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

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Abstract

Place-based policies may create spatial misallocation. We investigate a major policy in China that aims to reduce regional development gaps by distributing more urban land quotas to underdeveloped inland regions. We first show evidence that this policy decreased firm-level TFP in more developed eastern regions relative to inland regions. We then build a prefecture-level quantitative spatial equilibrium model with migration, land constraints, and agglomeration. The model reveals that this policy led to substantial national TFP and output losses. The regional output gap shrank, but workers from underdeveloped regions reduced their migration to developed regions and earned less. Counterfactuals show that national TFP and urban output would have been 6.4% and 2.3% higher in 2010 if the policy change had not been implemented, and workers from underdeveloped regions would have 1.1% higher incomes. This inland-favoring policy reduced geographical output gaps but at the cost of hurting workers from underdeveloped regions. Instead, regional monetary transfer policies could reduce regional inequality without increasing spatial misallocation.

Keywords: Place-based Policy; Land Policy; Spatial Misallocation; Migration; Labor Mobility; 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 areas (Neumark and Simpson, 2015). They commonly target underdeveloped regions to promote balanced development across regions. However, promoting such balanced development may come at the cost of generating spatial misallocation, especially in the presence of migration frictions. In this paper, we empirically and quantitatively study the consequences of a major place-based land allocation policy change on both spatial misallocation and balanced development in China. Specifically, we investigate a sudden shift in China’s land supply policy in 2003, transitioning from a demand-driven approach to a development-promoting approach, commonly referred to as the inlandfavoring 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 primary concern entering the 2000s, with the eastern coastal 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 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 in migration further reduces agglomeration effects in places with high productivity.

But has China achieved the goal of promoting balanced development despite such costs of spatial misallocation? 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 that offer higher wages. This is consistent with recent literature (Tombe and Zhu, 2019; Lagakos et al., 2020; Lagakos, 2020; Lagakos, Mobarak, and Waugh, 2023; Wu and You, 2023), reducing internal migration costs is particularly beneficial to workers in the underdeveloped area, especially rural regions because returns to migration opportunities are high. We find that the overall national welfare is reduced without improving the utility of workers.
from poorer and rural 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 regional transfers, China could increase both national output and 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). We find this policy decreases relative firm-level TFP in eastern areas compared with non-eastern (inland) areas. Second, we develop a spatial equilibrium model to quantify the aggregate impact of the policy. Developed eastern cities have higher fundamental productivity and face more severe land supply constraints. By conducting a counterfactual exercise of eliminating this inland-favoring land supply policy, we find that urban 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 lowers not only overall productivity and output but also the incomes of people from poorer areas. We show that a direct transfer can reduce regional inequality without increasing spatial misallocation and directly increase the incomes for those born in poor areas.

In the first part of this study, we causally investigate the effect of the inland-favoring land supply policy adopted in 2003 on the firm-level TFP gap between eastern and non-eastern regions. 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 which side they are located. Thus, firm-level TFP should have similar time trends. This allows us to implement an RD-DID strategy on these samples to identify the effects of the inland-favoring land policy.

The inland-favoring policy reduces the firm-level TFP gap between the eastern and inland regions by approximately 8%. The results remain consistent across various robustness exercises in our regression analysis and are supported by supplementary evidence in other outcome variables, including city-level wages, land prices, and housing prices. Moreover, we do not observe significant TFP improvements among inland firms. Our empirical analysis demonstrates that the inland-favoring land policy narrows the productivity gap between eastern and inland firms by adversely affecting eastern firms without significantly benefiting inland firms, suggesting that land constraints could be a potential cause. We also present further empirical analyses showing that the inland-favoring policy directly diminishes the regional gaps in land and housing prices, which could potentially distort firms’ and workers’ decision-making processes.

In the second step, we construct a spatial general equilibrium model based on Tombe and Zhu
(2019) 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 residence 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, which is reflected in 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, the Urban Statistical Yearbook of China, and other supplementary databases in both 2005 and 2010, we solve and quantify the model. We then estimate the agglomeration parameter by 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 what has been estimated for developed countries, consistent with the suggestion in Chauvin et al. (2017). 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, this increases land supply in eastern cities and decreases floor space prices. More migrants are attracted to these cities, resulting 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 developed cities, their incomes are actually higher, 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 direct regional monetary transfer could truly increase the incomes and welfare of workers from underdeveloped regions with minimal spatial misallocation.

**Literature Review** Evaluating the effects of place-based policies or land-use regulations in emerging markets is particularly challenging. Firstly, a clean causal identification of the effects of land-use regulations is usually hard to find. Secondly, empirically identified effects are usually
local and cannot be easily aggregated, while aggregated quantitative studies usually overlook the distributional effects. Thirdly, limitations in data availability usually confine the analyses to a few developed cities. Finally, the agglomeration effect is intrinsically difficult to estimate. In this paper, we attempt to address all four issues simultaneously.

Firstly, we draw on direct causal evidence for the effects of place-based land-use regulations. Earlier literature has studied the impacts of land-use regulations on housing and welfare both theoretically (Hamilton, 1978; Wallace, 1988; Brueckner, 1995; Helsley and Strange, 1995; Hilber and Robert-Nicoud, 2013) and empirically (Glaeser, Gyourko, and Saks, 2005; Glaeser and Ward, 2009; Gyourko and Molloy, 2015), focusing mainly on the housing market in a few developed U.S. cities due to data availability. Meanwhile, addressing the endogeneity of the effects of land-use regulations remains a challenge (Quigley and Rosenthal, 2005). To tackle this challenge, recent literature has adopted difference-in-difference (DID) strategies (Cunningham, 2007; Kahn, Vaughn, and Zasloff, 2010; Yu, 2019) and regression discontinuity (RD) design (Grout, Jaeger, and Plantinga, 2011; Turner, Haughwout, and Van Der Klaauw, 2014; Chiumenti, Kulka, and Sood, 2022). We leverage the sudden policy change and combine border regression discontinuity design (Black, 1999) and difference-in-differences approaches (RD-DID) to establish the causal impact of the policy.

Secondly, we develop a comprehensive quantitative spatial equilibrium model to capture the aggregate and distributional effects. Recent literature has investigated various frictions and place-based policies and that result in spatial misallocation or welfare losses, including (urban-rural) migration frictions (Tombe and Zhu, 2019; Lagakos et al., 2020; Lagakos, 2020; Lagakos, Mobarak, and Waugh, 2023; Wu and You, 2023), housing constraints (Hsieh and Moretti, 2019), urban land expansion frictions (Yu, 2019; Fu, Xu, and Zhang, 2021), political manipulation (Henderson et al., 2022), and combinations of several 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), which investigates the effect of the "Farmland Red Line Policy" on economic development in China. We comprehensively build our quantitative model to capture the aggregate effects by including urban-rural-skill-specific migration and housing frictions from the household side, and production space frictions and agglomeration effects in density from the firm side. Additionally, the rich prefecture-urban-rural-skill structure allows us to analyze distributional effects more carefully.

Third, we take our model to comprehensive individual-level, firm-level, and prefecture-level datasets to seriously address data limitations common in emerging markets. Much literature has studied migration and regional development in China and other developing countries. In the

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1These papers include 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), special economic zones (Wang, 2013; Lu, Wang, and Zhu, 2019), and community development (Eriksen and Rosenthal, 2010; Accetturo and De Blasio, 2012; Romero, 2009), among others.

2Yu (2019) finds that this restriction on converting rural farmland to urban construction land leads to severe spatial misallocation in land and labor, lowers GDP, and reduces welfare, which is consistent with our findings.
context of China, 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).

We take our model to the most granular level possible by combining the Chinese Population Census, City Statistical Yearbooks of each city (manually collected), the Land Parcel Trade Dataset, and other supplements to ensure the credibility of our aggregate and distributional quantitative results of China.

Finally, our study contributes to the literature by addressing the challenge of estimating the agglomeration effect, which is a difficult parameter to pin down due to the endogeneity of population and density (Combes and Gobillon, 2015). Previous studies have used various strategies to tackle this issue, such as instrumenting 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, due to data restrictions, there have been no successful attempts to identify the agglomeration effect in China. Previous studies in China have typically calibrated agglomeration parameters using values estimated from developed countries. In contrast, our paper employs a novel method similar to Ahlfeldt et al. (2015) to identify the agglomeration effect by exploiting the inland-favoring land supply policy natural experiment in an indirect inference regression. Our study is the first to causally estimate the agglomeration parameter in a spatial model in China.

In summary, our study contributes to the literature by empirically, theoretically, and quantitatively examining the effect of place-based land-use regulations on the aggregate and regional economies of China. We address several issues, such as endogeneity, data limitations, and the challenge of estimating the agglomeration effects. By combining comprehensive individual-level, firm-level, and prefecture-level datasets, we provide a granular analysis of the impact of place-based policies on various aspects of the Chinese economy.

