Political manipulation of urban land markets: Evidence from China

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Abstract

Over the last forty years, China has experienced extraordinary growth under output market reforms, but the growth rates are now tapering off. Reforms in factor markets and city governance have been much slower and are viewed as having the potential to yield considerable efficiency gains. In this paper, we explore this possibility, tackling the key issues of local political manipulation of land markets and objectives of local leaders, constraints on the local budgetary process to finance infrastructure, along with capital market favoritism of certain cities. We use a structural general equilibrium model with trade and migration frictions, based on prefecture level data. We model the political process of land misallocation within cities which drives up housing prices and estimate city-by-city local leaders' preferences over economic performance versus residents' welfare. Counterfactual analysis shows that equalizing capital prices across cities, changing the political scorecard for city leaders to reward just maximization of local consumer welfare, and relaxing local budget constraints together increase welfare of consumers and returns to capital by 13.7% and 2.25% respectively. Housing prices would decline in almost all cities; and the reforms would reduce the current excessive, often showcase investment in local public infrastructure by 49% nationally. These reforms would significantly reduce the population of favored cities with low capital costs like Tianjin and Beijing and raise the population of cities with high costs of capital and low local-leader weights on consumer welfare like Shenzhen and Dongguan.

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1. Introduction

Over the last four decades, China has undergone major reforms in output markets and experienced extraordinary GDP growth, but at a rate that has been tapering off. Factor market reforms have been slow, but they are heralded as the way to sustain higher growth rates (World Bank & DRC, 2019). Capital market misallocations (Hsieh & Klenow, 2007; Brandt, Tombe, & Zhu, 2013) and labor market frictions (Tombe & Zhu, 2019) in China have been studied in a general equilibrium context. However, land market reforms have not been integrated into such models. They turn out to be of first order importance and thus the focus of this paper. Reforms deal with two issues. First is misallocation of land between residential and industrial use by political leaders. Second is the role of land in financing local public expenditures, in particular local infrastructure investments.

In studying local governance, the starting point involves the incentives of local leaders. Key elements in the evaluation and promotion criteria for local political leaders in China are economic performance and related competence indicators (Li & Zhou, 2005; Chen, Li, & Zhou, 2005; Xu, 2011; Qian & Xu, 1993). This economic performance-based evaluation system provides strong incentives for local leaders to enhance local industry output and hence local GDP as currently measured in China, at the expense of maximizing the welfare of local residents.

Local leaders have two main levers to increase industry output: first is cheap land offered to firms. In China, urban land is owned by the state and sold as leaseholds with revenues going to the city treasury. As the sole supplier of land, local governments use their monopoly power to compete for footloose firms (Tao, Su, Liu, & Cao, 2010)[2], through higher allocations and thus lower pricing of land leaseholds for industrial usage (Tao, Su, Liu, & Cao, 2010 and Cao, Feng, & Tao, 2008). The second lever is provision of public infrastructure relevant to production. Infrastructure investment can further enhance firms' productivity and thus measured GDP growth (Wang, Zhang, & Zhou, 2020; Wu, Deng, Huang, Morck, & Yeung, 2014). Showcase infrastructure investments may also raise a leader and city's profile. However, allocating more land to industrial usage and devoting public revenues to overinvest in infrastructure will lead to higher residential housing prices and lower local consumer welfare.

While city leaders in China traditionally focus on enhancing industry output to cultivate promotion, they appear also to care in differing degrees about city residents' welfare. The scorecards for leaders now can involve items such as environmental and social considerations and tamping down escalating residential housing prices which have triggered social protests (Zheng, Kahn, Sun, & Luo, 2014; Su, Tao, Xi, & Li, 2012). The priorities of individual cities and their leaders as to how much to focus on industry output enhancement versus enhancement of local consumer welfare differ enormously across space and one novel aspect of this paper is to recover the relative weights for different cities on these objectives, enhancement

[2] This is subject to quota constrains on rural-to-urban land conversion set by the upper-level governments since 1998 (Wang, Zhang, & Zhou, 2020).

of measured GDP (which does not reflect market based imputed rents) versus residents' welfare (Wang, Zhang & Zhou, 2020).

On the land market lever, there is a large literature on the regulation of local land markets to achieve various objectives such as enhancing economic or industrial development, exploiting monopoly power, or regulating who enters communities (Fischel, 1999; McDonald & McMillen, 2011; Lin, 2018; Shertzer, Twinam, & Walsh, 2018). Glaeser, Gyourko, & Saks (2005) model a land market regulator who is lobbied by residents and by developers to limit versus expand residential development, a precursor to this paper in modeling competing objectives. Papers analyze how commercial developers may have played a salient role in influencing local land development policies (Molotch, 1976; Logan & Motloch, 2007; Solé & Viladecans-Marsal, 2012).[3] Granting firms preferred access to land is considered one important place-based policy (Rauch, 1993). Lin (2018) models the environmental and spatial consequences in the USA of tilting zoning towards industrial land development as an historical practice. For China, Adamopoulos, Brandt, Leight, & Restuccia (2017) look at agricultural land misallocation, while Deng, Tang, Wang & Wu (2020) examine how residential housing allocations differ across the urban hierarchy. Here we focus on residential versus industrial land allocation in prefectures, where the Chinese data and context allow us to model and explicitly quantify the trade-offs of local leaders and the welfare losses in land market regulation.

For the infrastructure lever, as in other urban contexts, constraints on local revenue raising and the financing of local infrastructure are critical as reviewed in Bahl (2003) and Glaeser (2013). Again, China has the data and a neat context to study key issues. As a background, in China, local fiscal resources are dominated by national tax sharing arrangements (Shen, Jin, & Zou, 2012), where subnational governments account for over 70% of total public expenditure, while having, with transfers and collections, less than 50% of total budgetary revenues (Wong & Bhattasali, 2003; Zhang, 2006). This has left local governments under great fiscal pressure. Understanding this, the central government allows local governments to collect and control land sale revenues as a major source of extra-budget revenue (Lin, 2007), with no sharing with the central government.[4] However, the use of these revenues is regulated.

[3] There are some studies that argue for the importance of local governments and business developers in urban development. Molotch (1976) proposes the idea of a "growth engine" and highlights how the close connections between local government officials and local business leaders help to create land policies that favor of local economic growth. Logan & Motloch (2007) argue that "urban growth machines", which combine real estate, banking, and commercial interests to support the expansion of cities, are a typical feature of many U.S. cities. However, these arguments do not provide a formal theory or empirical analysis of the role of developers in the formation of land development policies. Solé & Viladecans-Marsal (2012) find some indirect empirical evidence pointing to the influence of developers on local land development regulations in Spain.

[4] Note that before 2011, China had no property tax system. Since 2011, just two cities (Shanghai and Chengdu) have begun to levy property taxes on second houses and luxury villas. Property taxes are still in the experimental stage in China. Other local taxes such as resource and environmental taxes, real estate transaction taxes, and urban construction fees are limited in terms of both legal ways of implementation and the actual amount collected.

Since 2008, the national government *requires* that land sales revenues be used for infrastructure construction *only* (after paying demolish fees, urban utilities, and compensation fees to farmers or original residents on the land).[5] This regulation enshrines what was already in place. Land sales revenues directly funded over 50% of infrastructure investments such as highways and industrial parks in the 1990's and 2000's, with the remainder financed by loans using land as collateral (Peterson & Park, 2006; Ding, 2003). Cities use local government financing vehicles (LGFVs) to borrow from banks and issue bonds to finance infrastructure investments which have uncertain financial returns (Tsui, 2011), committing future land sales revenues to pay off these debts (Bai, Hsieh, & Song, 2016).

Local infrastructure investments are viewed as excessive in China.[6] Presumed excess is the foundation of papers like that by Li & Zhou's (2005), which models the tournament competition to rise in the ranks by political leaders, by growing GDP through excessive investment in their locality. Ansar, Flyvbjerg, Budzier, & Lunn (2016) document the low returns to a large sample of local road and some rail infrastructure projects in China. Wang, Zhang, & Zhou (2020) find suggestive evidence that two thirds of Chinese cities experienced excessive spatial expansion. The literature also suggests a potential oversupply of industrial parks ("special economic zones") and their associated infrastructure. Thousands of such parks have been built to compete for FDI and stimulate local growth by local leaders who want to improve local economic performance and raise their cities' profiles (Zhang, 2011; Bai, Hsieh, & Song, 2016). Many such parks perform poorly and some have become "ghost towns" (Zheng, Sun, Wu, & Kahn, 2017; Kahn, Sun, Wu, & Zheng, 2021).[7] Our structural model will suggest that, under current budget arrangements where all land revenues go to pay for infrastructure projects, local governments strongly overspend on infrastructure.

There is a final aspect to our analysis which involves capital markets. As detailed later, the state-owned banking sector favors certain cities with lower prices of capital, particularly big political players in the administrative hierarchy, as well as some smaller, historically industrial cities. Building on Chen, Henderson, & Cai (2017), we estimate the cost of capital in the private sector city-by-city using China's industrial survey data for 2006 and 2007.

We develop a spatial general equilibrium model to study the issues of local governance, land market allocations, and the financing of infrastructure investments, in a context with trade and migration frictions and capital market misallocations. In our benchmark case, we assume local leaders maximize an objective

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[5] In 2008, China's Ministry of Land Resources, Treasury, and People's Bank of China jointly issued *Regulations on the Use and Management of Land Sales Revenues,* to ensure appropriate use of revenues.

[6] A less mentioned aspect that holds universally across countries is that local infrastructure investments are ripe for corruption in both the contracting and construction phases.

[7] Projects have high cost-overruns and usually much lower than projected usage, which contributes to China's high local debt ratio. At the provincial level, the average debt to GDP ratio is between 30 to 40% in 2019. For Qinghai and Guizhou provinces, the debt-to-GDP ratios are 71% and 58% respectively, while Guangdong's ratio is 10% (Fang, Li and Nie, 2020). Bai, Hsieh, & Song (2016) argue that a lot of debt borrowed by LGFVs is not officially classified as local government debt. Their estimates suggest that the outstanding debt of LGFVs is twice as much as the official size of local government debt and about two-thirds of GDP in 2015.

function that has weights for measured GDP and for the welfare of the representative local resident. We impose that leaders are constrained to use only and all land sales revenues to finance public infrastructure. In this benchmark, leaders optimize their objective function with respect to the amount of local land designated for industrial use versus residential use. They face the following trade-off: on the one hand, more supply of low-price industrial land will attract firms and boost GDP; on the other hand, the resulting lower residential land supply will lead to higher housing prices and hurt consumers' welfare.[8]

We draw out features of the 2010 equilibrium that incorporates three factor markets: capital, land and labor. For land markets we estimate hedonic land prices by city in industrial and commercial versus residential use based on land transaction data between 2008 and 2015, based on which we calibrate the relative weights (priorities) in each city's objective function. For the labor market, the 2010 and 2000 population censuses are used to estimate the migration cost from city to city. After developing and calibrating the model, we study the welfare implications of reforms. We analyze counterfactuals to assess the impacts of capital market, land market, political and budgetary reforms on where people reside, returns to capital, overall welfare of workers, and inequality, given heterogeneous and mobile labor.

We note a few key findings here. Counterfactual analysis shows that equalizing capital prices across cities, changing the political scorecard for city leaders to reward just maximization of local consumer welfare, and relaxing local budget constraints together increase welfare of consumers and returns to capital by 13.7% and 2.25% respectively. Housing prices would fall in almost all cities; and the reforms would reduce the current excessive, often showcase investment in local public infrastructure by about 48.7% nationally. These reforms would significantly reduce the population of favored cities with low capital costs like Tianjin and Beijing and raise the population of cities with high costs of capital and low local-leader weights on consumer welfare like Shenzhen and Dongguan.

While reforms generally raise welfare, there are losers, especially people living in more historically industrial cities working in heavily subsidized firms, who would then face higher prices of capital in the face of high migration costs. The losses to these places mean inequality between them and other places will rise with reforms.

As a final note, apart from the literatures on land market regulations and local public finance, we connect with two other literatures. Political favoritism of certain regions or cities is a focus of the literature on urban bias (Lipton, 1977) and big city bias (Renaud, 1981; Ades & Glaeser, 1995; Moomaw & Shatter, 1996; Henderson & Kuncoro, 1996; Davis & Henderson, 2003; Duranton & Storper, 2008). Papers show empirically that favored cities, with national capitals being a prime example, tend to be larger than other cities ceteris paribus, especially in non-democratic countries, and that can affect national growth rates (Henderson, 2003; Castells-Quintana, 2017). Our paper demonstrates the welfare gains of removing

[8] In principle, the allocation of land between the two different uses may also influence the total land sale revenues used to finance infrastructure. Granting more land for industrial use squeezes residential supply and raises residential land and housing prices. Depending on the price elasticities of housing and industrial demand for land, sales revenues may rise or fall, in a context where, according to Wang, Zhang, & Zhou (2020), about three quarters of total land sale revenues came from residential land sales.

capital market favoritism through counterfactual analysis. Second, we connect to the literature on structural models of the within country spatial distribution of resources, for example Allen & Arkolakis (2014), Donaldson & Hornbeck (2016), Alder (2019), Redding (2016), Bryan & Morten (2019), and Balboni (2019). In a precursor paper to ours, Tombe & Zhu (2019) find that reducing trade and migration frictions in China has important spatial allocation and welfare implications.

