposition of Spatial Effects on Welfare

Regions (loc., dev.)	No. of Cities	Welfare	Regional Transfer (Year 2010) (Urban, High)	(Urban, Low)	(Rural, High)	(Rural, Low)
National	225	4.1%	-20.4%	-20.7%	9.6%	6.9%
(east, high)	21	4.1%	-28.7%	-30.6%	9.1%	5.0%
(east, mid)	51	0.3%	-17.8%	-19.8%	2.5%	8.6%
(east, low)	25	6.6%	-11.9%	-14.5%	6.1%	14.2%
(inland, high)	2	-3.6%	-16.1%	-18.6%	1.8%	4.5%
(inland, mid)	50	5.0%	-14.7%	-15.5%	6.0%	14.8%
(inland, low)	76	7.6%	-14.2%	-14.7%	13.9%	10.0%

Notes: This table displays a summary of welfare by city group (summations within group) in 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

C.5 A Simple Regional Transfer Rule

Without loss of generality, we design a very simple direct regional transfer rule. There are certainly more efficient regional transfer rules. The simple rule is as follows for each city i:

$$\widehat{DT}_{iu} = \underbrace{\hat{Q}_{iu}\hat{S}^R_{iu} \times \gamma^l_u \times \frac{-\Delta L_i}{L_i}}_{\text{urban land income transfer}} + \underbrace{(\hat{w}^l_{iu}H^l_{iu} + \hat{w}^h_{iu}H^h_{iu}) \times \gamma^w_u \times \frac{-\Delta L_j}{L_j}}_{\text{urban wage income transfer}}$$

$$\widehat{DT}_{ir} = \underbrace{(\hat{w}_{ir}H_{ir}) \times \gamma_r \times \frac{-\Delta L_j}{L_j}}_{\text{rural wage income transfer}}$$

where $\widehat{DT}_{iu}$ stands for direct transfer to urban workers and $\widehat{DT}_{ir}$ stands for direct transfer to rural workers. For a city losing $\frac{\Delta L_i}{L_i}$ (<0) of its land, urban workers will be compensated with a fraction γ^l_u of their floor space income $\hat{Q}_{iu}\hat{S}^R_{iu}$, and a fraction γ^w_u of their wage income $(\hat{w}^l_{iu}H^l_{iu} + \hat{w}^h_{iu}H^h_{iu})$. Since rural workers also face losses in their wage for losing access to their closest urban sector (the urban sector in their own city), they will be compensated with a fraction γ_r of their indirect wage income $\hat{w}_{ir}H_{ir}$. These direct transfers are feasible to implement because land-gaining cities ($\frac{\Delta L_i}{L_i} > 0$) have much higher floor space prices and wages.

The scale of the transfer depends on the tuning parameters $\{\gamma^l_u, \gamma^w_u, \gamma_r\}$. As we mentioned, we are not able to discuss the design of optimal redistribution policy in this paper. We simply show the results from one set of tuning parameters $\{\gamma_u^l, \gamma_u^w, \gamma_r\} = \{0.5, 0.1, 0.5\}$ for 2010 and $\{\gamma_u^l, \gamma_u^w, \gamma_r\} = \{0.75, 0.1, 0.5\}$ for 2005 which are sufficient to generate substantial redistribution and clarify the key mechanisms of the transfer results. We tested other sets of parameters and the results are similar.

This counterfactual is feasible to implement and still fulfills the central government's goal of balancing regional development. This mechanism mimics a policy called the "land quota market", which has been recommended by previous literature such as Lu and Xiang (2016). The basic idea is that the central government can balance the development of different regions by transferring revenues from developed cities to underdeveloped cities, rather than allocating the land supply directly. Since land and wage incomes in land-gaining cities are higher than in land-losing cities, and the total amount of land supply is unchanged, this redistribution is feasible and the central government even generates an additional financial surplus.