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. Sections 4 and 5 develop and estimate a spatial equilibrium model and solve it using administrative microdata. Section 6 conducts a counterfactual analysis to eliminate the place-based land policy. Section 7 provides model sensitivity checks and further discussions. Section 8 concludes.

Studies of other developing countries include Malaysia (Bertaud and Malpezzi, 2001), Indonesia (Bryan and Morten, 2019; Civelli et al., 2022), Brazil (Pellegrina, 2022), Columbia (Tsivanidis, 2019), Mexico (Monras, 2020), and India (Imbert and Papp, 2020), among others.
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. Next, construction companies need to buy the "use rights" from the local government. To ensure enough agricultural land for the domestic food supply (Yu, 2019), the central government strictly controls expanding urban areas. Each city is assigned a quota of construction land each year. Before 2003, the quota was mainly based on each city’s demand.

Figure 1: **The Inland-Favoring Land Allocation Policy Since 2003**

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


**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 quotas. However, since 2003, the central government started to focus on balancing economic development by allocating more land to underdeveloped inland provinces. In 2004, the central committee of the Chinese Communist Party made it clear that it is necessary to strengthen

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4Some 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. Another part of the policy was that about 70% of existing development zones, also known as special economic zones which subsides land usage, were closed in 2003–2004. The planned urban construction land supply for these closed development zones was also cut. Most of these closed development zones were along the eastern coast, and many newly opened development zones have since been established inland to support local economic development (Lu and Xiang, 2016; Chen et al., 2019).
the role of land supply policy in macroeconomic management. 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.

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 shows 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 more developed cities in the East.

2.2 Datasets

2.2.1 Data for the Empirical Analysis

In the empirical analysis, we use the National Industrial Enterprise Database, published by the National Bureau of Statistics. It covers all state- and non-state-owned enterprises “above scale” (main business revenue greater than 5 million RMB). This dataset accounts for over 90% of all industrial production in China. 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. 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) method in Appendix A, which yields similar results. Furthermore, we investigate other outcome variables, including city-level wage, land price, and housing price, in Appendix A.10.

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.

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5Decision of the State Council on deepening the reform of strict land management, issued on 12/21/2004 (link).
7Since there is a major missing data issue after 2007, we only use samples from 1998 to 2007.
8For unknown reasons, some companies provide missing or erroneous information. Some data cleaning and a 1% censoring process was applied to avoid abnormal observations.
Table 1: Summary Statistics

<table>
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<th>Variable</th>
<th>Description</th>
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<th>Std. dev.</th>
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<th>Median</th>
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<td>102.32</td>
<td>-199.99</td>
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<td>200</td>
</tr>
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</table>

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

All families must complete a short survey, which requires them to provide basic demographic information such as name, age, gender, education, and living address. Among all families, 10% of them must take a longer survey. The long survey questionnaire includes additional information such as job and place of birth. 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 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 (4,803,589) individuals in 2005 (2010), which covers 0.2% (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. Local branches of the National Bureau of Statistics edit the City Statistical Yearbooks. 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 summarizes key characteristics of all Chinese cities. We provide a complete list of cities with corresponding GDP, measured TFP, and land tightness, which is used in our quantitative analysis in Appendix B1.
3 Empirical Analysis

We empirically analyze how the inland-favoring land supply policy affected firms’ performance, emphasizing the effects on firm-level TFP. We show causal evidence that this policy shrank the TFP gap between eastern and inland firms. This reduction in the gap can be primarily attributed to the decreased TFP of eastern firms. Furthermore, we investigate other outcome variables, including city-level wages, land prices, and housing prices, as supplementary evidence.

3.1 Empirical Specification

The main empirical strategy in analyzing firm TFP combines a Border Regression Discontinuity Design as in Black (1999) and a Difference-in-Differences approach (RD-DID). The basic idea is to first compare firm TFP on the eastern and inland sides of the border. Then we compare this border TFP difference over time, particularly before and after the year when the central government implemented the inland-favoring land supply policy. If the 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 between the eastern and inland regions of China. Red dots represent firms on the eastern side of the boundary. Black dots represent firms on the inland side of the boundary. We use the region definitions published by the National Bureau of Statistics of China.

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

$$
\ln(y_{ibct}) = \alpha + \beta_1 East_{ibt} + \beta_2 f(Dist_{ibt}) + \beta_3 East_{ibt} \times f(Dist_{ibt})
+ Post_{2003} \times [\delta_1 East_{ibt} + \delta_2 f(Dist_{ibt}) + \delta_3 East_{ibt} \times f(Dist_{ibt})]
+ \beta_4 X_{ct-1} + \phi_{bt} + \gamma_t + \psi_i + \epsilon_{ibct} 
$$

(1)

where $y_{ibct}$ is the log TFP of firm $i$. $East_{ibt}$ is a dummy that equals one if the firm is located on the eastern side of the border, which carries a subscript $t$ since firms can change their locations across time. $f(Dist_{ibt})$ is a smooth function of the distance between the firm and the border, and $Post_{2003}$ is a dummy which equals one if $t$ is after 2003 (including 2003 itself).10 $X_{ct-1}$ is a set of lagged city-level control variables, including the log of GDP, the log of population, the log of city area, and the value added to the service sector. $\phi_{bt}$ is the border segment fixed effect for the firm at time $t$. We divide the border into five segments of equal length and designate each firm to the nearest segment. $\gamma_t$ is the year fixed effect. $\psi_i$ is the firm fixed effect.11

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9 We consider northeastern provinces as inland regions.
10 We also run all regressions in a specification where 2003 is excluded from the treatment group. The results are not qualitatively changed.
11 We also investigate a simpler regression setting without a firm fixed effect. The results are not qualitatively changed.
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 $f(Dist)$, $\beta_1$ captures the effect of being in the eastern region on outcome variable $y$. We use two fitting functions in this study: local linear regression and linear regression.

Second, we add the interaction between the post-2003 dummy and all previous RD terms. Coefficient $\delta_1$ then denotes the policy effect, which is interpreted as the change in the eastern region’s TFP premium over the inland region before and after the 2003 inland-favoring land allocation policy. This is a difference-in-differences estimation. The first difference is between the eastern and inland regions (at the border, within the bandwidth). The second difference is between the before-policy (2003) and the after-policy periods. In general, this specification combines border regression discontinuity design with difference-in-differences.
It is important to clarify that the inland-favoring land policy can potentially affect the TFP levels of both regions. Therefore, the regression coefficient should be interpreted as the policy’s effect on the regional gap (relative level) rather than on the absolute level of TFP for either region.

### 3.2 Regression Assumptions Validation

We validate our regression method by checking several important assumptions.

First, we investigate the existence of the boundary discontinuity by drawing an RD figure. Figure 3 depicts panel A, representing data before 2003, and panel B, representing data after 2003. The x-axis displays the distance of firms to the boundary, with a positive distance indicating firms located on the eastern side. The y-axis displays firm-level TFP, calculated using the Olley and Pakes (1992) method. This reveals a distinct discontinuity along the border of the eastern and non-eastern regions in both panels. Notably, this gap narrowed following the implementation of the 2003 inland-favoring land policy.

![Figure 3: Regression Discontinuity Changes](image)

Notes: The dependent variable is firm-level TFP calculated using the Olley and Pakes (1992) method. The smoothing function is linear. The bandwidth is 40 km from the border.

Second, we investigate the time trend of firm TFP in the eastern and inland regions. Our regression specification assumes that firm parcels on the eastern and inland sides of the border should have a similar time trend. Figure 4 shows the time trends of firm-level TFP. The black line is average TFP in the developed eastern region, and the grey line is average TFP in the inland region. The dashed vertical line is located just after 2003 when the inland-favoring land policy was implemented. We find no evidence of divergent time trends in firm productivity before the policy.
Despite the 2003 policy’s aim to boost inland development, we do not observe a corresponding increase in the growth rate of inland TFP. Instead, the policy seems to have stymied the growth of eastern TFP.

Figure 4: **Time Trends of Firm TFP**

![Figure 4: Time Trends of Firm TFP](image)

Notes: This figure shows the time trends of firm-level TFP calculated using the Olley and Pakes (1992) method and land parcel price. The black line is the average TFP in the developed eastern region, and the grey line is the average TFP 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. Firm-level TFP and land price followed similar trends before the policy.