The rest of the paper is organized as follows. Section 2 adds a few institutional details. Section 3 presents the model. In Section 4, empirical work and calibration results are discussed. We estimate migration costs, hedonic land prices and capital costs by city and infer trade costs. Then we discuss the calibration results of the model, check the plausibility of the results, and provide other supporting evidence for the model. In Section 5, we conduct counterfactual analysis based on the calibrated parameters from Section 4. Welfare implications of several reforms are discussed. Section 6 concludes.

2. Institutional details and some related patterns in the data

China's political system is centralized with strong top-down mandates. On the personnel side, local leaders are appointed by provincial leaders who in turn are appointed by national leaders, with strong systems of patronage within different factions of the Chinese Communist Party. As noted, the economic performance-based evaluation system provides strong incentives for local leaders such as party secretaries and mayors to enhance measured GDP, by attracting industrial and commercial firms.

On the institutional side, China operates under an administrative urban hierarchy which we account for in displaying results. There are three levels: provincial level cities of which there are 4 (Beijing, Shanghai, Tianjin and Chongqing), provincial capitals of which we will have 25, and ordinary prefectures. In addition, there are 5 deputy-province-level cities or separate-planning cities (Qingdao, Dalian, Xiamen, Ningbo, Shenzhen), which enjoy similar political power as provincial capitals in the hierarchy. We lump those together with provincial capitals. Provincial level cities have the same powers as provinces, enjoying greater revenue sources and fiscal freedoms. Then come provincial capitals which can favor themselves relative to other prefectures and which make many decisions for other prefectures within a province concerning, for example, major bank lending decisions. In the paper we work with the 266 prefectures in Han China which cover about 90% of China's population, avoiding minority areas due to differential governance and lack of accurate data.

As noted above, widespread underpricing and overallocation of land to industry as a lever to attract firms (Tao, Su, Liu, & Cao, 2010) results in reduced residential land supply and high residential land and housing prices, affecting consumer welfare. How big an issue is this? With details on the empirics in Section 4, we show the estimated ratio of residential to industrial land prices, for comparable land sold at auction in Figure 1. In Figure 1, the ratio of residential to industrial land prices is generally well over 1 with a median of 2.2. In some smaller, ordinary prefecture cities in grey dots the ratio can be close to 1, where those leaders are less likely to be on the fast track for promotion and thus GDP growth may not be so important an objective. For bigger political cities, with ambitious leaders, such as provincial level cities, the ratios are high: 3.8 for Shanghai and 7.9 for Beijing. For provincial capitals, a number are well over 4 with Nanjing at 8.7. In general, the ratio rises with the size and importance of the city. These are extraordinary wedges between prices in a market; and, below, they will reveal the weight leaders place on measured GDP versus resident welfare enhancement in different cities.

For capital markets, the slow reform in capital markets is a subject of many papers (Hsieh & Klenow, 2007; Gao, 2013; Chen, Henderson, & Cai, 2017; Brandt, Tombe, & Zhu, 2013; Jefferson & Singhe, 1999). Banks in China remain de facto state owned. There have been reforms to try to put banks on more of a market basis and reduce the extent of non-performing loans. However, these banks cannot operate freely. The Committee of the Chinese Communist Party retains the power to appoint the boards of directors and senior management of banks and offer directives. The state's interest is beyond the efficient allocation of capital and includes vague criteria such as “stability”, “fairness”, and “macroeconomic measures”. Individuals appointed to bank senior management posts are personnel with high-level standing in the Communist Party hierarchy (Howson, 2009) and move between government and state bank corporate functions. As such, it is difficult for state owned banks to operate independently while facing pressure from different levels of government. Well known is the favoritism displayed toward state owned firms with evidence in Jefferson & Singhe (1999), Au & Henderson (2006a), Dollar & Wei (2007), and Chen, Henderson, & Cai (2017).

Less well known and of focus here is spatial bias. Commercial banks in China have retrenched credit-extending authority from their local branches (Liu, 2007), so that below the provincial level, branches have limited autonomy to extend credit to new clients and investment projects. They are allocated funds for loans with stated priorities, with allocations influenced by the connections of local leaders to provincial and national leaders. Chen, Henderson, & Cai (2017) argues that there is a lot of variation locally in interest rates, charges and default provisions.[9]

In Figure 2a, we show the estimated, normalized capital prices faced by firms in each city, based on work reported in Section 4.2. The numbers are the prices of capital faced by *private* firms (only), which we think is the relevant margin for market expansion. We started by using a combined average of prices facing private and SOE firms, but decided that, by 2010, private firms were the relevant margin. Fortunately, the prices facing private firms and SOE’s are correlated as Figure 2b shows (with a simple correlation coefficient of 0.47). In Figure 2a, we note that many provincial level cities and provincial capitals face distinctly lower capital market prices, while other cities face heavy discrimination. Also, some small cities which have a tradition of a strong industrial presence face low prices. These distortions have considerable welfare implications.

[9] Corruption in the disbursement of loans is analyzed in Nan & Meng (2009).

For labor, migration restrictions are a subject of much analysis (Chan, 2010; Au & Henderson, 2006a; Au & Henderson, 2006b; Cai, 2006; Tombe & Zhu, 2019). While most formal restrictions under the hukou registration system were lifted by the early 2000's, informal restrictions keep moving costs high, especially for moves across provinces (Tombe & Zhu, 2019). Informal restrictions on immigrants are sometimes described as raising the doorsill especially in the biggest cities (Cai, 2006) and include poor access to public services such as schooling and to public utilities (e.g., indoor running water) in areas into which migrants are funneled (Zheng, Long, Fan, & Gu, 2009). Different regions have different policies towards migrant workers; and the histories of migration paths differ across provinces. Some regions have long-developed migration networks. These networks help new migrants find housing, jobs and information on how to navigate the city and its regulations. In this paper, we estimate how migration frictions vary across cities. At the end, we briefly describe one counterfactual based on a central government intention to divert migrants away from the largest cities by lowering the cost of migrating to less accessible hinterland locations.

3. Model

We develop a spatial, general equilibrium model incorporating the three factor markets. We consider a system of *N* cities with a fixed national population where workers can move across cities at differential migration costs. Non-traded intermediate goods are produced using capital, labor and land and are the only input into traded final goods production. Workers consume houses and a composite of tradable goods. Inter-city trade is costly. In the benchmark equilibrium, capital is allocated to cities at different prices set by the central government. Public infrastructure and land allocations are set by city leaders, who use all land revenues and, in counterfactuals, also wage taxes at either a positive or negative rate to finance infrastructure. The objective of the city government is to maximize the weighted average of the representative local worker's welfare and the city's measured GDP. We now describe the model in detail.

3.1 Preferences

Consider a worker who lives in city *i* and provides one unit of effective labor. His base utility upon which market good allocations are made is $U_i = {h_i}^{\beta} {E_i}^{1-\beta}$ where h_i is housing and $E_i = \left[\int_0^1 e_i(v)^{\frac{\sigma-1}{\sigma}} dv\right]^{\frac{\sigma}{\sigma-1}}$ is a CES composite good made up of a continuum of tradable goods. His realized utility is $Z_i V_i$, where Z_i is the amenity level offered in city i , which will include a "congestion" cost that is a function of city population. In this standard problem we have a base indirect utility function, V_i, corresponding to U_i and a price index of the composite good, Q_i, where

$$V_i = \frac{(1-\tau_i)\, w_i}{Q_i^{1-\beta} P_{hi}^{\beta}} \;\; ; \;\; Q_i \equiv \left[\int_0^1 q_i(v)^{1-\sigma} dv\right]^{\frac{1}{1-\sigma}} ; \quad \sigma > 1 \; . \qquad (1)$$

The only worker income source are wages at rate w_i , which, in a counterfactual will be taxed by the city at a rate τ_i. P_{hi} is the price of housing, and the shares of worker income spent on housing and the composite good are β and $(1-\beta)$.

3.2 Production and the factor demand

The city produces housing from land and capital. It produces an intermediate good with inputs of land, labor and capital, the value of which, given how "GDP" is calculated at the city level in China (see Section 3.7), we call the GDP of the city, Y_i . The intermediate good is the only input into the production of public goods and tradable goods. We look at these sectors in turn.

3.2.1 Housing

Houses are produced by real estate firms according to $H_i = X_{\mathrm{Ri}}^{1-\rho} K_{Ri}^{\rho}$ where X_R is residential land and K_R is capital used in housing production. Given the price for residential land $P_{X_R i}$, and the capital price r_i which is specific to city *i*, the dual for technology from cost minimization is

$$P_{hi} = (1-\rho)^{\rho-1}\rho^{-\rho} {P_{X_R i}}^{1-\rho} {r_i}^{\rho}. \qquad (2)$$

We also know that factor demand equations given the demand for housing take the form, for example, for residential land of $P_{X_R i} X_{Ri} = (1-\rho)\beta w_i (1-\tau_i) L_i$, where L_i is total units of effective labor in the city paid at rate w_i.

3.2.2 Production of the intermediate good

Traded goods production and public goods are made just from non-traded intermediate inputs, a competitive sector where all firms have the same CRS production function, so total output is $y_i = A_i {L_i}^{\epsilon} X_{Ii}^{\alpha_X} {L_i}^{\alpha_L} K_{Ii}^{\alpha_K}$, where $\alpha_X + \alpha_L + \alpha_K = 1$; *A* is the city's (endogenous) TFP; *L* is the city's effective labor used only in intermediate goods production; X_I and K_I are industrial land and capital; and there is an agglomeration economy which is captured by L^{ε}, $\varepsilon > 0$. Where $P_{X_I i}$ is the price of industrial land in city *i*, from the firm's profit maximization problem, we can derive factor share equations and solve for the unit cost function

$$c_i = \varphi (A_i {L_i}^{\epsilon})^{-1} {P_{X_I i}}^{\alpha_X} {r_i}^{\alpha_K} {w_i}^{\alpha_L}. \qquad (3a)$$

Intermediate goods are sold at price c_i in city *i*. For later use, we define city GDP, Y_i, as

$$Y_i = c_i y_i. \qquad (4)$$

As detailed later, measurement of local GDP in China ignores market rents and imputed rents on housing and almost exclusively reflects value added in industry.

Relevant footnoted expressions give φ, a wage equation, the derived demands for capital and land in intermediate goods production and then the demands for land and capital by the city's housing sector, with more details in Henderson, Su, Zhang, & Zheng (2020).[10]

3.2.3 Pubic infrastructure

The public sector in each city supplies public infrastructure, G_i , such as transportation and communications, improving the efficiency of intermediate good producers operating in the city by helping firms interact and even reducing commuting times so workers are more efficient. For simplicity *G,* is modeled as improving firm TFP of the city such that

$$A_i = A_i{}' G_i{}^{\gamma}, \qquad (5)$$

where $A_i{}'$ is a measure of the city's base production amenities assumed to be exogenous, and $\gamma > 0$ captures how effective the government's investment in public goods is in enhancing TFP. The government decision as to the level of public investment is modeled later. Here implications of the government budget constraint are discussed.