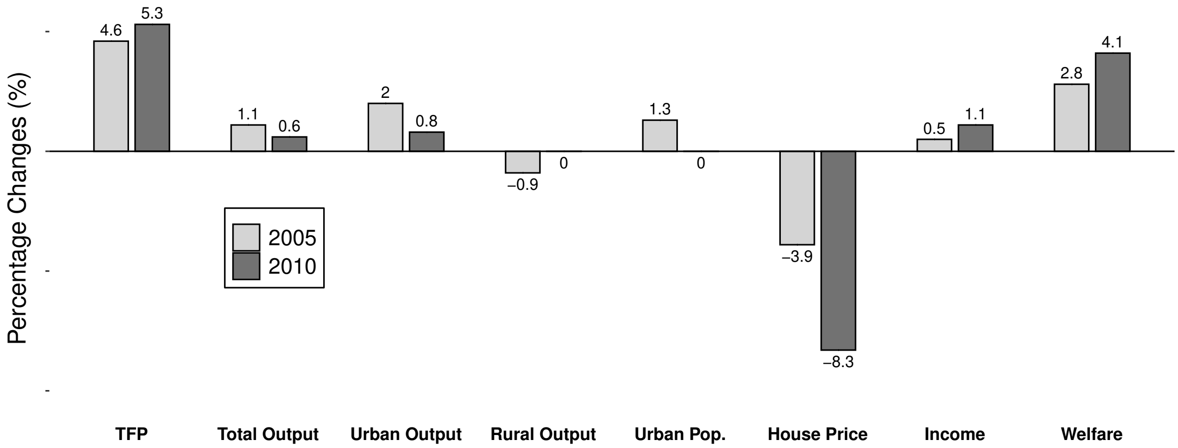
C.6 Additional Results on the Regional Transfer

We also show additional results on the counterfactual analysis with regional transfer.

Aggregate Effects of the Regional Transfer We show the aggregate effects of replacing the inland-favoring land policy with the regional transfer on national TFP, output, urban output, rural output, urban population, and national average income and welfare. The results are plotted in Figure D1. We find that removing the place-based land policy leads to significant gains in TFP, urban output, income, and welfare in both 2005 and 2010. It also helps to increase urban population due to lower residential floor space prices in more developed cities. Rural output falls due to worker emigration.

Spatial Effects on Economic Development We show the spatial effects on economic development in Table D12 on changes of TFP, urban output, rural output, urban population, and house price, Table D13 on changes in the decomposition of TFP, Table D14 and on changes in migration.

Figure D1:
Aggregate Effects of Replacing the Inland-Favoring Policy with the Regional Transfer



Notes: This figure shows the aggregate effects of replacing the inland-favoring policy with the regional transfer on the Chinese economy in 2005 and 2010. We find substantial national gains in TFP, total output, urban output, urban population, income, and welfare.

Table D12:
Replacing the Inland-Favoring Policy with the Regional Transfer: Spatial Effects on Economic Development

Regions	No. of	Δ TFP		Δ Urban Output		Δ Rural Output		Δ Urban Pop.		Δ House Price	
(loc., dev.)	Cities	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$	$\widehat{2005}$	$\widehat{2010}$
National	225	4.6%	5.3%	2.0%	0.8%	-0.9%	0.0%	1.3%	0.0%	-3.9%	-8.3%
(east, high)	21	2.9%	6.0%	5.8%	12.2%	-0.7%	0.4%	5.7%	10.3%	-18.9%	-35.7%
(east, mid)	51	0.0%	-1.3%	-0.7%	-4.7%	-0.5%	0.9%	-0.7%	-3.5%	1.2%	11.5%
(east, low)	25	-0.4%	-1.8%	-0.8%	-4.3%	-1.4%	-2.2%	-0.6%	-2.6%	-3.5%	3.3%
(inland, high)	2	-0.2%	-2.4%	0.0%	-3.3%	0.0%	2.1%	0.0%	-1.2%	1.6%	18.4%
(inland, mid)	50	-0.2%	-5.6%	-2.4%	-10.9%	-1.1%	0.0%	-1.9%	-7.5%	1.7%	10.2%
(inland, low)	76	0.2%	-3.4%	-1.3%	-6.1%	-1.3%	-0.8%	-1.4%	-4.7%	-3.5%	-1.1%