Finally, 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 regression for the event study:

\[
\ln(y_{ibt}) = \alpha + \beta_1 East_{ibt} + \beta_2 f(Dist_{ibt}) + \beta_3 East_{ibt} \times f(Dist_{ibt}) \\
+ \sum_{s \neq 2003} 1(s = t) \times [\delta_{1s} East_{ibt} + \delta_{2s} f(Dist_{ibt}) + \delta_{3s} East_{ibt} \times f(Dist_{ibt})] \\
+ \beta_4 X_{ct-1} + \phi_b + \gamma_i + \psi_i + \epsilon_{ibt}
\]

(2)

We plot the evolution of the coefficient \(\delta_{is}\) across time \(s\) in Figure 5, illustrating the changing 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 became statistically and economically distinguishable from zero only after implementing the policy. 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 the firm productivity gap between the eastern
and inland regions.

### 3.3 Empirical Results

**Main Results**  Table 2 shows the regression results based on TFP. In the two columns, we use a local and linear fit for the smoothing function, respectively. We use the optimal bandwidth for the local linear fit based on Imbens and Kalyanaraman (2012). The bandwidth we use for the linear fit is 40 km.\(^{12}\) We find that the reduction in land supply after 2003 reduced the measured TFP gap of eastern firms relative to inland firms by about 8%.

**Other Variables**  Furthermore, we investigate the policy’s effect on additional outcome variables, including city-level wages, land prices, and housing prices, in Appendix A.10. Our findings reveal that the inland-favoring land policy led to a reduction in the wage gap and increases in both the eastern-inland land price and housing price gaps. These results further suggest that the land supply shift resulting from the inland-favoring policy directly contributed to changes in land and housing prices, which can distort firms’ and workers’ choices.

**Robustness Checks**  We also implement nine groups of robustness analyses to address an extensive set of potential empirical concerns. The results are available in Appendix A.

\(^{12}\)We also try other bandwidths, and the results are similar. Please refer to Appendix A for details.
Table 2: **RD-DID Results on TFP (OP)**

<table>
<thead>
<tr>
<th></th>
<th>(1) Local Linear</th>
<th>(2) Poly RD (Poly=1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post2003×East</td>
<td>-0.0803**</td>
<td>-0.0782*</td>
</tr>
<tr>
<td></td>
<td>(0.0356)</td>
<td>(0.0426)</td>
</tr>
<tr>
<td>City Lagged Controls</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Border FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>131,250</td>
<td>100,054</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1203</td>
<td>0.1162</td>
</tr>
</tbody>
</table>

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

bustness by conducting the empirical analysis using firm-level TFP calculated with the methods proposed by *Levinsohn and Petrin (2003)*. Table A1 shows that the results are very similar to the main results. The second group addresses concerns with the robustness of our bandwidth choice. We vary the bandwidths for the linear and quadratic smoothing functions between 20 and 70 km in Tables A2 and A3. The results are very robust qualitatively. The third group addresses concerns with potential bad control issues. We run all main regressions without city-level lagged control variables to address any potential bad control issues. Tables A4 and A5 show that the resulting estimates are similar to those with control variables. Both point estimates and R-squares exhibit minimal changes, validating our regression results according to Oster (2019).

In the fourth group, we simplify the regression discontinuity functional form by keeping slopes unchanged at the boundary. Table A6 shows minimal change compared with the baseline results. In the fifth group, we alleviate potential contamination from special geographical characteristics at the provincial boundary by excluding firms within 10 km on either side. Table A7 shows that the results are not changed. In the sixth group, we investigate the effect of firms moving their locations. In Figure A1 and Table A8, we show that the number of relocating firms is minimal, and no regression results change if we drop these firms. This is reasonable since the firms in the National Industrial Enterprise Database are all "above scale" large firms that rarely change their locations. In Table A9, we perform a placebo test by shifting the boundary to the west or the east. We do not observe significant changes in the gaps for these artificial boundaries before and after 2003.

We also address concerns about possible confounders around 2003. In the seventh group, 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 A10, A11, A12 and A13 show that the main conclusions are not changed. In the eighth group, we try to rule out the effects of some other subsidy and tax policies happening at this point which may distort our estimates. Tables A14, A15, and A16 show that the main results are maintained.

3.4 Remarks on the Empirical Analysis

In this empirical analysis, we show that the inland-favoring land policy decreased the firm productivity gap between the developed eastern regions and the underdeveloped inland regions. Based on the time trends of firm TFP in Figure 4, the relative changes are mainly due to the reduction in eastern firm productivity growth rather than changing inland productivity. These findings indicate that although the government achieved the goal of shrinking the regional gap between the eastern and inland regions, it potentially came at a substantial cost of distorting land prices and the productivity of eastern firms. In other words, such regional convergence comes at the cost of spatial misallocation. Although our empirical analysis gives us a clean policy effect on the regional TFP changes, it is only a local effect 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, precisely, cities (prefectures), 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 and subject to migration costs. Each worker is either low-skill \( s = l \) or high-skill \( s = h \). Each location \( i \) has an inelastic supply of urban floor space \( S_i^u \), produced by a fixed amount of urban land supply \( L_i^u \). In urban areas, floor space can be used for production or residence. We denote the endogenous fractions of floor space allocated to production and residential use by \( \theta_i \) and \( (1 - \theta_i) \), respectively. Rural housing markets are simplified such that their rents are proportional to the average urban rent in the same city.\(^{13}\)

After observing idiosyncratic utility shocks between each possible pair of destinations and their original location, workers decide whether and where to move. Firms produce a single final

---

\(^{13}\)This model reflects rural China’s unique land distribution system. All land in rural China is owned by the village collectively but not by individuals. There is no housing market in rural areas. The village council first distributes land to farmers (housing land, or in Chinese, Zhaijidi), then farmers build their houses by themselves. They almost cannot sell or buy houses. Thus, the housing cost for them is the building cost.
good, which is costlessly traded within the country and is chosen as the numeraire.\footnote{We do not specifically model city-to-city trade flows mainly due to data limitations. The most dis-aggregate intra-China trade flow is the trade flows between Chinese provinces constructed from China’s 2002 inter-regional input-output table, which is insufficient to support our analysis of city-to-city flows. Literature that includes trade and migration (Tombe and Zhu, 2019; Fan, 2019; Zi, 2020) shows that reducing internal and external trade costs would accelerate labor reallocation towards more developed regions. In our model that does not include trade, such an effect would be mapped into urban final goods productivity.} Locations differ in terms of their final urban 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, agglomeration effects exist in urban production, where city-level productivity in urban areas is positively related to the density of workers. We estimate the agglomeration parameters using our empirical findings above, joined with our structural model with an indirect inference method.

### 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 ($s_{in,jk}^o$), migration costs ($\tau_{in,jk}^s$), and an idiosyncratic shock ($z_{in,jk}^o$) in a Cobb-Douglas form:

$$U_{in,jk}^o = \frac{z_{in,jk}^o}{\tau_{in,jk}^s} \left( \frac{c_{in,jk}^o}{\beta} \right)^{\beta} \left( \frac{s_{in,jk}^o}{1 - \beta} \right)^{1 - \beta}$$

(3)

We model the heterogeneity in the utility that workers derive from working in different parts of the economy following the migration literature (Tombe and Zhu, 2019; Fan, 2019). We also do not distinguish between urban and rural residences 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 ($z_{in,jk}^o$) is drawn from an independent Fréchet distribution:

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

where the shape parameter $\epsilon > 1$ controls the dispersion of idiosyncratic utility. We assume that the migration costs can be separated into two parts $\tau_{in,jk}^s = \tau_{in}^s d_{in,jk}$ where $d_{in,jk}$ captures the physical distance and institutional costs due to the Hukou system and other frictions in migrating from city $i$ sector $n$ to the city $j$ sector $k$, and $\tau_{in}^s$ captures cost differences between individuals with different skills which may include skill-biased migration policies or differences in their preferences for specific amenities such as education for children, entertainments, or transportation.\footnote{The Hukou system is a household registration system in China that restricts workers’ mobility. A household’s social welfare programs, including education, medical, and other public services, are tied to their Hukou registration. Households who attempt to use such services in non-Hukou-registered cities pay a substantially higher cost of both money and time. For more details, please refer to Song (2014).}
After observing the realizations of idiosyncratic utility for each pair of origination and potential employment locations, workers choose their locations and sectors 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. Taking the final goods as numeraire and combining the worker's first-order conditions, 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 \( k \):

\[
\begin{align*}
\zeta_{in,jk}^o &= \beta v_{in,jk}^s, \\
\xi_{in,jk}^o &= (1 - \beta) \frac{v_{in,jk}^s}{Q_{jk}}
\end{align*}
\]

where \( v_{in,jk}^s \) 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 the city \( i \) sector \( n \) is not tradable and is owned in common by Hukou-registered workers 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 \( v_{in,jk}^s \) 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 the city \( i \) sector \( n \):

\[
v_{in,jk}^s = w_{jk}^s + \frac{Q_{in} S_{in}^R}{H_{in}^R}
\]

where \( H_{in}^R \) denotes all Hukou registrants, including those who migrated to work elsewhere, and \( S_{in}^R \) denotes all the residential floor space ownership by \( H_{in}^R \) Hukou registrants.\(^\text{16}\) Substituting equilibrium consumption of the final good and residential land use into utility, we obtain the following expression for the indirect utility function:

\[
U_{in,jk}^o = \frac{\zeta_{in,jk}^o v_{in,jk}^s Q_{jk}^{\beta-1}}{\tau_{in,jk}^s}
\]