In the Chinese context, the city government collects fiscal revenues from selling industrial land and residential land and uses just that money to finance these infrastructure investments. In the key counterfactual, we will also allow the city to tax wages at an endogenous rate τ , either positive or negative. A tax rate of zero corresponds to our current baseline situation. Local taxation of worker income (tax rate > 0) may not be an institutional option at the moment. However, since in counterfactuals the optimal tax rate will turn out to be negative, it is more plausible that cities could rebate some portion of land revenue sales directly or indirectly to residents (through other public good provision), although in current practice they do not and, as explained above, in principle they cannot. Related, we do not cover local consumer public goods like schools and green parks, many of which are provided at the district or even neighborhood level. One could think of these being Tiebout (1956) public goods where sorting across neighborhoods leaves them akin to private consumer goods. For infrastructure investments, *G*, the public budget constraint is

$$G_i = \left(P_{X_I i} X_{Ii} + P_{X_R i} X_{Ri} + w_i \tau_i L_i\right) c_i{}^{-1}, \qquad (6a)$$

where *G* is produced one-for-one out of intermediate goods. Using the factor demand relationships and the demand for housing, (6a) can be written as

[10] $\varphi \equiv \alpha_L^{-\alpha_L} \alpha_K^{-\alpha_K} \alpha_X^{-\alpha_X}$; $\varphi_1 \equiv \alpha_K^{\frac{\alpha_K+\alpha_L}{\alpha_L}} \alpha_X^{\frac{\alpha_X}{\alpha_L}}$; *and* $\varphi_2 \equiv \alpha_X^{\frac{\alpha_L+\alpha_X}{\alpha_L}} \alpha_K^{\frac{\alpha_K}{\alpha_L}}$. $w_i = [\varphi^{-1} c_i A_i L_i{}^{\varepsilon} P_{X_I i}{}^{-\alpha_X} r_i{}^{-\alpha_K}]^{1/\alpha_L}$; $K_{Ii} = \varphi_1 [c_i A_i L_i{}^{\varepsilon+\alpha_L} P_{X_I i}{}^{-\alpha_X} r_i{}^{-(\alpha_L+\alpha_K)}]^{1/\alpha_L}$; $X_{Ii} = \varphi_2 [c_i A_i L_i{}^{\varepsilon+\alpha_L} P_{X_I i}{}^{-(\alpha_X+\alpha_L)} r_i{}^{-\alpha_K)}]^{1/\alpha_L}$; $X_{Ri} = (1-\rho)\beta(1-\tau_i)[\varphi^{-1} c_i A_i L_i{}^{\varepsilon+\alpha_L} P_{X_I i}{}^{-\alpha_X} r_i{}^{-\alpha_K} P_{X_R i}{}^{-\alpha_L}]^{1/\alpha_L}$; *and* $K_{Ri} = \rho\beta(1-\tau_i)[\varphi^{-1} c_i A_i L_i{}^{\varepsilon+\alpha_L} P_{X_I i}{}^{-\alpha_X} r_i{}^{-(\alpha_L+\alpha_K)}]^{1/\alpha_L}$.

$$G_i = [\alpha_X + (1-\rho)\beta(1-\tau_i)\alpha_L + \tau_i\alpha_L]\, y_i. \tag{6b}$$

We can also rewrite the unit cost function as

$$c_i^{1-\gamma} = (\alpha_X + (1-\rho)\beta(1-\tau_i)\alpha_L + \tau_i\alpha_L)^{-\gamma}(A'L_i^{\epsilon})^{-1}X_{I,i}^{-\alpha_X}L_i^{-\alpha_L}\left(\frac{r_i}{\alpha_K}\right)^{\alpha_K}Y_i^{\alpha_X+\alpha_L-\gamma} \tag{3b}$$

3.3 Trade and consumer market access

We adopt a conventional trade framework based on Eaton & Kortum (2002) as applied, for example, in Donaldson & Hornbeck (2016) or Alder (2019). Each city produces a continuum of tradable goods of mass one. For variety *v* in city i, the production technology is $t_i(v) = B(v)y_i(v)$, where $t_i(v)$ is the city's output of variety *v*, $y_i(v)$ is the amount of intermediate goods used in the production of *v*, and $B(v)$ is a productivity shock to variety *v* in city *i*. The shock follows a Frechet distribution with cdf $F(B(v)) = exp(-B(v)^{-\theta_t})$ and is i.i.d. across cities and varieties. The unit cost of variety *v* is thus $c_i/B(v)$, noting that we already have a production amenity that is city specific, $A_i{}'$. The trade cost between city *i* and *n* is defined in iceberg fashion: if one unit of good is to arrive at city *n*, then $d_{in} \geq 1$ units of good need to be shipped from city *i*. We assume symmetric pairwise trade cost so $d_{in} = d_{ni}$. Given the trade cost, the actual price that city *n* pays for one unit of variety *v* from city *i* is $p_{in}(v) = d_{in}c_i/B(v)$. Traded goods producers are competitive, so they earn zero profits. The workers in city *n* choose different varieties of tradable goods from all cities.

In this framework with standard derivations in Appendix A2, one has the probability that a city buys a variety from any other city and the total demand for any city's tradable goods is based on the share of labor incomes spent on goods in all cities and their likelihoods of buying this city's varieties. On the supply side, the value of production is the value of inputs going into traded good production in city *i*. Those inputs are total intermediate good production less inputs into *G* and payments to capital owners, or $c_iy_i - c_iG_i - r_i(K_{Ii} + K_{Ri})$. Equating demand and supply for a city and incorporating eqn. (6b) will yield

$$(1-\tau_i)Y_i = \sum_n \frac{(c_id_{in})^{-\theta_t}}{\sum_{i=n}^{N}(c_id_{in})^{-\theta_t}}(1-\tau_n)Y_n, \tag{7a}$$

with detailed derivation in Henderson, Su, Zhang, & Zheng (2020).

Next let us introduce some key expressions which we shall use later in our model derivations. These are Donaldson & Hornbeck's (2016) terms for consumer market access to products through trade, CMA_i, and firm market access to selling opportunities through trade, FMA_i. Specifically, the definitions of CMA_i and FMA_i are given by

$$CMA_i \equiv Q_i{}^{-\theta_t} = \left[\Gamma\left(\frac{\theta_t+1-\sigma}{\theta_t}\right)\right]^{\frac{-\theta_t}{1-\sigma}} \cdot \left[\sum_{j=1}^{N}\left(c_jd_{ji}\right)^{-\theta_t}\right], \tag{8a}$$

$$FMA_i \equiv \sum_n \frac{(d_{in})^{-\theta_t}}{CMA_n}(1-\tau_n)Y_n \ , \qquad \text{(8b)}$$

where Q_i is the realized price index in eqn. (1). Intuitively, the higher the production costs in the surrounding cities of city *i* (discounted by respective distance to city *i*), the higher the price index faced by consumers in city *i* and hence the lower the consumer market access of city *i*. Also, the higher the total income in the surrounding cities of city *i* (discounted by respective distance to city *i*), the higher the demand faced by firms in city *i* and hence the higher the firm market access of city *i*. Using the above expressions and eqn. (3b), we can then rewrite eqn. (7a) and get an expression for city output which is a function of variables we optimize over (e.g., s_i , the land share going to residential use) or we treat as given to the city (e.g., r_i and $\bar{X}_i$):

$$Y_i = F_i\left[A_i{}'\varphi_4\, r_i{}^{-\alpha_K}\bar{X}_i{}^{\alpha_X}(1-s_i)^{\alpha_X}L_i^{\epsilon+\alpha_L}\right]^{\frac{\theta_t}{(1-\gamma)+\theta_t(\alpha_X+\alpha_L-\gamma)}}, \qquad \text{(7b)}$$

where $F_i \equiv \left(\left[\Gamma\left(\frac{\theta_t+1-\sigma}{\theta_t}\right)\right]^{\frac{-\theta_t}{1-\sigma}}.FMA_i\right)^{\frac{1-\gamma}{(1-\gamma)+\theta_t(\alpha_X+\alpha_L-\gamma)}}$ and $\varphi_4 \equiv \alpha_K{}^{\alpha_K}[(1-\rho)\beta(1-\tau_i)\alpha_L+\tau_i\alpha_L+\alpha_X]^{\gamma}(1-\tau_i)^{\frac{\gamma-1}{\theta_t}}$.

3.4 Realized utility, migration and the spatial allocation of population and effective labor

In this subsection, we derive the amount of effective labor for each city, and national effective labor supply. Our framework involves heterogeneous labor, and we spell out some of the needed details. A worker who moves from city n to city i has the following realized utility

$$U_{ni} = Z_i a_i V_i g_{ni},$$

where Z_i denotes the amenity of living in city i and V_i is the base utility of city *i* defined in eqn. (1). There are three key components to this. First, a worker gets a random productivity draw a_i in city i from a Frechet distribution with cdf $\Psi(a_i) = e^{-a_i{}^{-\theta}}$, for θ the dispersion parameter. The draw is independent across cities and workers. The worker's effective labor supply is a_i and she earns $a_i w_i$ if she moves from city *n* to city *i*. Second, $g_{ni} \leq 1$ is the fraction of utility left-over net of migration costs. We assume $g_{ii} = 1$ so that the stayers suffer no migration cost. In this formulation, we have simplified the Chinese context by not distinguishing people within a city by local "citizenship" (*hukou*) status, where in-migrants typically may take some years to obtain local *hukou*. Ours is a long run equilibrium model not a dynamic one, and part of migration costs is the cost of eventually obtaining local hukou.

Third, Z_i consists of two components, $\bar{Z}_i$, the base (exogenous) amenity level for any city *i*, and an endogenous component dependent on city labor force, so that

$$Z_i = \bar{Z}_i \exp(-\omega L_i). \qquad \text{(9)}$$

The motivation for adding this term is the local residents' concern with over-population of especially bigger cities due to "congestion" costs. Introducing this term has modest effects on our calculations of welfare costs but does affect the allocation of population in counterfactuals. Cities like Beijing which are "over-populated" in the baseline will lose less population in counterfactuals than without this term, because even small reductions in population improve outcomes just due to less congestion, making Beijing increasingly attractive as its population falls. While in (9) congestion appears as having a direct effect on consumer welfare, in the local leader's optimization problem below, this congestion factor could also represent the leader's preferences about city over-population, a political issue in China.

How do we relate city populations to migration flows? Workers move to the city offering them the highest utility and as is standard, the proportion of people moving from n to i is $M_{\mathrm{ni}} = Prob(U_{ni} > \max\{U_{ns}, s \neq i\}) = \frac{(Z_i V_i g_{ni})^{\theta}}{\sum_s (Z_s V_s g_{ns})^{\theta}}$. For N cities in the economy, the migration flow matrix determined by this equation implies a relationship between initial and final population that

$$\tilde{L}'_i = \sum_{\mathrm{n}\in\mathrm{N}} \frac{(Z_i V_i g_{ni})^{\theta}}{\sum_{k\in N}\left((Z_k V_k g_{nk})^{\theta}\right)} \cdot \tilde{L}_n. \qquad (10)$$

$\tilde{L}_i$ is the population of city i in an initial year (which will be 2000), while $\tilde{L}'_i$ is the population of city i in the current equilibrium (which will be 2010). We normalize the 2000 population to be the same as the 2010 given national population growth is not a focus. Thus, the population constraint is

$$\sum_{n\in N} \tilde{L}_n = \sum_{n\in N} \tilde{L}'_n = \bar{\tilde{L}}. \qquad (11)$$

Eqn. (11) gives a count of bodies. But we also need to know the allocation of effective labor. The total effective labor at city *i* is given by $L_i = \sum_n E(a_i | moving\ from\ n\ to\ i) * \tilde{L}_n * M_{ni}$. Thus total effective labor of city *i* is provided by workers from various origins multiplied by their corresponding average productivity conditional on moving to city *i*. The average productivity conditional on moving from city *n* to city i is given by $E(a_i | moving\ from\ n\ to\ i) = \left(\frac{1}{M_{ni}}\right)^{\frac{1}{\theta}} \cdot \Gamma(1 - \frac{1}{\theta})$. Here the average labor productivity conditional on moving from city n to city i is inversely related to the migration share. Intuitively, more people moving to the same city means that the productivity draws reach further down into the distribution. Combining the above two conditions yields

$$L_i = \sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta}} \Gamma(1 - \frac{1}{\theta}). \qquad (12)$$

A greater inflow of migrants to city *i* will increase total effective labor, but average labor productivity will be lower.

3.5 City government's decision on land supply and infrastructure provision

As discussed in the introduction, each local government maximizes an objective function, given city specific weights to the welfare of a representative worker, $(1-f_i)$, versus to total output value, f_i. The local government chooses the allocation of industrial land versus residential land from the city supply of land and, in one counterfactual, the rate of worker income taxation, τ_i, to maximize the objective function. Thus, for any city *i*, the local government's objective is

$$\max_{s_i,\tau_i} (Z_i V_i)^{1-f_i} Y_i^{f_i}$$

$$s.t. \quad s_i \bar{X}_i = X_{Ri},\ (1-s_i)\bar{X}_i = X_{Ii} \text{ and } G_i = \left(P_{X_I i} X_{Ii} + P_{X_R i} X_{Ri} + w_i \tau_i L_i\right) c_i^{-1}, \qquad (13)$$

where $\bar{X}$ is the total amount of available land in city *i* and s_i is the share going to residential use. In solving the problem, we need to express the two equilibrium outcomes *Y* and *V* as functions of X_I, X_R (or *s*) and τ_i. We already have *Y* from eqn. (7b). For *V*, with substitutions, we get

$$V_i = \Omega_i B_i \left\{ \left[(1-s_i)^{\alpha_X} L_i^{\epsilon+\alpha_L}\right]^{\frac{\theta_t(1-\beta(1-\rho))}{(1-\gamma)+\theta_t(\alpha_X+\alpha_L-\gamma)}} s_i^{\beta(1-\rho)} / L_i \right\}, \qquad (14)$$

$$B_i \equiv \left[r_i^{-\beta\rho - \frac{\alpha_K \theta_t(1-\beta(1-\rho))}{(1-\gamma)+\theta_t(\alpha_X+\alpha_L-\gamma)}} F_i^{(1-\beta(1-\rho))} CMA_i^{\frac{1-\beta}{\theta_t}} \right],$$

where Ω_i is a city constant given by

$$\Omega_i = (1-\tau_i)^{1-\beta(1-\rho)}\, \alpha_L \left((1-\rho)^{\rho-1}\rho^{-\rho}\left((1-\rho)\beta\alpha_L\right)^{1-\rho}\right)^{-\beta} \left[A_i{}'\varphi_4\, \bar{X}_i{}^{\alpha_X}\right]^{\frac{\theta_t(1-\beta(1-\rho))}{(1-\gamma)+\theta_t(\alpha_X+\alpha_L-\gamma)}} \cdot \bar{X}_i^{\beta(1-\rho)}.$$

We notice that the city constant contains information about the tax rate τ_i and φ_4, with the latter also depends on τ_i. Note in the calibration exercise right below, τ_i is set to 0.