Notes: This table displays a summary of changes in core economic development variables by group (weighted by population) in 2005 and 2010. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D13:
Replacing the Inland-Favoring Policy with the Regional Transfer: Spatial Effects on Measured TFP

Regions (location, development)	No. of Cities	2005 Total	2005 Fund	2005 SP	2005 LSP	2010 Total	2010 Fund	2010 SP	2010 LSP
National	225	4.6%	4.5%	-0.7%	0.8%	5.3%	5.6%	-0.5%	0.2%
(east, high)	21	2.9%	3.0%	-2.8%	2.8%	6.0%	3.8%	-2.2%	4.5%
(east, mid)	51	0.0%	0.2%	0.1%	-0.3%	-1.3%	0.5%	0.4%	-2.2%
(east, low)	25	-0.4%	-0.8%	0.1%	0.3%	-1.8%	-0.6%	-0.1%	-1.0%
(inland, high)	2	-0.2%	0.0%	0.0%	-0.2%	-2.4%	0.0%	0.0%	-2.4%
(inland, mid)	50	-0.2%	0.9%	-0.1%	-1.1%	-5.6%	-1.7%	-0.3%	-3.7%
(inland, low)	76	0.2%	0.4%	0.1%	-0.3%	-3.4%	-1.5%	0.2%	-2.1%

Notes: This table displays a summary of changes in measured TFP $ln(\widetilde{TFP}_{ju})$ by city group (weighted by population) in 2005 and 2010 as well as its decomposition: Fund stands for fundamental, SP stands for skill premium, and LSP stands for land scale premium. Regions are classified by location of the city (east or inland) and level of development (GDP per capita) in 2005 according to the data. For the level of development, we divide all cities into three categories {high, mid, and low} to capture {10%, 45%, 45%} of the distribution of GDP per capita. Each region consists of the same cities in both 2005 and 2010 for consistent comparisons over time.

Table D14:
Replacing the Inland-Favoring Policy with the Regional Transfer: Spatial Effects on Migration in 2005

Regions (loc., dev.)	No. of Cities	Urban Pop. High-skill	Urban Pop. Low-skill	Rural Pop. High-skill	Rural Pop. Low-skill
National	225	0.0%	1.0%	-4.6%	-0.9%
(east, high)	21	2.8%	6.5%	-4.6%	-0.6%
(east, mid)	51	-0.9%	-0.7%	-7.3%	-0.6%
(east, low)	25	-1.0%	-0.7%	-7.4%	-1.3%
(inland, high)	2	-0.2%	0.0%	-1.9%	0.1%
(inland, mid)	50	-1.5%	-1.7%	-3.2%	-1.1%
(inland, low)	76	-1.4%	-1.3%	-2.1%	-1.4%

Notes: This table displays a summary of economic development variables by city group (weighted by population) in 2005. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.

Table D15:
Replacing the Inland-Favoring Policy with the Regional Transfer: Spatial Effects on Migration in 2010

Regions (loc., dev.)	No. of Cities	Urban Pop. High-skill	Urban Pop. Low-skill	Rural Pop. High-skill	Rural Pop. Low-skill
National	225	0.0%	0.0%	1.1%	0.0%
(east, high)	21	9.2%	10.5%	2.5%	0.9%
(east, mid)	51	-2.5%	-3.7%	0.4%	1.3%
(east, low)	25	-4.1%	-3.0%	0.6%	-0.7%
(inland, high)	2	-1.2%	-1.1%	3.0%	1.9%
(inland, mid)	50	-6.3%	-8.0%	1.3%	0.5%
(inland, low)	76	-3.4%	-4.8%	1.5%	-0.6%

Notes: This table displays a summary of economic development variables by city group (weighted by population) in 2005. Regions are classified by the location of the city (east or inland) and the level of development (GDP per capita) in 2005, consistently as in Table 5.