### 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 moving to the city \( j \) sector \( k \) is also Fréchet distributed:

\(^{\text{16}}\)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 the 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.
\[ G_{in,jk}^s(u) = \Pr[U \leq u] = F \left( \frac{u r_{in,jk}^s Q_{jk}^{1-\beta}}{v_{in,jk}^s} \right) \]

\[ G_{in,jk}^s(u) = e^{-\Phi_{in,jk}^s u^{\sigma}} \]

\[ \Phi_{in,jk}^s = (r_{in,jk}^s Q_{jk}^{1-\beta})^{\sigma} (v_{in,jk}^s)^{1-\sigma} \]

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

\[ 1 - G_{in}^s(u) = 1 - \prod_{jk=11}^{JK} e^{-\Phi_{in,jk}^s u^{\sigma}} \]

Therefore we have

\[ G_{in}^s(u) = e^{-\Phi_{in}^s u^{\sigma}} \]

\[ \Phi_{in}^s = \sum_{jk=11}^{JK} \Phi_{in,jk}^s \]

We could derive the gravity equation of migration flow in spatial equilibrium models as follows. Let \( \pi_{in,jk}^s \) 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

\[ \pi_{in,jk}^s = \frac{(r_{in,jk}^s Q_{jk}^{1-\beta})^{\sigma} (v_{in,jk}^s)^{1-\sigma}}{\sum_{j'k'=11}^{JK} (r_{in,j'k'}^s Q_{j'k'}^{1-\beta})^{\sigma} (v_{in,j'k'}^s)^{1-\sigma}} \]

(6)

### 4.3 Production

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 \( S_j^M \):

\[ Y_{ju} = (X_{ju})^\alpha (S_{ju}^M)^{1-\alpha}, \]  

where \( X_{ju} = [(A_{ju}^h H_{ju}^h)^{\frac{\alpha}{\sigma}} + (A_{ju}^l H_{ju}^l)^{\frac{\alpha}{\sigma}}]^\frac{1}{\alpha \sigma} \) \n
(7)

where \( X_{ju} \) is a CES combination of high skill labor \( H_{ju}^h \) and low skill labor \( H_{ju}^l \) multiplied by their corresponding city-level efficiencies \( A_{ju}^h \) and \( A_{ju}^l \). 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 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 \( r \).\(^{17}\)

**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

\(^{17}\)We make a simplification such that \( w_{jr}^h = w_{jr}^l = w_{jr} \).
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 the following:

\[ w^l_{ju} = \alpha X^\alpha_{ju} S^M_{ju}^\frac{1}{\alpha} X_{ju}^\frac{\alpha}{\alpha} H^l_{ju}^{\frac{1}{\alpha}} \]  
(8)

\[ w^h_{ju} = \alpha X^\alpha_{ju} S^M_{ju}^\frac{1}{\alpha} A^h_{ju}^\frac{\alpha}{\alpha} X_{ju}^\frac{\alpha}{\alpha} H^h_{ju}^{\frac{1}{\alpha}} \]  
(9)

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

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:

\[ q_{ju} = (1 - \frac{\alpha}{W_{ju}})^{\frac{\alpha}{1-\alpha}} \]  
(11)

**Agglomeration**  
We now introduce endogenous agglomeration forces as in Ahlfeldt et al. (2015) with slight modifications to the prefecture level. We allow urban labor productivity for both skills to depend on production fundamentals \((a^h_{ju} \text{ and } a^l_{ju})\) and production externalities \((D_j)\). Production externalities impose structure on how the productivity of a given region is affected by the density of workers within the urban area of the prefecture,\(^\text{18}\)

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

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

### 4.4 Land Market Clearing

**Urban Regulations**  
Before moving to urban land market clearing, we highlight the regulation of the supply of urban floor space. For total supply, the central and local governments jointly directly determine a quota on how much floor space can be constructed each year in each city (prefecture). Such a quota is determined by the regulated density of development \(\phi_j\) (the ratio

\(^{18}\)Considering administrative zones are fixed, the changes in density are identical to changes in the population.
of floor space to land) and the geographic construction land $L_j$. Therefore, we assume that floor space $S_{ju}$ is supplied by a highly-regulated construction sector that uses geographic construction land $L_j$ and a regulated density of development $\phi_j$ to produce:

$$S_{ju} = \phi_j L_j$$  \hspace{1cm} (13)$$

The local governments then determine the usage allocation between production and residences exogenously by their preferences. Such preferences are heterogeneous across cities and depend on many characteristics. We treat this preference heterogeneity as creating a reduced form wedge between prices of production ($q_{ju}$) and residential ($Q_{ju}$) floor space:

$$q_{ju} = \eta_j Q_{ju}$$  \hspace{1cm} (14)$$

where $\eta_j$ captures the prefecture-specific land use regulations that restrict the price of production land relative to the price of residential land. Let $\theta_j \in (0, 1)$ be the measured proportion of floor space allocated to production use.\textsuperscript{19}

**Urban Clearing** Production land market clearing requires that the demand equals the supply of floor space allocated to production use in each location: $\theta_j S_{ju}$. Using the first-order conditions for profit maximization, this production land market clearing condition is:

$$S_{ju}^M = \left(\frac{1 - \alpha}{q_{ju}}\right)^{\frac{1}{\alpha}} X_{ju} = \theta_j S_{ju}$$  \hspace{1cm} (15)$$

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: $(1 - \theta_j)S_{ju}$. 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:

$$S_{ju}^R = E[s_{ju}H_{ju}] = (1 - \beta) \frac{E[v_{ju}]H_j}{Q_{ju}} = (1 - \theta_j)S_{ju}$$  \hspace{1cm} (16)$$

**Rural Clearing** Rural housing markets are more straightforward 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 floor space to build.

\textsuperscript{19}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, $\theta_j \in (0, 1)$ always hold.
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\}.

**Definition 1** A Spatial General Equilibrium for this economy is defined by a set of exogenous economic conditions \{\tau_{in,jk}, A_{j,k}, \eta_j, \phi_j, L_j, H_{in}^i\}, a list of endogenous prices \{Q_{ju}, q_{ju}, w^i_{jk}\}, quantities \{v^i_{in,jk}, Y_{jk}, H_{jk}^i, S_{ju}\}, and proportions \{\pi_{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_{in,jk}, A_{j,k}\} and the aggregate prices \{Q_{ju}, w^i_{jk}\} as given, workers’ optimal migration choices pin down the equilibrium labor supply in each city \(H_{jk}^i\) and the migration flow between each city pair \(\pi_{in,jk}^i\).

(ii). **[Firm Optimization]** Taking the exogenous economic conditions \{\tau_{in,jk}\} and the aggregate prices \{Q_{ju}, q_{ju}, w^i_{jk}\} as given, firms’ optimal production choices pin down the equilibrium labor demand \(H_j^i\) and equilibrium production floor space demand \(\theta_j S_{ju}\) in each city.

(iii). **[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^i_{jk}\}, equilibrium floor space \(S_{ju}\), and equilibrium output \(Y_{ju}\).

5 Equilibrium 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 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 (\(\epsilon\)).