In solving (13) we assume the local leader takes CMA_i, FMA_i, L_i and r_i as given, since her city is one of many. In Appendix A4, we discuss experiments trying to assess the impact of these assumptions by fully or partially relaxing $dlnL_i/ds_i = 0$ and we show this will not affect the results of our key counterfactuals with $f = 0$.[11] Using $s_i\bar{X}_i = X_{Ri}$, $(1-s_i)\bar{X}_i = X_{Ii}$, and optimizing with respect to *s* in (13), we get

$$\frac{1-s_i}{s_i} = \frac{\theta_t \alpha_X (1-(1-f_i)\beta(1-\rho))}{(1-f_i)\beta(1-\rho)(1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma))}. \qquad (15)$$

If, as in calibration, $\tau_i = 0$ and total *cG* equals total land rents, we solve out land prices (given consumer and firm FOC's related to X_{Ri} and X_{Ii}) as

[11] We can relax the assumption that $dL/ds = 0$ in solving the benchmark calibration to some degree and recalculate f's. Appendix A4.1 shows these *f*'s are very highly correlated with the ones we solve under the assumption $dL/ds = 0$. In counterfactuals where the leader just maximizes welfare (i.e., *f* = 0) we do not have to assume that the leader sees $dL/ds = 0$. In fact, when s is optimized with *f* = 0, its marginal impact on local welfare is zero, which in turn means there is no incentive to migrate any more, thus $dL/ds = 0$.

$$\frac{P_{X_R i}}{P_{X_I i}} = \frac{\theta_t \alpha_L (1-(1-f_i)\beta(1-\rho))}{(1-f_i)(1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma))}. \qquad (16a)$$

In (16a), in the calibrated equilibrium, the higher the weight, *f*, that a city government places on GDP, the higher is the share of industrial land in the city's total land supply, and the higher the resulting residential relative to industrial land price.[12] We will use (16a) and the data on city land prices to solve for each city's *f*. We note that, if *f* = 0, under the parameter values we use in the paper, this ratio is 0.64 so the industrial price exceeds the residential, while in Figure 1 residential prices in the benchmark equilibrium generally strongly exceed industrial ones.

In our key counterfactual we relax the local government budget constraint with $\tau_i \neq 0$ and set *f*=0, so governments act just to maximize the welfare of the representative agent in the city, V_i. Then optimizing gives

$$\tau = \frac{-\beta(1-\rho)\alpha_L - \alpha_X + \gamma}{\alpha_L(1-\beta(1-\rho))}. \qquad (17)$$

Under reasonable parametric values, τ will be negative. This implies that forcing the city to spend all rents on *G* leads to over-provision of *G* in the benchmark case. For this case where *f* = 0 and $\tau_i \neq 0$, the price ratio is given by

$$P_{X^R}/P_{X^I} = \frac{\theta_t(\alpha_X+\alpha_L-\gamma)}{\theta_t(\alpha_X+\alpha_L-\gamma)+1-\gamma}, \qquad (16b)$$

which is 0.70 under the parameter values we use, or residential land is underpriced. Why are prices not equalized, even though the public budget constraint is relaxed, and leaders act to maximize just the welfare of residents?

The reason is that cities have monopoly power in trade, facing downward sloping demand curves for their varieties. In the case of (16b), with *f*=0 and a relaxed budget constraint, higher-priced industrial land raises output prices. To illustrate this point, we consider two hypothetical cases. If there is no trade but still capital in the model, in this case, $P_{X^R}/P_{X^I} = 1$, so there is no land market distortion. Second, if there is no capital in the model when *f* = 0, but there is trade, under a relaxed budget constraint, P_{X^R}/P_{X^I} is less than one as in (16b) at $\theta_t/(1+\theta_t)$.

3.6 Closing the model

To close the model, we sum within city so demand for land equals the city's land supply ($\bar{X}_i$) and we sum within and across cities so capital demand equals the national supply of capital ($\bar{K}_{agg}$):

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[12] Note if $f = 1$, there will be a corner solution where the government would like to lower land for residential use to zero. And this pushes housing production towards 0 and raises housing price towards infinity.

$$X_{Ri} + X_{Ii} = \bar{X}_i, \qquad (18a)$$

$$\sum_{\mathrm{i}} K_{I,i} + \sum_i K_{R,i} = \bar{K}_{agg}. \qquad (18b)$$

To assess counterfactuals, we need a welfare measure for workers, where capital income is a separate welfare item applying to "capital owners". Total national consumer welfare, as is conventional, is expressed as[13]

$$W = \sum_{i=1}^{N} \frac{\tilde{L}_i}{\sum_{j=1}^{N} \tilde{L}_j} \cdot ב\left[\sum_{k \in N} (Z_k V_k g_{ik})^{\theta}\right]^{\frac{1}{\theta}}, \qquad (19)$$

where $ב = \Gamma(\frac{\theta-1}{\theta})$, from the gamma function (Tombe & Zhu, 2018). Note that the expected utility of all people originating from city i is

$$E[U_i] = ב\left[\sum_{k \in N} (Z_k V_k g_{ik})^{\theta}\right]^{\frac{1}{\theta}}. \qquad (20)$$

Relative inequality (weighted by the initial population) is thus measured by

$$Inequality_o = \sum_i^N \frac{\tilde{L}_i}{\sum_{j=1}^{N} \tilde{L}_j} \cdot (E[U_k]/W - 1)^2. \qquad (21)$$

3.7 Calibrating the model

To calibrate the model, we need data for each city on the price of capital, the prices of residential and industrial land, GDP (*Y*), initial and final populations, and migration and transport costs to all other cities. Transport cost data are taken from Baum-Snow, Henderson, Turner, Zhang, & Brandt (2020) as explained in Appendix A2. We have data on GDP and populations from Yearbooks and the Census. Note, most crucially in Chinese cities, GDP statistics only include a very low symbolic housing component, unrelated to local housing prices[14]. The Chinese method differs from the North American and European methods which use rents for rental units and imputed rents (based on a market comparison approach) for owner-occupied units to calculate the value-added for housing service. China's GDP estimation method uses a national constant construction cost per square meter multiplied by the total floor area to get the total book value for the housing stock, and then takes a fixed depreciation rate of this total housing stock cost as the

[13] It is also possible to derive expressions to calculate average welfare and inequality based on where people end up. With the Frechet distribution, $E[U_i] = E[U_i|moving\ to\ city\ k]$, for any destination city k. Therefore, the average welfare of people currently living in city k (after migration) is given by $E[\tilde{U}_k] = \sum_{i \in N} \frac{\tilde{L}'_{ik}}{\tilde{L}'_k} E[U_i|moving\ to\ city\ k] = \sum_{i \in N} \frac{\tilde{L}'_{ik}}{\tilde{L}'_k} \cdot ב\left[\sum_{s \in N} (Z_s V_s g_{is})^{\theta}\right]^{\frac{1}{\theta}}$. Thereby we can also define another measure of inequality using $E[\tilde{U}_k]$, $Inequality_d = \sum_k^N \frac{\tilde{L}_k}{\sum_{j=1}^{N} \tilde{L}_j} \cdot \left(E[\tilde{U}_k]/W - 1\right)^2$.

[14] See http://www.stats.gov.cn/tjzs/cjwtjd/201308/t20130829_74319.html from the National Statistical Bureau.

value-added of housing service from owner-occupied housing units (which are well over 80% of units in China). Thus, this component has nothing to do with the land values and housing prices in each city; it is just mechanically proportional to the total housing floor area of the city. This estimation method greatly under-estimates the housing component and makes it negligible in GDP (Liu, Zheng & Xu 2003). Thus, we treat GDP as equivalent to Y in our model. In the next section, we show how we derive hedonic residential and industrial land prices, capital prices, and migration costs for every city. Given these data we can calibrate the model and solve for the f's. What are the steps?

Given migration costs and population in eqns. (10)-(12) we can pin down migration flows, M_{ni} , $Z_i V_i$, and effective labor, L_i, for each city. Given land prices, eqn. (16a) gives f_i's and then eqn. (15) gives inferred s_i's. Using eqn. (3a) and wage equations, with manipulation and substitutions, we can solve for A_i given GDP and then pin down A'_i and G_i in eqn. (5). We use equations in footnote 10 to solve for each city's use of land and capital in residential and industrial use, given land prices. Summing within the city for land gives us each city's land supply ($\bar{X}_i$) and summing within and across cities gives the national supply of capital ($\sum_{\mathrm{i}} K_{I,i} + \sum_i K_{R,i} = \bar{K}_{agg}$). Eqns. (2), (8a), (3a) and (1) give $P_{hi}, CMA_i\ Q_i,$ and V_i . Having already solved for $Z_i V_i$, we then know consumer amenities Z_i which can be decomposed in eqn. (9) into $\bar{Z}_i$ and congestion costs, $\exp(-\omega L_i)$. Later we can use this information to calculate worker welfare. More details are in Appendix A1.

4. Deriving benchmark prices and costs

We now turn to estimation of hedonic land prices by use type in each city, migration costs, and the prices of capital by city.

4.1 Hedonic land prices

We estimate land prices in every city in the residential versus industrial sector. We have a large micro-level dataset that covers all the land transactions in Chinese cities for 15 years. This includes all land parcels that are sold through public auction of land in China (prevalent for residential land transactions since August 2004 and for industrial land since July 2007). We also have some negotiated sales transactions, common for industrial land transactions before July 2007. The data contain residential, commercial, and industrial land transactions. The sole allowed land use of a parcel is specified prior to auction, based on the overall supply decisions of the city. This is the most comprehensive land transaction data of urban China, obtained from http:// landchina.mlr.gov.cn.

To have sufficient sample by use in each city, we use the data for the years 2008-2015, after the auction reforms in 2007. We exclude the small number of negotiated sales transactions during this period, mostly for industrial land transactions, as outliers.[15] We run hedonic regressions to compare prices for equal

[15] Since July 2007, the central government of China has enforced public auction for industrial land. Since then, the majority of industrial land deals have been through auction (see Tian, Wang, & Zhang 2022), and those that are not we suspect are one-off either very corrupt or unusual transactions (de facto transfer of ownership among state owned

quality land in different cities in different uses. To fit our model, we combine industrial land transactions with pure commercial land transactions (a small portion of total transactions) to form what we label as industrial land transactions. We also drop outlier transactions with either zero price or price per square meter greater than 100k RMB.

There are 120,019 industrial (and commercial) land transactions, and 60,753 residential land transactions with no missing information, covering 266 cities nationwide. With eight years pooled, all cities have more than 40 land transactions and a majority have more than 100. We run regressions for each city *i:*

$$log\left(P^{\mathrm{i}}_{X,\mathrm{j}t}\right) = b^{\mathrm{i}}_{0} + \beta^{\mathrm{i}} R^{i}_{j} + I^{\mathrm{i}}_{t} + D^{i} Type^{i}_{j} + m^{i}_{jd} + \epsilon^{\mathrm{i}}_{\mathrm{j}t} \ . \qquad (22)$$

In (22), $P^{\mathrm{i}}_{X,\mathrm{j}t}$ is the unit (sq. mt.) sale price of the land parcel *j*, R^{i}_{j} is a vector of parcel characteristics including land area, maximum floor-to-area ratio [FAR], land quality tier, auction format, and distance to city center and its interaction with land area.[16] Coefficients vary by city. I^{i}_{t} is a year fixed effect. $Type^{i}_{j}$ is a land use type dummy with "1" for "residential" and "zero" for "industrial" for parcel *j*. Thus $exp(\, D^{i})$ is the hedonic price *ratio* of residential land to industrial land in city *i* for otherwise identical plots. A concern is that parts of a city may be exclusively industrial or residential. To enhance identification, we add a district (*d*) fixed effect, m^{i}_{jd}, so as to compare parts of the city where these two uses are competing.

To solve out A' and land stocks in calibration, we also need absolute land prices. For each city we save the estimated coefficient vector denoted as π^{j}. We predict the hedonic land price for city *j* by land use type using π^{j} and the same set of characteristics of a national prototype land parcel. The characteristics of the prototype land parcel are chosen as the national means of the above noted land characteristics of the combined residential land and industrial land sample.[17] This then gives us, for a nationally representative piece of land, price by city by type of use.

In Figure 1 above, we plotted the relative price of residential to industrial land. The ratios range between 0.68 and 8.7 for the same quality land, with a median of 2.2 across all cities.[18] As noted above, cities like Beijing and Shenzhen which are testing grounds for future national leaders who are tasked with growing the local economy have very high ratios and consequently also very high housing prices.

enterprises at symbolic prices).

[16] The tier quality of the parcel is given by indicator variables, where the city government categorizes tiers based on the amenity quality of land, the land parcel's distance to city center. For auction formats, there are English auction, two-stage auction, and sealed-bid auction. Cai, Henderson, & Zhang (2013) show transaction format may significantly impact the land sale price.

[17] For the district fixed effects, we do a weighted (by transactions) average for each city.

[18] One city with a ratio of the lowest ratio 0.49, Deyang in Sichuan, was winsorized at the next lowest ratio in the data of 0.68.

4.2 Capital costs

From the Annual Survey of Medium and Large Industrial firms for 1998-2007 accounting for 95% of industrial sales in China, Chen, Henderson & Cai (2017) estimate an average revenue product [ARP] equation to quantify specific differentials in the price of capital faced by firms under different circumstances, just as in Song & Wu (2013) and Dollar & Wei (2007). Like Dollar & Wei (2007), Chen, Henderson & Cai (2017) find that SOE's have deep discounts on the price of capital. However, they also find that some provincial level and coastal cities have strong discounts for private firms which persist from year to year.

Using the data from the Annual Survey of Medium and Large Industrial Enterprises for 2006-2007, we estimate the price of capital faced by private firms in each city. We use an ARP equation based on the model, but allow differences in capital intensity by industry, j, and city differences in items, J_{ji}, which influence firms elasticities of demand and hence revenue products. For firm *s* in industry j in location *i*, from profit maximization

$$ln\left(\frac{p*_j^i\ y_s}{k_s}\right) = ln(r_i) - ln\alpha_{Kj} + J_{ji} + \epsilon_{ijs}. \qquad (23)$$

$p *_j^i$ is the output price to the firm net of VA taxes. y_s and k_s are output and input of capital. r_i is the price of capital specific to city *i*, identified by city fixed effects. The α_{Kj} are industry fixed effects, capturing differences in capital intensity. For the $J_{ji}'s$, we control items affecting price, such as the (log) number of firms in the prefecture in the industry of the firm from the 1995 Industrial Census (supply), distance to the coast, and (log) GDP in 1990 within 150 kilometers of the prefecture city center (demand factors). While these measures are not explicitly derived from the model, they are reduced form historical controls, which mitigate current endogeneity issues. Estimation of (23) uses firm level data pooled for 2006 and 2007 (with a time fixed effect).

The resulting prices of capital normalized to Guangzhou at 1 were shown above in Figure 2. Three things are of note. First, the price of capital rises modestly with city size, where smaller and typically more remote cities such as in the north may be favored historically. Second, as noted earlier, certain political cities face very low prices. Finally, there is the wide dispersion in prices, a key issue in the Hsieh & Klenow (2007) paper.

4.3 Estimation of migration costs

We quantify migration costs with our own data. Despite some differences in approach and data, results are similar to Tombe & Zhu (2019). We do not dwell on this aspect of factor markets for two reasons. First our model is static, whereas migration involves forward looking dynamic behavior (Kennan & Walker, 2013; Balboni, 2019). We simply want a way to incorporate migration restrictions to explain equilibrium utility differences across cities. Second it is not clear how to formulate a counterfactual other than to pick an ad hoc arbitrary reduction in migration costs.

In quantification, we do not assume symmetry in migration costs (Bryan & Morten, 2019). Provincial barriers to in-migration and the history of migration paths may differ across provinces, so that the cost of moving from Beijing to Sichuan may differ than that for moving from Sichuan to Beijing (Tombe & Zhu, 2019). In the Chinese context, we assume there are asymmetric fixed costs of *entering* a province, but variable symmetric travel time costs. From eqn. (10), migration costs (fraction of utlity lost at the destination when migrating) are denoted as g_{ni}, which we decompose into $g_{ni} = t_{ni} * \tilde{t}_i$, where t_{ni} is variable, time- distance-based part of migration costs, and $\tilde{t}_i$ is a destination sunk cost. To get these costs, we first use a formulation of province-to-province migation costs and run a gravity model regession, based on the 2010 census data. These give fixed and variable costs of inter-provincial migration. The formulation is standard, where in eqn. (10) migration costs are inferred from flows. Then based on 2000 census information, we adjust these data to further infer within province fixed costs of movement. We then apply these results to specifying city-to-city fixed and variable migration costs (versus the province to province ones that we estimate). Appendix A3 gives more details and the assumptions under which the method of using province to province costs to infer city-to-city costs is valid.

Figure 3 plots the relative fixed costs of entering a province, with the 3 regions of China marked by color. Note a higher value of $\tilde{t}_i$ means lower costs, or more real income survives. The places with the lowest entry costs are Guangdong and Zhejiang provinces, but Beijing and Shanghai have also relatively low entry costs. Note these are east coast provinces. The most difficult places to enter are Shanxi, Ningxia, and Henan. Beijing and Shanghai resist immigration by offering migrants poor living conditions with poor housing facilities in migrant areas and poor access to state schools.[19] Yet they have relatively low fixed costs of entry inferred from larger inflows. The reality is that these cities have developed extensive long term migration networks, with, for example, many neighborhoods named after the origin of migrants there. These networks help migrants find housing and jobs and provide information on how to navigate the city and its regulations and restrictions. It is clear that typical policies to make life miserable for migrants are not enough to offset the years of development of the networks and their benefits. While intending not to be, Beijing, in net, given its history of migration, is a relatively welcoming place.

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[19] There is a 2011 survey conducted by China's National Health and Family Planning Commission which covers 106,000 migrant families nationally, although these may be longer term migrants. We examined the data, which after controlling for household characteristics, suggests that in cities like Beijing, Shangahi and Tianjin households are significantly less likely to have indoor toilets and showers relative to east coast ordinary prefecture level cities. Such cities tend to offer migrants poorer access to social security and health care (Cai, 2006), but schooling is a big issue. In the biggest cities, migrant children may be denied entry to local state schools. Parents can send children to local 'private' schools which have quasi-legal status, are subject to shut-down, and have unqualified teachers (Kwong, 2004) or can 'leave children behind' in home villages where they are cared for by grandparents and others. Based on the 2011 survey noted above, we find the stated cities tend to have significant fractions of children in private school and left behind, even though the survey may tend to capture longer term migrants.

In Figure A3.2, we plot total pairwise migration costs. While many within province moving costs are *relatively* low, for the vast majority, it still costs more than half of a person's real income to move. Second, the vast majority of city pairs involving interprovincial moves leave much smaller fractions of real income. These numbers on what real income is left after migration are actually higher than in Tombe & Zhu (2019). While one can quibble over absolute magnitudes, for our last counterfactual, they will give *relative* gains from changing migration regimes, as well as impacts on city populations.

5. Calibration results

To calibrate, we need to specify parameters we do not estimate. These are in Table 1, with sources noted. Most are close to standard international numbers, with some deviation based on estimates for China. For agglomeration economies, given estimates tend to vary substantially by individual paper given the details of estimation, we use a "commonly accepted" number 0.04 from Rosenthal & Strange (2004) and also from de la Roca & Puga (2017). Counterfactual results are robust to raising or lowering the estimate by 0.02.[20] For capital intensity we adjust the commonly accepted number of 0.25 upward, given the literature on China which shows high capital intensity (e.g., Jefferson & Singh (1999) and Bai & Qian (2010)). A difficult one is land's share in production, where we know of no modern econometric study using Chinese data. Given China's high historical industrial land intensity[21], we adjust the USA estimate of 0.05 upward to 0.07. We note our counterfactual results are robust to lowering the share to 0.05 or raising it to 0.08.[22] For the measure of infrastructure productivity in production, γ, we use Melo, Graham, & Brage-Ardao (2013)'s meta study number of 0.06. While some developing countries reported in Melo, Graham, & Brage-Ardao (2013) have higher numbers, we balance that against Wang, Wu, & Feng's (2019)'s estimates of 0.031 and 0.046 for China for transport and utilities infrastructure respectively. Finally, there is the congestion cost parameter, ω . We set $\omega = 4 \times 10^{-8}$. At a population of 4 million, this gives a population elasticity of -16 %, for *Z*. This is higher than Combes, Duranton & Gobillon's (2019) estimates for "agglomeration" costs in French cities which range to 8% for larger cities. However, French cities are typically much smaller; and the agglomeration cost is just about housing prices in a monocentric model with commuting and no congestion. For China, Wang & Zhang (2022) for the same commuting distances estimate a density, or congestion elasticity of about 16% to 20%.

Given those parameters, the data, and the process described in Section 3.7 and in Appendix A1, we can solve for city-specific parameters as well as the equilibrium quantities of endogenous variables of the

[20] We did some sensitivity checks for ϵ equal to 0.02 and 0.06. The counterfactual results change only modestly, and can be provided upon request.

[21] Industrial land use has dominated other land uses in urban China: over 50% of newly developed urban land is for industrial use based on data from the 2004–2012 editions of the *Yearbooks of Land and Resources* and the official website of China's Ministry of National Land and Resources (www.landchina.com). In terms of stock, on average 20% of cities' urban built-up land area is for industrial use based on data from the *Yearbooks of Urban Construction*, which is much higher than USA.

[22] In doing this we adjust capital's share up or down so factor shares still sum to 1. For the welfare results in Table 4 below, in the CF-2 comparison with the baseline, the percent changes vary by less than 7% of the reported values. In going from CF-2 to CF-3, for a share of 0.05 the incremental percent gain is reduced by 41%; while, for a share of 0.08, the incremental percent gain is increased by 20%. The counterfactual results can be provided upon request.

model. These are A_i', $G_i, c_i, f_i, X_{Ii,} X_{Ri,} K_{Ii,} K_{Ri}$ and $\bar{Z}_i$. From the *X*'s and *K*'s we know total land supply for each city and total capital stock of the nation, both in fictitious units. The numeraire is the price of capital in Guangzhou, so initial capital rents are divided by the price in Guangzhou.

The focus in this subsection is on evaluating the validity of our baseline model by seeing if our benchmark estimates of A_i', G_i, c_i and f_i, vary across cities as expected, and by checking the model's ability to predict relative trade flows, land supplies by city, and house prices. In Table 2, we provide a simple table of regressions of A', G, c and f on a set of covariates. City productivity, A', in col. (1) rises with education as expected because labor is not in education units. Productivity rises with scale, or population, and better political status of the city, the latter reflecting Chinese policy on how resources affecting innovation were handled historically. Related, as we can see that cities that received initial high levels of FDI right after China opened have higher A'. Distance to the coast has the "right" sign but is not significant, given we have accounted for trade costs, albeit not flows of information from coastal cities about technical innovations. For unit cost, *c*, covariate effects mirror those for A' with opposite sign as expected, although here the distance to the coast effect is significant.

Calibrated infrastructure levels, *G*, as expected, rise with population, political status, manufacturing share and education. While the model does not breakout manufacturing versus other sectors, manufactured goods are the main export goods from the city requiring infrastructure. These *G* levels are accumulations of flow investments. We have the city-level data on: (1) average annual local spending on infrastructure over 2008-2011[23] and (2) average annual city government's land sale revenue over the same period. In the left panel of Table 3, the pairwise raw correlation coefficients between our calibrated *G*, infrastructure investments and land revenues range from 0.77 to 0.83. Even after factoring out a control for population, or scale, in the right panel of Table 3, these pairwise coefficients range from 0.65 to 0.68. We interpret these results as affirming our characterization of the public good sector.

Finally, in Table 2 there is the political weight on GDP enhancement, f. These are graphed against city population in Figure 4. These *f*'s average 0.66 with a median of 0.69. 25% of the f's are over 0.8 and they are especially high for some political cities like Beijing (0.91) and Tianjin (0.85), presumably assigned to ambitious political leaders. In Figure 4, there are more "enlightened" places with low *f*'s which appear to value the welfare of residents, such as Yueyang or provincial capitals like Kunming and Jinan (0.59).

There is a conceptual issue. The *f*'s reflect leader preferences. We think there is persistence over time in *f*'s because more ambitious leaders who seek promotion (by growing GDP) are more likely to be assigned to big, political, and coastal cities. In the regression in Table 2 col. (4), f rises with population and also with manufacturing share, where such cities may face pressure to lead the country's GDP growth. f

[23] We obtain this variable from Chinese city statistic yearbooks. City government spending on infrastructure is the sum of the funds from the city government's local fiscal expending on infrastructure investment, loans and securities (principle only) the city government borrows to finance infrastructure investment, and the city government's self-raised fund (through local bonds, etc.) for infrastructure investment. This variable does not include funds from upper-level governments (such as provincial and central governments) used for infrastructure investment.

declines with distance to major seaports perhaps because those interior and far west cities have experienced de facto neglect in assignment of leaders. There is also a link from f's to local leaders' own career concerns. Based on Wang, Zhang, & Zhou (2020), in col. (6) in Table 2, we experiment with a key 'political' variable, the age of the local leader, the Party Secretary (averaged over 2000-2010). In Wang, Zhang, & Zhou, local leaders are on a path to promotion, where promotion depends heavily on economic achievement measured by local GDP. However, maximizing GDP involves effort to manipulate constraints imposed by the center and placate local citizens. Older leaders have a glass ceiling based on mandatory retirement ages and promotion is unlikely, so they exert less effort. Very young leaders are not at a critical stage yet, or may be more reform minded in 2010, placing more weight on the welfare of residents. Wang, Zhang, & Zhou find that effort to be promoted is maximized about age 50. In Table 2, remarkably, that is also the inflection point for average age of leaders in terms of a maximal f.[24]

There are other equilibrium outcomes that can be backed out of the model, such as housing prices, built area of the city, and trade flows between provinces. In the Appendix A5, graphs show that actual housing prices from China's Regional Statistic Yearbooks correlate well with model ones, as do land areas. Similarly, in Appendix A.2, we look at imports in 2012 from province v by province u for all such pairs and compare them to the model predictions. Figure A2.1 shows that the data and our model predictions correlate well, with an Rsq. of 0.68.