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 the ratio of production land
Table 3: Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>From Our Microdata</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>share of consumption in utility</td>
<td>0.77</td>
<td>Urban Household Survey</td>
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<tr>
<td>$\alpha$</td>
<td>share of labor in production</td>
<td>0.88</td>
<td>Enterprise Surveys</td>
</tr>
<tr>
<td>$\eta_j$</td>
<td>relative cost of production to residential land</td>
<td>city-specific</td>
<td>China Land Market Website</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>migration elasticity</td>
<td>1.9</td>
<td>Fang and Huang (2022)</td>
</tr>
<tr>
<td>$\tau$</td>
<td>relative cost of rural housing</td>
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<td>Population Census</td>
</tr>
<tr>
<td>From Literature</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>elasticity of substitution between H/L-skills</td>
<td>1.4</td>
<td>Katz and Murphy (1992)</td>
</tr>
</tbody>
</table>

Notes: This table summarizes calibrated parameters. We first match $(1 - \beta)$ to the cost share of residential floor space in consumer expenditure from the Urban Household Survey of China, $(1 - \alpha)$ to the cost share of production floor space in firm costs from the Enterprise Surveys of Chinese manufacturing firms conducted by the World Bank in 2005, and $(\eta_j - 1)$ to the ratio of production land price to residential land price from the land price differences in each city from land transaction data via the China Land Market Website (http://www.landchina.com/). We then calibrate the city pair migration elasticity ($\epsilon$) to be 1.9, which is estimated in Fang and Huang (2022) using the same Census data and the relative cost of rural housing ($\tau$) to be 0.34 using the average rent paid by rural workers over the average rent paid by urban workers in the Population Census. Unfortunately, we failed to generate a robust estimate for $\sigma$ using our microdata and various empirical methods. As a result, we rely on Katz and Murphy (1992) to choose the elasticity of substitution between high and low skill ($\sigma$) to be 1.4. We have conducted various sensitivity checks with respect to all of our parameters and ensured the robustness of the model mechanisms.

price to residential land price. To match $(1 - \beta)$, we use the average accommodation expenditure share of total consumption from the Urban Household Survey of China (UHS). The survey was conducted by the National Bureau of Statistics of China and was partially redesigned in 2012. We believe the post-2012 measurement standard is more realistic, which gives us an average share of roughly 23% from 2013 to 2017.\footnote{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, the average expenditure share is very stable across time.} Hence, we choose $\beta$ to be 0.77. Second, to match $(1 - \alpha)$, we use the average production floor space cost per output unit. 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 reported 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 ($\alpha$) to be 0.88. Finally, to match $(\eta_j - 1)$, we need to compare the prices of production and residential land. 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 $\eta_j$ 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
The elasticity of substitution between high and low skill ($\sigma$) 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 ($\epsilon$) is calibrated to be 1.9. Tombe and Zhu (2019) estimates this elasticity at the province-sector pair level and finds 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 ($\tau$) is calculated using the average rent paid by rural sector workers over the 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 $\{H_{jk}^s, \pi_{in,jk}^s, w_{jk}^s, Q_{jk}, q_{jk}\}$, we can calculate all unobserved variables except the agglomeration parameters: productivities $\{A_{lk}^{hl}, A_{hk}^{hl}\}$; migration costs ($\tau_{in,jk}$), floor spaces $\{S_M^s, S_R^l, S_R^h\}$, and construction density ($\phi_i$) 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 $A_{hk}^{hl}$ as a function of $A_{lk}^{hl}$ using the first order conditions $A_{hk}^{hl} = A_{lk}^{hl} \left( \frac{w_{hk}^{hl}}{w_{lk}^{hl}} \right)^{\frac{1}{\sigma - 1}} \left( \frac{H_{hk}^{hl}}{H_{lk}^{hl}} \right)^{\frac{\sigma}{\sigma - 1}}$. Plugging $A_{hk}^{hl}$ into the definition of $X_{ju}$, we have

$$X_{ju} = A_{lk}^{hl} H_{ju} \left( \frac{w_{lk}^{hl} H_{lk}^{hl} + w_{hk}^{hl} H_{hk}^{hl}}{w_{hk}^{hl} H_{hk}^{hl}} \right)^{\frac{1}{\sigma - 1}} \equiv A_{lk}^{hl} H_{ju} (\Xi_{ju}^l)^{-\frac{1}{\sigma - 1}}$$

where $\Xi_{ju}^l = \frac{w_{lk}^{hl} H_{lk}^{hl} + w_{hk}^{hl} H_{hk}^{hl}}{w_{hk}^{hl} H_{hk}^{hl}}$ is the share of labor income distributed to low skill workers. We also assume that agricultural productivity equals agricultural wages $A_{jr}^s = w_{jr}^s$, for both $s = \{h, l\}$. Combining the previous equation with the definition of $W_{ju}$, we have $W_{ju} = \frac{w_{lk}^{hl} H_{lk}^{hl} + w_{hk}^{hl} H_{hk}^{hl}}{X_{ju}} = \frac{w_{lk}^{hl}}{A_{lk}^{hl}} (\Xi_{ju}^l)^{\frac{1}{\sigma - 1}}$. Plugging $W_{ju}$ into the price function of $q_{ju}$, we can solve

$$A_{lk}^{hl} = q_{ju}^{\alpha \sigma} \left( \frac{w_{lk}^{hl}}{w_{hk}^{hl}} \right)^{\frac{1}{\sigma - 1}}, \quad A_{hk}^{hl} = \frac{q_{ju}^{\alpha \sigma} w_{hk}^{hl} (\Xi_{ju}^h)^{\frac{1}{\sigma - 1}}}{\alpha (1 - \alpha)^{\frac{1}{\sigma - 1}}}$$

where $\Xi_{ju}^h = 1 - \Xi_{ju}^l$. Intuitively, higher production floor prices, wages, and skill shares $s$ in total payroll require higher skill $s$ productivity at equilibrium.

**Land Market Clearing** Second, from workers’ first-order conditions for residential floor space,
the summation of 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:

$$S_{Rj}^u = \frac{1 - \beta}{\beta Q_{ju}} \left[ w^j_{ju} H^j_{ju} + w^H_{ju} H^H_{ju} \right], \quad S_{Mj}^u = \frac{1}{\beta Q_{ju}} \left[ \frac{(1 - \alpha)}{q_{ju}} \right]^{\frac{1}{\gamma}} X_{ju}, \quad S_{Rj}^r = \frac{1 - \beta}{\beta Q_{jr}} \left[ w_{jr} H_{jr} \right]$$

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

**Migration Costs** To compute migration costs, we need first to compute the city-level equally-divided rent income for residents $Q_i$ from the residential floor space $S_i^R$ calculated above, which we can add to observed wages to determine incomes of workers of skill $s$ and sector $n$ moving from $i$ to $j$: $v_{in,jk}^s = w_{jk}^s + Q_{jn} S_n^R$. Then from the gravity equations, we can calculate all migration costs between all city pairs. We assume the iceberg migration cost for staying in one’s original city is $\tau_{in,in}^s = 1$. With $Q_{in}, v_{in,jk}^s$ and $\pi_{in,jk}^s$ in hand, along with the gravity equation, we have:

$$\Phi_{in} = \sum_{jk=11}^{JK} (\tau_{in,jk}^s Q_{jk}^{1-\beta})^{-\varepsilon} (v_{in,jk}^s)^\varepsilon = \frac{(Q_{jk}^{1-\beta})^{-\varepsilon} (v_{in,jk}^s)^\varepsilon}{\pi_{in,jk}^s}$$

by inserting $\Phi_{in}$ into the original gravity equation, we have:

$$\tau_{in,jk}^s = \frac{v_{in,jk}^s}{Q_{jk}^{1-\beta} (\pi_{in,jk}^s \Phi_{in}^{1/\varepsilon})^{1/\varepsilon}}, \text{ for } i \neq j$$

and for city-sector pairs with zero migration flow, we assign a migration probability $\pi_{in,jk}^s \sim 0$, 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:

$$\log(A_j) = \gamma \log(D_j) + a_j$$

However, the above regression suffers from a severe endogeneity issue. Fundamental productivity $a_j^s$ 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 the city-level agglomeration effect in China due to data limitations.
Fortunately, we can pin down these parameters using the indirect inference method. The basic idea is to find the parameter value that can reproduce the observed effect of the inland-favoring land policy within the model. We first execute a city-level difference-in-differences regression to obtain the real-world impact of the inland-favoring policy on observed city-level TFP. Next, we simulate the model to examine city-level TFP if we eliminate the land supply policy. By employing these simulated data, we conduct the same city-level regression and match the simulated regression coefficients with their corresponding ones in the empirical regression.

To estimate the agglomeration parameters in this way, we need a consistent comparison between TFP in the model and the empirical analysis. This requires us to calculate measured TFP in the model for two reasons. First, the labor productivities $A^h_{ju}$ are inconsistent with the TFP used in our empirical analysis. Our measurements of TFP in the empirical analysis follow Olley and Pakes (1992) and Levinsohn and Petrin (2003), 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 TFP in the model as output net of measured labor inputs:

$$\ln(\tilde{TFP}_{ju}) = \ln \left( \frac{Y_{ju}}{(H^h_{ju} + H^l_{ju})^{a}} \right)$$ \hspace{1cm} (19)

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

**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:

$$\ln(\bar{TFP}_{ju}) = \alpha + \delta_1 Post2003 \times East_{ju} + \phi_{ju} + \gamma_1 + \epsilon_{jut}$$ \hspace{1cm} (20)

where $\bar{TFP}_{ju}$ is the city-level average TFP calculated from our firm-level data in the empirical analysis, and the coefficient $\delta_1$ is the effect of the 2003 inland-favoring policy on city-level average TFP. We can estimate $\delta_1$ by running this regression using data from our empirical analysis and obtain a real-world estimation of $\hat{\delta}_1$.