6. Counterfactuals

For counterfactuals, we are primarily interested in three experiments. The main one we call CF-3. There, all restrictions are relaxed: capital prices are set by the market and equalized across cities; f is set to 0 so city leaders maximize just the welfare of residents; and the city budget constraint is relaxed to allow positive or negative taxation of wage income, as well as use of land rents to finance infrastructure. Between the benchmark and CF-3, there are two interim steps. First in CF-1, we ask what happens if we just remove capital market favoritism while keeping the national total capital supply fixed, so the endogenous price of capital is equalized across cities. Then, in CF-2, we can ask what happens if, in addition to freeing capital markets, f's are set to zero so leaders seek to maximize the welfare of residents in allocating land, but still face the same current type of public budget constraint.[25] Finally we move to CF-3, where we additionally relax the public budget constraint to allow worker income taxation.[26] These steps allow neat comparisons, where we can ask hypotheticals. For example, if capital markets are already freed up, what are the additional benefits of setting f's to zero or to relaxing the public budget constraint.

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[24] By adding the (calibrated) exogenous component of consumer amenities, $\bar{Z}$, to col. (5) in Table 2, we also find that f's are not significantly correlated with consumer amenities. This is consistent with the notion that f's mainly reflect city leaders' preferences towards GDP.

[25] Note we cannot run the counterfactuals on f alone, since this would have capital markets impacts and we do not know how the politically driven prices of capital would then adjust.

[26] Note in CF-2 and CF-3 in optimization from the end of Appendix A4 we can fully relax the assumption that leaders see city population as fixed.

The detailed counterfactual solutions and methods are explained in Appendix A1 and involve resolving the model (rather than "hat-algebra").[27]

6.1 Basic results

In counterfactuals there are overall national effects given in Table 4. We note two points about these, before we detail results. First, since capital is the numeraire, once capital markets are freed up in CF-1, in all remaining counterfactuals relative to CF-1, capital income is unchanged. Welfare effects in CF-2 and CF-3 are due to changes in consumer welfare. Second, in moving from freed capital markets and f=0 in CF-2 to the final counterfactual, CF-3, where the public budget constraint is additionally relaxed, there are no effects on the allocation of population and effective labor across cities (see Appendix A1.3). Intuitively, in (17), in CF-3, the (negative) tax rate on wage income is the same across all cities, so *relative* utility levels across cities are unaffected in moving from CF-2 to CF-3. The impact of freeing up the budget constraint is to lower infrastructure expenditures and raise consumer consumption and welfare everywhere by the same fraction.

In Table 4, row 1 gives the benchmark numbers for worker welfare, capital income, infrastructure, TFP, effective labor, national output, and the measure of inequality. In row 2 is CF-1, where just capital prices are equalized across cities while the national total capital supply is fixed unchanged. In this, f's are taken as given and infrastructure is still financed out of land rents. Capital markets clear such that every city faces a capital price of 1, the numeraire and baseline price in Guangzhou. That raises the price of capital in some cities and lowers it in others, so there are winners and losers. Overall, for the national economy, going to CF-1 relative to the benchmark increases the returns to capital owners by about 2.25%, as capital is efficiently reallocated. That efficient reallocation helps consumers raising overall consumer welfare by 3.0%, while also modestly raising average TFP, effective labor, national output and total infrastructure investment.

In Table 4 in row 3 for CF-2, we additionally set f's to zero, so that leaders focus only on the welfare of residents. The effects are intuitive. Cities increase the allocation of land to residential use monotonically in line with the value of initial f's, correspondingly reducing industrial land usage. Residential land prices decline, and industrial use prices rise in all cities. This lowers housing prices almost everywhere as shown below. This is the main channel in Table 4 leading to national utility gains of 4.9% relative to CF-1 and

[27] Hat-algebra involves rewriting the model so that everything is expressed as percentage changes from the baseline equilibrium. This is especially useful if we have detailed true data for the baseline equilibrium, since we can avoid potential modeling errors at the calibration stage. But unfortunately, the data on city-level migration flows and trade flows are not available. Doing hat-algebra in this case is only an alternative way to express the model and does not provide additional new insights. In fact, if we take the baseline equilibrium calibrated in Section 5 as the true data and use hat-algebra in counterfactuals, the results in counterfactuals would be exactly the same as the ones we provide in the text.

of 8.1% relative to the benchmark. Average TFP and effective labor are little changed, while output and *G* decline modestly relative to CF-1.

In row 4, in CF-3 which is the main result, we additionally relax the public budget constraint. Here there are no cities gaining or losing population relative to CF-2 since relative utilities are unaffected. As noted, every city sets its tax rate at the same optimal level, which is the same negative rate of -0.104 in eqn. (17). Allowing a portion of rents to be rebated to consumers lowers the optimizing *G* nationally by a whopping 49% relative to CF2 and to the benchmark, with modest declines in *y* and TFP nationally relative to the benchmark.[28] Welfare rises because of increased consumption of *y*, given so much less of *y* goes into *G* provision. The result is just over a 5.2% increase in consumer welfare relative to CF-2; and the overall gain in consumer welfare of moving from the benchmark through all phases to CF-3 is 13.7%. These figures are sensitive to γ, the exponent on *G* in the production function for *y*, which reflects the productivity of infrastructure. Our γ of 0.06 was picked prior to results, and based on the relevant empirical literature as noted in Table 1. Raising γ to, say, 0.10, the gain in consumer welfare from going from CF-2 to CF-3 is reduced to 1.03% and the decline in *G* to 12.8%. That noted, in setting parameters in Table 1, a γ of 0.10 for China would seem implausibly high from the literature. Moreover, to have a positive tax rate on wages would require a γ of over 0.113.[29]

The final issue concerns inequality in the last column of Table 4. These joint reforms contribute to an increase in national labor inequality, across our heterogeneous labor. Why? Some cities with low capital returns in the benchmark are in low welfare and high migration cost places to begin with. When we raise the price of capital, they lose and are trapped in even lower wage and still high migration cost places, so inequality rises nationally. Put another way, current capital subsidies in some cities forestall the wage and employment losses that would result if these heavy industry and subsidized cities had to compete on a level playing field.

6.2 Heterogeneity of impacts across cities

As noted above, relative to the benchmark, in the counterfactuals there are winning and losing cities in terms of population and welfare. In Table 5, in the first 4 rows, we show a basic 4-way comparison at different tails of pairs of *r* and *f* values. We show the results of the move from the benchmark to CF-3. In counterfactuals we expect gains to cities which start with either high *r*'s or high *f*'s, because they are rewarded with either lower prices of capital or a greater focus on consumer welfare by local leaders. The 4-way comparison and general expectations as to outcomes are as follows. (i) Cities can start with a high *r* and a high *f*. Such cities like Dongguan in going from the benchmark to CF-3 gain population and welfare for two reasons: a lower price of capital and a major switch to enhancing consumer welfare, realized by reallocating more land to residential use. (ii) Cities can start with a high *r* and low *f* like Yueyang, in which

[28] Having more income from getting a share of land rents means demand for housing and prices increase relative to CF-2, but the changes in all cities are under 2.331%.

[29] That would be even more if we think our land share parameter in y production of 0.07 is too low.

case under CF-3, they benefit from cheaper capital, but there can be some offset with the more modest change in *f*, in comparison to some competitors which started with higher *f*'s. However, in the end, Yueyang has strong gains. (iii) Cities can start with a low *r* and a low *f*, like Kunming, in which case relative to their competitors, they are likely to lose population and welfare, as they are disadvantaged with both *r* rising and *f* declining relatively modestly. (iv) Finally, cities like Beijing start with a low *r* and high *f*, so they lose from the rise in *r* but have some offset from the change in the leader's focus to consumer welfare and lowering of housing prices. Note Beijing's changes are smaller than Kunming where both start with low *r* but Beijing with a much higher *f*. Apart from the illustrated cases in the first 4 rows in Table 5, we show gains and losses for 5 other well-known cities for those who are interested including three giant provincial level cities, Shanghai, Tianjin and Chongqing, in addition to two very visible and important cities, Shenzhen and Guangzhou.

Figures 5-7 compare CF-3 to the benchmark. In Figure 5, housing prices generally fall because of the reform setting $f = 0$, so that land is allocated more to residential use. Prices fall the most in originally high-*r* and high-*f* cities with the decline in capital prices and the increase in land allocated to residential use. However even in low-*r* cities where capital costs rise, housing prices decline if *f* is large. To get the rise in house prices in the handful of cities shown in the figure requires both an initial low *r* and low *f*.

In Figures 6 and 7, we graph the changes in population and welfare of initial residents against initial *r*'s and *f*'s. Relative population and welfare changes mirror each other. We see cities starting with the lowest capital costs generally all lose population regardless of initial *f*'s; and, correspondingly, those with the highest initial capital costs all gain relative to the benchmark regardless of initial *f*. However, two sets of points are important. First, for cities with capital costs initially more modestly above 1, high-*f* cities tend to gain population relative to low-*f* ones. In Table 5, we gave specific examples. Kunming with both low *f* and low *r* loses population in going from the benchmark to CF-1 and then again in going from CF-1 to CF-3, as does Chongqing. Second, in many cases for cities with very low initial *r*'s and high *f*'s, like Beijing and Tianjin, the population losses are large in going to CF-1 (-7.7 and -11.2, respectively) as seen in Table 5, while the offset (to -5.4 and -10.1 % net) from lowering *f* is more modest. Similarly, the gain to high-*r* Shenzhen is large in going to CF-1 (12.7%), while the further enhancement (going to 15.2%) of lowering *f* is more modest.

A feature of Figures 6 and 7 is the peaks and valleys that interrupt smooth changes as we raise or lower *r* or *f*, holding the other fixed. An important take-away is that effects are heterogeneous even across cities with similar benchmark *r*'s and *f*'s, based on their province and locations, which drive migration costs and firm and consumer market access. Those in remote or high in-migration cost provinces will have smaller population responses. Note in Figure 7 on welfare almost no cities lose welfare in absolute terms in going from the benchmark to CF-3, because of the consumer gains from the rebate of land revenues. To lose, a city must start with a very low price of capital like Tianjin and Kunming.

6.3 An extension: Lowering the fixed cost of high-cost migration destinations to that of Jiangsu province

Part of our results are driven by the fact that in losing cities, it is costly in many places for residents to move out. That drives the rise in inequality we saw. Relaxing migration barriers would help the residents trapped in poor locations to leave and would lower inequality. As an example, we ask what would happen if we lowered the fixed cost to enter each province by raising the ease of access to 0.34 if the current one is below 0.34, the same as that of Jiangsu. The idea is to follow the intended national government policy of diverting migration away from attractive coastal provinces, towards middle and hinterland ones. As a counterfactual this is strained, in the sense the government can ease hukou based restrictions for migrants to these less favored places, in terms of access to housing, education, and social services. However, it cannot install strong migration networks in these locations, although it could facilitate job and house search. Nevertheless, in comparison to CF-2 or CF-3 above, there are changes

In this counterfactual, cities such as Beijing and Shanghai where this experiment does not change migration costs because their provinces have higher ease-of-access than Jiangsu should lose some population to places to which it is easier to migrate. However, the diversion from cities like Beijing and Shanghai is modest. Relative to CF-3, Beijing and Shanghai would lose population by an additional 3.1 and 2.0 percentage points. These population changes relative to Table 5 are shown in Appendix Table A6.1, for the example cities. A much more profound effect is on national inequality. Relative to CF-3 in Table 4, the inequality measure falls by about 50%, from 0.0165 to 0.00793, given the lowered cost of migration and ability to move to better jobs. Note we do not compare national welfare since it rises due to the mechanical effect of lowered utility loss from lowering migration barriers and costs.

7. Conclusions

China has experienced enormous economic growth over the last four decades, driven by reforms in output markets. However, reforms in factor markets have lagged. The ability of China to sustain growth in the future may depend crucially on factor markets reforms. This problem was clearly acknowledged in a policy directive issued in 2020 by China's Central Government and Central Committee of the Communist Party, which called for new reforms to improve "factor market allocation mechanisms" in capital, labor and land markets[30]. While the current literature has studied factor misallocations in China from various perspectives, the focus has been on capital market and migration friction issues. Here we focus more on land market and fiscal reforms, and reforms in the priorities of city leaders as to how much to focus on GDP enhancement versus enhancement of local consumer welfare. Our paper quantifies these differences between cities in priorities and studies reforms in local governance, land markets and public budgeting in a spatial general equilibrium framework, while at the same time incorporating the effects of correcting capital market misallocations across cities, to evaluate the net gains to be made by key reforms.

Key to understanding the issues is China's characteristic political centralization and fiscal decentralization system. The model structure conforms to China's institutional background and our empirical work utilizes large up-to-date datasets on all three factor markets covering 266 prefectures in China. We do calibration

[30] See the policy directive here: http://www.gov.cn/zhengce/2020-04/09/content_5500622.htm

and counterfactual analyses. One counterfactual reforms capital market, so that all cities compete on a level playing field, eliminating favoritism of certain types of cities and firms. A second counterfactual adds a local land market reform by changing priorities of local leaders, so industrial land allocations are not favored over residential ones, and a third adds relaxation on the local budgeting process. Currently, local leaders in striving for promotion are encouraged to enhance GDP by competing for footloose firms. The levers they hold are cheap industrial land and excessive public infrastructure investments. A reform policy which levelled the playing field in capital markets, reallocated land towards residential use, and allowed for (positive or negative) wage taxation as well as use of land rents in financing infrastructure would increase aggregate welfare by 13.7% and raise returns to capital by 2.25%. Reforms would lower the population of the biggest cities like Beijing and Tianjin while other cities like Shenzhen and Dongguan would gain population. And it would lower housing prices everywhere, in a context where rising housing prices in China are a critical political and social issue.

Labor market reforms which would lower migration barriers are trickier, because we think a key part of migration costs are destination based migrant networks which arise from sustained migration. Still, policies raising or lowering 'doorsills', or eroding or improving migrant quality of life matter. Lowering doorsills would help people leave low productivity places to go to higher productivity ones or cities with higher quality of life and lower living cost. Then as the extent of migration cost declines rise, cities start to gain population. However, the main impact of this reform is to lower inequality, since people can leave low wage places to go to high wage ones at a lower cost.

References

Adamopoulos, Brandt, L., Leight, L., and Restuccia, D. (2017). Misallocation, selection, and productivity: A quantitative analysis with panel data from China. National Bureau of Economic Research WP 23039.

Ades, A. F., & Glaeser, E. L. (1995). Trade and Circuses: Explaining Urban Giants. *The Quarterly Journal of Economics*, *110*(1), 195–227.

Alder, S. (2019). Chinese Roads in India: The Effect of Transport Infrastructure on Economic Development. *SSRN Electronic Journal*.

Allen, T., & Arkolakis, C. (2014). Trade and the topography of the spatial economy. *Quarterly Journal of Economics*, *129*(3), 1085–1139.

Ansar, A., Flyvbjerg, B., Budzier, A., & Lunn, D. (2016). Does infrastructure investment lead to economic growth or economic fragility? Evidence from China. *Oxford Review of Economic Policy, 32*(3), 360-390.

Au, C. C., & Henderson, J. V. (2006a). Are Chinese cities too small?. *The Review of Economic Studies*, 73(3), 549-576.

Au, C. C., & Henderson, J. V. (2006b). How migration restrictions limit agglomeration and productivity in China. *Journal of Development Economics*, *80*(2), 350–388.

Bai, C. E., & Qian, Z. (2010). The factor income distribution in China: 1978-2007. *China Economic Review*, *21*(4), 650–670.

Bai, C.E., Hsieh, C.T., and Song, Z. (2016). The Long Shadow of China's Fiscal Expansion. Brookings Papers on Economic Activity, 129-165.

Bahl, R. (2003) *Restructuring of local government finances in developing countries*. Edward Elgar.

Balboni, C. A. (2019). *In harm's way? infrastructure investments and the persistence of coastal cities* (Doctoral dissertation, The London School of Economics and Political Science (LSE)).

Baum-Snow, N., Henderson, J. V., Turner, M. A., Zhang, Q., & Brandt, L. (2020). Does investment in national highways help or hurt hinterland city growth? *Journal of Urban Economics*, *115*, 103124.

Brandt, L., Tombe, T., & Zhu, X. (2013). Factor market distortions across time, space and sectors in China. *Review of Economic Dynamics*, *16*(1), 39–58.

Bryan, G., & Morten, M. (2019). The aggregate productivity effects of internal migration: Evidence from Indonesia. *Journal of Political Economy*, *127*(5), 2229–2268.

Cai, F. (2006). Floating Population: Urbanization with Chinese Characteristics. *Chinese Academy of Social Sciences, Beijing*.

Cai, H., Henderson, J. V., & Zhang, Q.H. (2013). China's land market auctions: evidence of corruption? *The Rand Journal of Economics*, 44(3), 488-521.

Cao, G., Feng, C., & Tao, R. (2008). Local “land finance” in China’s Urban expansion: Challenges and solutions. *China and World Economy*, *16*(2), 19–30.

Cao, Y., J. Chen and Zhang, Q.H. (2018). Housing Investment in Urban China: Evidence from China’s Urban Household Survey Data, *Journal of Comparative Economics*, 46(1), 212-247.

Castells-Quintana, D. (2017). Malthus living in a slum: Urban concentration, infrastructure and economic growth. *Journal of Urban Economics*, *98*, 158–173.

Chan, K. W. (2010). The household registration system and migrant labor in China: Notes on a debate. *Population and Development Review*, *36*(2), 357–364.

Chen, Y., Henderson, J. V., & Cai, W. (2017). Political favoritism in China’s capital markets and its effect on city sizes. *Journal of Urban Economics*, *98*, 69–87.

Chen, Y., Li, H., & Zhou, L. A. (2005). Relative performance evaluation and the turnover of provincial leaders in China. *Economics Letters*, *88*(3), 421–425.

Combes, P-P, Duranton, G., and Gobillon, L. (2019). The costs of agglomeration: House and land prices in French cities, *Review of Economic Studies*, 86, 1556-1589

Davis, J. C., & Henderson, J. V. (2003). Evidence on the political economy of the urbanization process. *Journal of Urban Economics*, *53*(1), 98–125.

De la Roca, J., & Puga, D. (2017). Learning by working in big cities. *Review of Economic Studies*, *84*(1), 106–142.

Deng, Y., Tang, Y., Wang, P., & Wu, J. (2020). Spatial Misallocation in Chinese Housing and Land Markets. National Bureau of Economic Research WP 27230.

Ding, C. (2003). Land policy reform in China: Assessment and prospects. *Land Use Policy*, *20*(2), 109–120.

Dollar, D., & Wei, S.-J. (2007). Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China. *IMF Working Papers*, *07*(9), 1.

Donaldson, D., & Hornbeck, R. (2016). Railroads and American economic growth: A "market access" approach. *Quarterly Journal of Economics*, *131*(2), 799–858.

Duranton, G., & Storper, M. (2008). Rising trade costs? Agglomeration and trade with endogenous transaction costs. *Canadian Journal of Economics*, *41*(1), 292–319.

Eaton, J., & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741-1779.

Feng, Y., Li, G., & Nie, H. (2018). Regulating the Transition of Local Government Debts. *China's Pengpai News, 2020.8.10*. https://www.thepaper.cn/newsDetail_forward_8658042.

Fischel W. (1999) Does the American way of zoning cause the suburbs of metropolitan areas to be too spread out? in *Governance and Opportunity in Metropolitan America*. A. Altshuler, W. Morrill, H. Wolman, & F. Mitchell (eds.). Transport Research Board and National Research.

Gao, H. (2013). Factor market distortion in China's manufacturing industry. *University of Leuven*.

Glaeser. E. (2013). Urban Public Finance (Ch. 4) in *Handbook of Public Economics, Vol. 5*. A. Auerbach, R. Chetty, M. Feldstein, and E. Saez (eds). Elsevier

Glaeser, E.L., Gyourko J. & Saks R.E. (2005). Why have housing prices gone up? *Papers and Proceeding of the American Economic Association*. 329-333

Henderson, J. V., & Kuncoro, A. (1996). Industrial centralization in Indonesia. *World Bank Economic Review*, *10*(3), 513–540.

Henderson, J. V. (2003). The urbanization process and economic growth: The so-what question. *Journal of Economic Growth*, *8*(1), 47–71.

Henderson, J. V., Su, D., Zhang, Q.H., & Zheng, S. (2020). The Costs of Political Manipulation of Factor Markets in China. MIT Center for Real Estate Research Paper No.6. Available at SSRN: https://ssrn.com/abstract=3726863 or http://dx.doi.org/10.2139/ssrn. 3726863.

Howson, N. (2009). China's Restructured Commercial Banks: Nomenklatura Accountability Serving Corporate Governance Reform?. *China's Emerging Financial Markets: Challenges and Global Impact*, *123*.

Hsieh, C. T., & Klenow, P. J. (2007). Relative prices and relative prosperity. *American Economic Review*, *97*(3), 562–585.

Jefferson, G. H., & Singh, I. (1999). *Enterprise reform in China: Ownership, transition, and performance*. Oxford University Press.

Kahn, M. E., Sun, W., Wu, J., & Zheng, S. (2021). Do political connections help or hinder urban economic growth? Evidence from 1,400 industrial parks in China. *Journal of Urban Economics*, 121, 103289.

Kennan, J., & Walker, J. R. (2013). Modeling individual migration decisions. In *International handbook on the economics of migration*. Edward Elgar Publishing.

Kwong, J. (2004). Educating migrant children: Negotiations between the state and civil society. *The China Quarterly*, 1073-1088.

Li, H., & Zhou, L. A. (2005). Political turnover and economic performance: The incentive role of personnel control in China. *Journal of Public Economics*, *89*(9–10), 1743–1762.

Lin, G. C. S. (2007). Reproducing spaces of Chinese urbanisation: New city-based and land-centred urban transformation. *Urban Studies*, *44*(9), 1827–1855.

Liu, H. Zheng, S, & Xu, X. (2003) Discussing the housing service component in GDP calculation. *Statistical Research* (8): 24-27 (in Chinese)

Liu, Q. (2007). Analysis of Credit Concentration in China's Commercial Banks (Zhong Guo Shang Ye Yin Hang Xin Dai Ji Zhong Wen Ti Fen Xi). *Hainan Finance (Hai Nan Jin Rong)*, Vol. 1.

Lin Y. (2018). The Long Shadow of Industrial Pollution: Environmental Amenities and the Location of Service Jobs. LSE processed

Lipton, M. (1977). *Why poor people stay poor: a study of urban bias in world development*. Temple Smith; Australian National University Press.

Logan, J. R., & Molotch, H. L. (2007). *Urban fortunes: The political economy of place*. University of California Press.

Melo, P. C., Graham, D. J., & Brage-Ardao, R. (2013). The productivity of transport infrastructure investment: A meta-analysis of empirical evidence. *Regional Science and Urban Economics*, 43(5), 695-706.

McDonald J.F. & McMillan D.P. (2011). Economics of Zoning (Ch. 19) in *Oxford Handbook of Urban Economics and Planning*. N. Brooks, K. Donaghy and G-J Knapp (eds.) Oxford University Press.

Molotch, H. (1976). The City as a Growth Machine: Toward a Political Economy of Place. *American Journal of Sociology*, *82*(2), 309–332.

Moomaw, R. L., & Shatter, A. M. (1996). Urbanization and economic development: A bias toward large cities? *Journal of Urban Economics*, *40*(1), 13–37.

Nan, X. G., & Meng, W. D. (2009). A Comparative Study on Approval Corruption and Disbursement Corruption in Credit Financing (Xin Dai Rong Zi Zhong Shen Pi Fu Bai He Zheng Fu Fu Bai Bi Jiao Yan Jiu). *East China Economic Management* (*Hua Dong Jing Ji Guan Li*), 23:127-130.

Peterson, C., & Park, N. (2006). Character strengths in organizations. *Journal of Organizational Behavior*, *27*(8), 1149–1154.

Qian, Y., & Xu, C. (1993). Why China's economic reforms differ: the M‐form hierarchy and entry/expansion of the non-state sector. *Economics of Transition*, *1*(2), 135–170.

Rauch, James E. (1993). "Does History Matter Only When It Matters Little? The Case of City-Industry Location." *The Quarterly Journal of Economics.* 108(3): 843–867.

Redding, S. J. (2016). Goods trade, factor mobility and welfare. *Journal of International Economics*, *101*, 148–167.

Renaud, B. (1981). National urbanization policy in developing countries. Oxford University Press.

Rosenthal, S. S., & Strange, W. C. (2004). Chapter 49 Evidence on the nature and sources of agglomeration economies. In *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2119–2171).

Shen, C., Jin, J., & Zou, H. F. (2012). Fiscal decentralization in China: History, Impact, Challenges and Next Steps. In *Annals of Economics and Finance* (Vol. 13, Issue 1, pp. 1–51).

Shertzer, A., Twinam,T. & Walsh R.T. (2018). Zoning and the economic geography of cities." *Journal of Urban Economics*. 105, 20-392.