In the second step, we construct a counterfactual 2005 equilibrium by guessing the agglomeration parameter $\gamma^0$ (and correspondingly, $a^h_{ju}^0$) and derive simulated TFP. Given all the variables and parameters we have derived, we can solve for the 2005 equilibrium, except $\gamma$ and $a^l_j$. For an initial guess of $\gamma^0$, we 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 $A^l_{ju}$. Then, given the counterfactual labor productivity $A^l_{ju}$, we calculate the counterfactual measured TFP $\tilde{TFP}^0_{ju}$ using equation (22).
In the third step, we run the same regression (20) using the simulated data from both the original equilibrium and the counterfactual equilibrium as follows:

$$\ln(\widehat{TFP}_{jut}) = \alpha + \delta_1 Post2003 \times East_{jut} + \phi_{jut} + \gamma_t + \epsilon_{jut}$$  \hspace{1cm} (21)

where $Post2003 = 1$ indicates the original equilibrium and $Post2003 = 0$ indicates the counterfactual equilibrium without the inland-favoring land policy. This yields the estimate of $\hat{\delta}_1^0$.

In the final step, we calculate the absolute distance between $\hat{\delta}_1^0$ and the real-world estimate $\hat{\delta}_1^*$. We then repeat this process, say $n$ times, until we find the $\gamma^*$ that minimizes this distance between the simulated regression coefficient $\hat{\delta}_1^n$ and the real regression coefficient $\hat{\delta}_1^*$. 

<table>
<thead>
<tr>
<th>Table 4: City-level DID Results on TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) OP</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>Post2003×East</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Trend Variables</td>
</tr>
<tr>
<td>Year FE</td>
</tr>
<tr>
<td>City FE</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is the city average firm-level TFP measured by the OP and LP methods. The trend variables include province linear time trends, city-level GDP per capita linear time trends, and city-level industry share linear time trends. The standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Results Table 4 shows the city-level regression estimate from the real data. We use two different methods to measure firm TFP (OP and LP) and then calculate the average firm TFP in each city, weighted by total firm employment.\(^{22}\) We find that the 2003 inland-favoring policy leads to a 5-7% decrease in eastern city average TFP relative to inland. Appendix B.3 shows the event study plots of this regression. We did not find any significant differences in pre-trends between eastern area and inland area before 2003. This yields an estimate of $\hat{\delta}_1^* = -0.075$.

Figure 6 shows the relationship between the value of the agglomeration parameter $\gamma$, and the regression estimate of $\hat{\delta}_1$ from the 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 in the model. Matching $\hat{\delta}_1^* = -0.075$ gives us an estimate of $\gamma = 0.207$. This is larger than the estimated 0.05 common in developed countries (Combes and Gobillon, 2015). As documented in Chauvin et al. (2017), the estimates in developing countries tend to be larger than

\(^{22}\)We also investigate the results by trying different weighting schemes, including by value-added, by total production, and by the number of employees. The results are very similar and are available upon request.
in developed countries. There are two explanations. First, China has much higher regional trade and migration costs than developed countries (Fan, 2019; Tombe and Zhu, 2019), making supply chain integration much more profitable. Second, it is very hard for inland regions to benefit from technological progress in developed areas when China is still relatively underdeveloped. Thus, knowledge spillover effects are strong within Chinese cities or regions relative to across regions. Our result also aligns 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 $\gamma$, and there are no qualitative changes.

5.4 The Spatial Distribution of Productivity and Land Tightness

Our model quantifies the spatial distribution of productivity and land tightness. The complete list of cities by TFP and land tightness is provided in Appendix B1; here, we show only the crucial 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 model-implied spatial correlation of TFP and land tightness in the equilibrium.

Spatial Distribution of Productivity To start, we first decompose measured TFP:
\[
\ln(TFP_{j\mu}) = \ln \left( \frac{Y_{j\mu}}{H_{j\mu}^h + H_{j\mu}^l} \right)
\]
\[
= d \ln \left( \frac{[\left( A_{j\mu}^h H_{j\mu}^h \right)^{\frac{\phi-1}{\sigma}} + \left( A_{j\mu}^l H_{j\mu}^l \right)^{\frac{\phi-1}{\sigma}}} {H_{j\mu}^h + H_{j\mu}^l} }{H_{j\mu}^h + H_{j\mu}^l} \right) + (1 - \alpha) \ln(S_{j\mu}^M)
\]
\[
= \frac{\alpha \sigma}{\sigma - 1} \ln(A_{j\mu}^l) + \frac{\alpha \sigma}{\sigma - 1} \ln \left( \frac{A_{j\mu}^h}{A_{j\mu}^l} \frac{\Gamma_{j\mu}^h}{\Gamma_{j\mu}^l} \frac{H_{j\mu}^h}{H_{j\mu}^l} \right) + (1 - \alpha) \ln(S_{j\mu}^M)
\]

where \( \Gamma_{j\mu}^h = \frac{H_{j\mu}^h}{H_{j\mu}^h + H_{j\mu}^l} \) and \( 1 - \Gamma_{j\mu}^h = \frac{H_{j\mu}^l}{H_{j\mu}^h + H_{j\mu}^l} \) are the corresponding high-skill and low-skill labor shares. The decomposition shows that \( \ln(TFP_{j\mu}) \), measured TFP in city \( j \), can be decomposed into three components: fundamental low-skill labor productivity, a skill premium from a 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

<table>
<thead>
<tr>
<th>Regions (loc., dev.)</th>
<th>No. of Cities</th>
<th>2005</th>
<th>2010</th>
<th>2005</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total</td>
<td>Fund</td>
<td>SP</td>
<td>LSP</td>
</tr>
<tr>
<td>National</td>
<td>225</td>
<td>38.17</td>
<td>35.31</td>
<td>0.66</td>
<td>2.19</td>
</tr>
<tr>
<td>(east, high)</td>
<td>21</td>
<td>39.73</td>
<td>36.73</td>
<td>0.75</td>
<td>2.25</td>
</tr>
<tr>
<td>(east, mid)</td>
<td>51</td>
<td>38.15</td>
<td>35.34</td>
<td>0.56</td>
<td>2.25</td>
</tr>
<tr>
<td>(east, low)</td>
<td>25</td>
<td>36.78</td>
<td>34.08</td>
<td>0.57</td>
<td>2.13</td>
</tr>
<tr>
<td>(inland, high)</td>
<td>2</td>
<td>38.00</td>
<td>35.27</td>
<td>0.67</td>
<td>2.06</td>
</tr>
<tr>
<td>(inland, mid)</td>
<td>50</td>
<td>37.18</td>
<td>34.30</td>
<td>0.78</td>
<td>2.11</td>
</tr>
<tr>
<td>(inland, low)</td>
<td>76</td>
<td>36.65</td>
<td>33.92</td>
<td>0.63</td>
<td>2.09</td>
</tr>
</tbody>
</table>

Notes: This table displays a summary of measured TFP \( \ln(TFP_{j\mu}) \) in the model by group (weighted by population) in 2005 and 2010, as well as its decomposition. \( \text{Fund} \) stands for fundamental, \( \text{SP} \) stands for skill premium, and \( \text{LSP} \) 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 has the same cities in 2005 and 2010 for consistent comparisons.

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 (east 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 several alternate summary presentations, but the results are consistently robust to classification. Each region has the same cities in 2005 and 2010 for consistent comparisons.
Table 5 shows a summary of measured TFP and its decomposition following equation (22) across regions. There are four observations. First, the significant difference in measured TFP across regions is from the fundamentals. The more developed eastern cities have much higher fundamental productivity than inland or less developed cities. Second, 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 populations and geographic size. Fourth, however, eastern and more developed cities do not necessarily have higher skill premiums.

We calculate national TFP as the average of city-level TFP weighted by the number of workers. Using our decomposition, we can investigate the changes in national 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 magnitude, making it clear that having more workers in big cities increases the national TFP.

**Spatial Distribution of Land Tightness** 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 tightness. We measure across-city differences in land tightness using land per thousand workers.

Table 6: Spatial Distribution of Land Tightness

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

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 city location (east or inland) and the level of development (GDP per capita) in 2005, as in Table 5.

Table 6 summarizes land tightness across regions. The across-city differences in land tightness show that eastern and more developed cities have much lower and decreasing land tightness, 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. Though the total con-
struction land supply is growing nationally, many land quota increments are distributed to cities with net outmigration. Hence, the population-weighted national average land tightness is worsening even though the total land supply is increasing faster than the Chinese population.

Figure 7: Correlation between Productivity and Land Tightness

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

Correlation Between Productivity and Land Tightness  We further show the correlation between productivity and land tightness in Figure 7. 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 tightness. More developed eastern cities are much more productive but much more land constrained. Second, land tightness 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 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 potential losses in productivity and equality due to the place-based land policy that reallocates construction land quotas 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. The losses may be further strengthened when agglomeration effects are taken into consideration.

6 Eliminating the Inland-favoring Land Policy

This section simulates a counterfactual land allocation policy to alleviate 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, classical hat algebra is not feasible. 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 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.\(^{23}\) The following equation shows the details of the new supply rule:

\[
\hat{L}_j(t) = L_j(2003) + \sum_j [L_j(t) - L_j(2003)] \times \frac{L_j(2003)(1 + g_{L_j})^{t-2003}}{\sum_j L_j(2003)(1 + g_{L_j})^{t-2003}}
\]

\(^{23}\)We choose the 2000-2003 growth rate because pre-1999 land supply data at the city level is primarily unavailable.
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 would be a multiplication of the actual national total increment of land $\sum_j [L_j(t) - L_j(2003)]$ 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 the national total urban land supply.

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

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>National</td>
<td>225</td>
<td>22268</td>
<td>28336</td>
<td>22268</td>
<td>28336</td>
</tr>
<tr>
<td>(east, high)</td>
<td>21</td>
<td>5838</td>
<td>7272</td>
<td>6597</td>
<td>10958</td>
</tr>
<tr>
<td>(east, mid)</td>
<td>51</td>
<td>5875</td>
<td>7832</td>
<td>5734</td>
<td>6551</td>
</tr>
<tr>
<td>(east, low)</td>
<td>25</td>
<td>1418</td>
<td>1681</td>
<td>1472</td>
<td>1596</td>
</tr>
<tr>
<td>(inland, high)</td>
<td>2</td>
<td>169</td>
<td>206</td>
<td>169</td>
<td>169</td>
</tr>
<tr>
<td>(inland, mid)</td>
<td>50</td>
<td>5131</td>
<td>6578</td>
<td>4537</td>
<td>4819</td>
</tr>
<tr>
<td>(inland, low)</td>
<td>76</td>
<td>3837</td>
<td>4767</td>
<td>3760</td>
<td>4244</td>
</tr>
</tbody>
</table>

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

A key question is whether there is enough land in developed regions to fulfill these allocations. We contend that this issue is not a concern. First, according to satellite data, in 2005, only 23% of land in tier-1 cities (the most developed) was developed, and a mere 9.3% of land in tier-2 cities was developed (Wu and You, 2023). Second, a significant portion of land in developed regions remains farmland due to the farmland redline policy (Yu, 2019).

Policy Summary The counterfactual land allocation policy is summarized in Table 7. Columns 3-4 present the actual land supply under the policy, while Columns 5-6 display the counterfactual land supply based on the allocation rule in equation (23). Without the inland-favoring policy in 2003, more developed cities would have received more land. For example, the land quota for highly developed eastern cities would have been 10,958 $km^2$ in 2010 without the inland-favoring policy, as opposed to the observed 7,272 $km^2$. Conversely, the land quota for low-development inland cities would have been 4,244 $km^2$ in 2010 without the policy, compared to the observed 4,767 $km^2$. Further details are in Appendix C.1.

6.2 Aggregate Effects

We first present the aggregate effects of removing the inland-favoring land policy on national TFP, urban output, rural output, urban population, and national average income and welfare (the welfare calculation method can be found in Appendix C.2). The results are illustrated in Figure 8.
Figure 8: **Aggregate Effects of Removing the Inland-Favoring Policy**

<table>
<thead>
<tr>
<th></th>
<th>2005</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>4.8</td>
<td>6.4</td>
</tr>
<tr>
<td>Total Output</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Urban Output</td>
<td>2.2</td>
<td>2.3</td>
</tr>
<tr>
<td>Rural Output</td>
<td>-0.9</td>
<td>-1.7</td>
</tr>
<tr>
<td>Urban Pop.</td>
<td>1.3</td>
<td>1.2</td>
</tr>
<tr>
<td>House Price</td>
<td>-3.7</td>
<td>-7.1</td>
</tr>
<tr>
<td>Income</td>
<td>1.1</td>
<td>1</td>
</tr>
<tr>
<td>Welfare</td>
<td>3.7</td>
<td>10.6</td>
</tr>
</tbody>
</table>

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 represented changes in 2005. In both years, we find substantial national gains in TFP, total output, urban output, urban population, income, and welfare.

Eliminating the place-based land policy led to significant increases in TFP, urban output, average income, and welfare in 2005 and 2010. The national gain in TFP was 4.8% in 2005 and 6.4% in 2010, while total output rose by 1.2% in both years. Removal of the policy also boosts the urban population by lowering the price of residential floor space in developed cities’ urban areas. In contrast, rural output declines due to worker emigration. Welfare gains (3.7% in 2005 and 10.6% in 2010) are notably higher than income gains (1.1% in 2005 and 1.0% in 2010) since housing-constrained workers now have significantly better access to floor space (housing prices drop by 3.7% in 2005 and 7.1% in 2010). The substantial reduction in housing prices leads to real incomes rising 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 in TFP, urban output, rural output, urban population, and housing prices across different regions. Three main conclusions can be drawn. First, after eliminating the inland-favoring land policy, housing prices significantly decreased in developed eastern cities but increased in other cities. Second, more workers migrated to developed eastern cities, resulting in a 13.1% rise in the urban population in 2010. Third, productivity and output increase in eastern developed cities and decrease in other cities. Specifically, measured TFP rose by 6.7% and urban output grew by 14.4% in 2010 under our counterfactual. The declines in TFP and output in
Table 8: Removing the Inland-Favoring Policy: Spatial Effects on Economic Development

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>National</td>
<td>225</td>
<td>4.8%</td>
<td>6.4%</td>
<td>2.2%</td>
<td>2.3%</td>
<td>-0.9%</td>
<td>-1.7%</td>
<td>1.3%</td>
<td>1.2%</td>
<td>-3.7%</td>
<td>-7.1%</td>
</tr>
<tr>
<td>(east, high)</td>
<td>21</td>
<td>2.9%</td>
<td>6.7%</td>
<td>6.3%</td>
<td>14.4%</td>
<td>0.0%</td>
<td>4.0%</td>
<td>6.2%</td>
<td>13.1%</td>
<td>-18.7%</td>
<td>-34.5%</td>
</tr>
<tr>
<td>(east, mid)</td>
<td>51</td>
<td>0.0%</td>
<td>-1.2%</td>
<td>-0.7%</td>
<td>-3.8%</td>
<td>-0.5%</td>
<td>-0.9%</td>
<td>-0.4%</td>
<td>-2.6%</td>
<td>1.5%</td>
<td>12.4%</td>
</tr>
<tr>
<td>(east, low)</td>
<td>25</td>
<td>-0.3%</td>
<td>-1.7%</td>
<td>-0.4%</td>
<td>-3.9%</td>
<td>-1.4%</td>
<td>-3.5%</td>
<td>-0.6%</td>
<td>-2.6%</td>
<td>-3.1%</td>
<td>3.6%</td>
</tr>
<tr>
<td>(inland, high)</td>
<td>2</td>
<td>-0.2%</td>
<td>-2.2%</td>
<td>0.0%</td>
<td>-3.1%</td>
<td>0.0%</td>
<td>2.1%</td>
<td>0.1%</td>
<td>-0.9%</td>
<td>1.7%</td>
<td>18.8%</td>
</tr>
<tr>
<td>(inland, mid)</td>
<td>50</td>
<td>0.0%</td>
<td>-5.2%</td>
<td>-2.1%</td>
<td>-10.0%</td>
<td>-1.5%</td>
<td>-2.9%</td>
<td>-1.6%</td>
<td>-6.6%</td>
<td>1.9%</td>
<td>11.3%</td>
</tr>
<tr>
<td>(inland, low)</td>
<td>76</td>
<td>0.2%</td>
<td>-3.2%</td>
<td>-1.3%</td>
<td>-5.5%</td>
<td>-1.7%</td>
<td>-3.2%</td>
<td>-1.4%</td>
<td>-4.2%</td>
<td>-3.5%</td>
<td>-0.6%</td>
</tr>
</tbody>
</table>

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 city location (east or inland) and the level of development (GDP per capita) in 2005, as in Table 5.

other cities are smaller in magnitude. We provide additional results in Appendix C.3, including a TFP decomposition and changes in the urban population by skill type. We discover that most of the increases in national TFP result from improvements in fundamental productivity through two channels. First, the reform encourages more workers to migrate to developed regions with higher TFP, thus raising national TFP. Second, the influx of migrant workers enhances the agglomeration effect on local productivity in developed regions.

In general, our findings indicate that removing the inland-favoring policy exacerbates the regional development gap and attracts more migrations to developed areas. Consequently, the inland-favoring land policy does achieve its original objective of balancing the development between eastern and inland regions. However, when we observe this geographic convergence, does it mean workers from underdeveloped regions benefit from this policy? Not necessarily.

6.4 Spatial Effects on Income and Welfare

The first four columns in Table 9 display income and welfare (utility) changes for workers from different regions when we remove the inland-favoring policy. Incomes of workers from all regions increase in 2005. Incomes of workers from inland (eastern) cities with low development levels rise by 1.7% (0.9%) in 2005 and by 1.1% (1.1%) in 2010. This highlights a paradox: the inland-favoring land policy narrows the regional output gap but reduces incomes of workers from impoverished regions because the policy diminishes land supply in developed areas, leading to higher housing costs and reduced labor demand. Consequently, many workers from underdeveloped regions who would have migrated remain in their hometowns with lower wages.
Table 9: Removing the Inland-Favoring Policy: Spatial Effects on Income and Welfare

<table>
<thead>
<tr>
<th>Regions (loc., dev.)</th>
<th>No. of Cities</th>
<th>Without Transfer</th>
<th>Regional Transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td>National</td>
<td>225</td>
<td>1.1% 1.0%</td>
<td>3.7% 10.6%</td>
</tr>
<tr>
<td>(east, high)</td>
<td>21</td>
<td>2.1% 5.7%</td>
<td>9.8% 17.9%</td>
</tr>
<tr>
<td>(east, mid)</td>
<td>51</td>
<td>0.2% -0.3%</td>
<td>-0.2% -3.9%</td>
</tr>
<tr>
<td>(east, low)</td>
<td>25</td>
<td>0.9% 1.1%</td>
<td>-1.7% 0.8%</td>
</tr>
<tr>
<td>(inland, high)</td>
<td>2</td>
<td>0.0% -1.6%</td>
<td>-0.5% -5.1%</td>
</tr>
<tr>
<td>(inland, mid)</td>
<td>50</td>
<td>0.7% -1.1%</td>
<td>-0.3% -5.5%</td>
</tr>
<tr>
<td>(inland, low)</td>
<td>76</td>
<td>1.7% 1.1%</td>
<td>2.3% -3.7%</td>
</tr>
</tbody>
</table>

Notes: This table displays a summary of total urban land supply data by group (summations within the group) in 2005 and 2010, as well as the counterfactual land supply in 2010 (unit: km²). Regions are classified by city location (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.

What 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 observe that the changes in utility for workers from underdeveloped cities are mixed. By eliminating the inland-favoring policy, the average utility of workers from eastern low-development level cities decreases by 1.7% in 2005. In contrast, the average utility of workers from inland low-development level cities increases by 2.3%. However, the situation is reversed in 2010. Overall, we find no evidence that the inland-favoring land supply policy enhances the welfare of workers from poorer regions. This policy significantly reduces national welfare without assisting workers from impoverished regions.

6.5 Direct Regional Transfers

As demonstrated above, the inland-favoring land supply policy results in significant spatial misallocation and reductions in national output and productivity. It creates an illusory regional convergence by narrowing the geographic output gap without benefiting workers from impoverished regions. In this section, we design a second counterfactual that produces less spatial misallocation and genuinely assists people from poor regions. The concept is that, rather than implementing the place-based land policy, the central government opts to redistribute the additional land income generated by the counterfactual land allocations from developed to underdeveloped cities. The sole difference between this Regional Transfers counterfactual and the Removing the Inland-Favoring Policy counterfactual is that the former incorporates a feasible direct regional transfer on top of the latter. For a detailed discussion of an elaborate transfer rule and the regional trans-
fer’s additional results on economic development and income, please refer to Appendices C.4 and C.5. We also provide Appendices C.6 and C.7 for a simpler transfer rule.

Columns 5-8 in Table 9 display the income and welfare (utility) changes experienced by workers from different regions when we replace the inland-favoring land supply policy with the direct regional transfer. There are two main findings. First, the direct regional transfer effectively reduces the income disparities between workers from developed and underdeveloped regions. Incomes of workers from inland cities with low (middle) development levels increased by 15.9% (5.1%) in 2005 and 4.8% (4.9%) in 2010. Incomes of workers from eastern and developed regions decrease. Second, national welfare continues to rise following the regional transfer. Workers from nearly all regions benefit from the direct transfer in terms of utility. Specifically, the utility of those from eastern high-development cities increased by 8.0% and by 4.4% for eastern low-development cities in 2010. Workers from underdeveloped regions migrate to developed cities for higher wages, while workers from developed regions benefit from significantly 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 resulted in lower national output and TFP. The observed regional convergence is merely an illusion. The government achieved its goal of reducing regional output and productivity gaps; however, workers from both developed and underdeveloped regions lost. The income gap narrowed not because the income of people from impoverished areas increased but because everyone’s income decreased, and those from affluent areas were impacted more severely. Furthermore, this policy also reduced national welfare without improving the welfare of workers from poor regions. In essence, this place-based land policy aided poor regions but failed to help the people from those regions. We ultimately demonstrate that a direct regional transfer policy is a superior alternative to the inland-favoring land policy. It effectively reduces inequalities by significantly assisting workers from poorer regions rather than causing a substantial spatial misallocation of land and labor.

7 Sensitivity Checks and Discussions

To address concerns regarding model robustness, we perform several sensitivity checks for our quantitative model, focusing on critical parameter values and counterfactual policy specifica-
These results are available upon request to avoid redundancy. We also discuss optimal land allocation policies and whether they are feasible to simulate.

**Sensitivity Checks of Parameter Values** We have tested our quantitative and counterfactual results with alternative specifications of parameter values. Our alternative specifications include variations in agglomeration ($\gamma \in [0.0, 0.4]$), migration elasticity ($\epsilon \in [1.3, 2.5]$), elasticity of substitution between H/L-skills ($\sigma \in [1.0, 2.0]$), share of consumption in utility ($\beta \in [0.60, 0.90]$), share of labor in production ($\alpha \in [0.75, 0.95]$), and relative cost of rural housing ($\tau \in [0.20, 0.40]$). None of these alternatives overturn the positive correlation between TFP and land tightness, though effect magnitudes vary.

**Sensitivity Checks of Counterfactual Policies** In the paper, we choose the 2000-2003 city-level land supply growth rates for the counterfactual post-2003 land allocation policy across cities, which follows the trend in Figure 1. We also test two alternative specifications of counterfactual policies. The first is to use the pre-2003 city-level GDP growth rates, and the second is to use the pre-2003 city-level migration inflow growth rates. Since the alternative trends are highly correlated with the pre-2003 city-level land supply growth rates, all the results qualitatively hold though the magnitudes vary.

**Discussions on Optimal Land Allocation Policy** Our framework appears suitable for discussing optimal land allocation policy. A theoretical optimal policy could be achieved by enforcing equal marginal revenue productivity of land (MRPL) across all cities ($q_{ju} = q_{ku}$ for any $j, k$). In practice, however, we still face two constraints. The first is data availability on natural limits that would break the MRPL equality. We are only confident that our current counterfactual analysis is within the potential natural geographical limits found in the literature (Liang, Lu, and Zhang, 2016; Yu, 2019; Fang and Huang, 2022). The second constraint is data availability concerning local governments’ objectives for production and housing. Equation (14) ($q_{ju} = \eta_jQ_{ju}$) breaks the MRPL equality when governments choose their production/housing land supply ratio based on their objective functions. Such objectives are also not feasible to recover from our current datasets. Consequently, we cannot study optimal policy in this paper, but it would be an intriguing topic for future work when more microdata is available.

### 8 Conclusion

This paper studies how place-based land allocation policy creates spatial misallocation. We focus on a significant land policy in China that favors less-developed inland regions, intending to balance regional growth and reduce spatial inequality. Causal evidence demonstrates that this policy...
lowered 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. The counterfactual of removing this inland-favoring policy suggests that resolving this spatial misallocation would increase national productivity and output.

Despite sacrificing national productivity and output, the inland-favoring policy did not necessarily benefit workers from underdeveloped regions. Eliminating this policy would increase incomes of workers from underdeveloped regions through increased migration to developed areas. Although the inland-favoring policy reduced regional output gaps, it adversely affected workers from underdeveloped regions by restricting their migration opportunities to higher-wage developed regions. Instead of the inland-favoring land supply policy, we propose that a direct regional transfer could promote regional convergence by enhancing income and welfare for workers from underdeveloped regions with fewer efficiency losses due to spatial misallocation.

References


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