Solé-Ollé, A., & Viladecans-Marsal, E. (2012). Lobbying, political competition, and local land supply: Recent evidence from Spain. *Journal of Public Economics*, *96*(1–2), 10–19.

Song, Z., & Wu, G. (2013). *A structural estimation on capital market distortions in Chinese manufacturing* (No. 1306). Nanyang Technological University, School of Social Sciences, Economic Growth Centre.

Su, F., Tao, R., Xi, L., & Li, M. (2012). Local Officials' Incentives and China's Economic Growth: Tournament Thesis Reexamined and Alternative Explanatory Framework. *China and World Economy*, *20*(4), 1–18.

Tan, Y., Wang, Z., & Zhang, Q. (2020). Land-use regulation and the intensive margin of housing supply. *Journal of Urban Economics*, *115*.

Tao, R., Su, F., Liu, M., & Cao, G. (2010). Land leasing and local public finance in China's regional development: Evidence from prefecture-level cities. *Urban Studies*, *47*(10), 2217–2236.

Tian, W., Wang, Z., & Zhang, Q.H. (2022). Transaction Mechanism and Industrial Land Allocation Efficiency in China: Evidence from the 2007 Auction Reform. Peking University Guanghua School of Management Working Paper. Available at SSRN: https://ssrn.com/abstract=4016228 or http://dx.doi.org/10.2139/ssrn.4016228.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of political economy*, *64*(5), 416-424.

Tombe, T., & Zhu, X. (2019). Trade, migration, and productivity: A quantitative analysis of China. *American Economic Review*, *109*(5), 1843–1872.

Tsui, K. Y. (2011). China's infrastructure investment boom and local debt crisis. *Eurasian Geography and Economics*, 52(5), 686-711.

Valentinyi, Á., & Herrendorf, B. (2008). Measuring factor income shares at the sectoral level. *Review of Economic Dynamics*, *11*(4), 820–835.

Wang, Z., Zhang, Q.H., & Zhou, L. A. (2020). Career Incentives of City Leaders and Urban Spatial Expansion in China. *Review of Economics and Statistics*, 102, 897-911.

Wang, Z., & Zhang, Q.H. (2022). Build up a metropolis: the spatial development of Shanghai? Peking University Guanghua School of Management Working Paper.

Wang,Z., G.L. Wu, and Q. Feng (2019). Productivity of Core Infrastructure Investment in China: An Input-Output Approach. Working paper. https://www.ntu.edu.sg/home/qfeng/WangWuFeng_20190118.pdf

Wong, C. P., & Bhattasali, D. (2003). *China-National development and sub-national finance: a review of provincial expenditures* (No. 39943, pp. 1-260). The World Bank.

World Bank Group & DRC of the State Council of P.R. China. (2019). *Innovative China: New Drivers of Growth.* Washington DC: World Bank.

Wu, J., Deng, Y., Huang, J., Morck, R., & Yeung, B. (2014). Incentives and Outcomes: China's Environmental Policy. *Capitalism and Society*, *9*(1).

Xu, C. (2011). The fundamental institutions of China's reforms and development. *Journal of Economic Literature*, *49*(4), 1076–1151.

Zhang, J. (2011). Interjurisdictional competition for FDI: The case of China's "development zone fever". *Regional Science and Urban Economics*, *41*(2), 145-159.

Zhang, X. (2006). Fiscal decentralization and political centralization in China: Implications for growth and inequality. *Journal of Comparative Economics*, 34(4), 713-726.

Zheng, S., Long, F., Fan, C. C., & Gu, Y. (2009). Urban villages in China: A 2008 survey of migrant settlements in Beijing. *Eurasian Geography and Economics*, 50(4), 425-446.

Zheng, S., Kahn, M. E., Sun, W., & Luo, D. (2014). Incentives for China's urban mayors to mitigate pollution externalities: The role of the central government and public environmentalism. *Regional Science and Urban Economics*, *47*(1), 61–71.

Zheng, S., Sun, W., Wu, J., & Kahn, M. E. (2017). The birth of edge cities in China: Measuring the effects of industrial parks policy. *Journal of Urban Economics*, 100, 80-103.

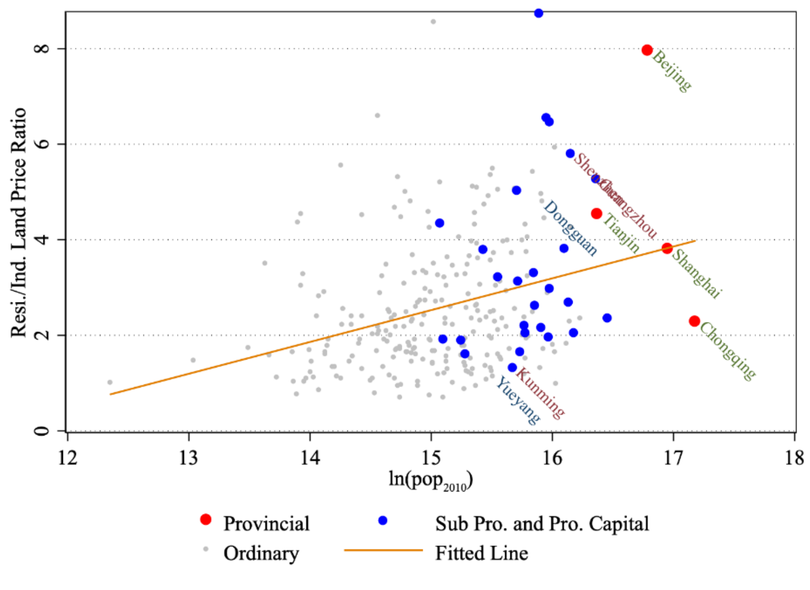
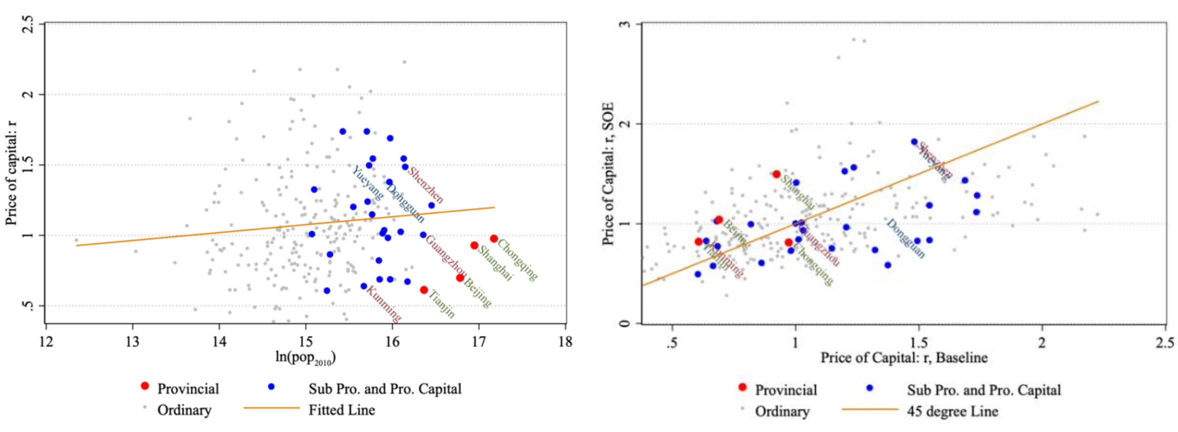


Figure 1. Residential versus industrial land prices

The graph shows the ratio of hedonic residential land prices to those for industrial land, The x-axis is the log of prefecture population in 2010.



a. Initial price of capital (private firms) **b. Price of capital: SOE's vs private firms**

Figure 2. Capital market prices

Part a shows the price of capital normalized to 1 for Guangzhou against the log of population in 2010. Part b shows the strong correlation between prices of capital facing private firms (x-axis) vs SOE's (y-axis).

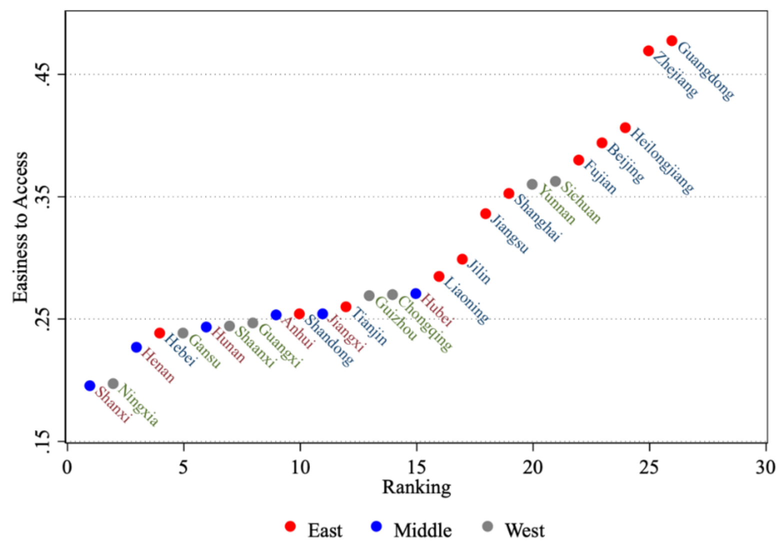


Figure 3. Fixed costs of migration

Notes: The figure shows the fixed cost of migration as the reverse: ease of migration (income left over after migration), against provinces ranked by ease of migration

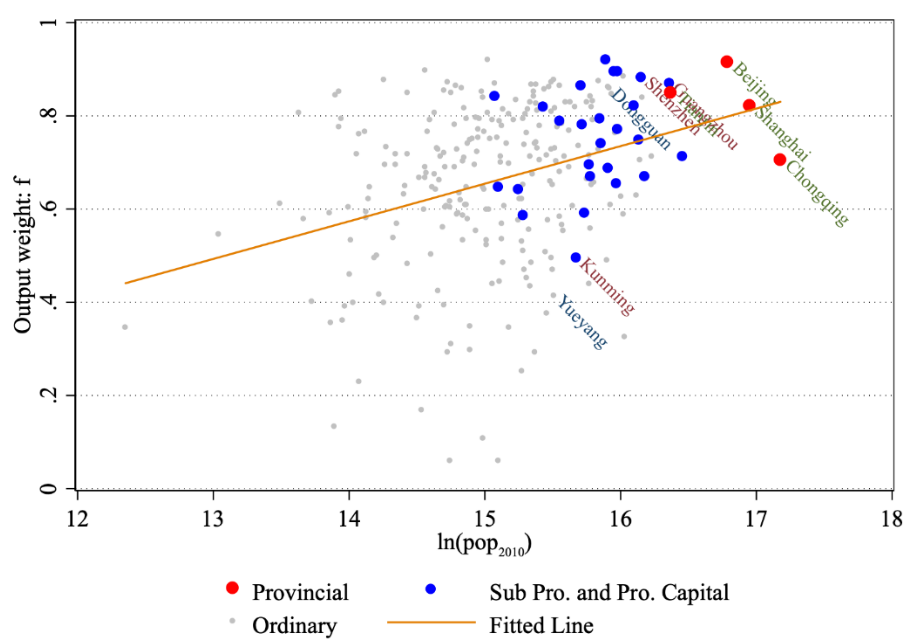


Figure 4. The calibrated values of the leaders' weight on GDP, *f*

Notes: The figure plots the inferred vales of *f*, the weight on GDP in city-leader preferences, against log population in 2010.

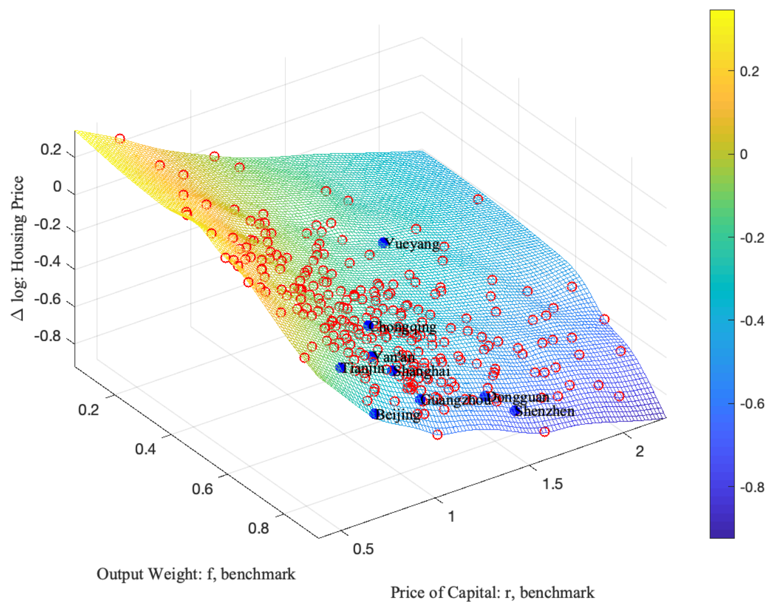


Figure 5. A 3-D representation of housing price changes

Notes: The two "x"-axes are for the benchmark price of capital and *f*. The vertical axis is the change in housing prices of CF-3 relative to the benchmark

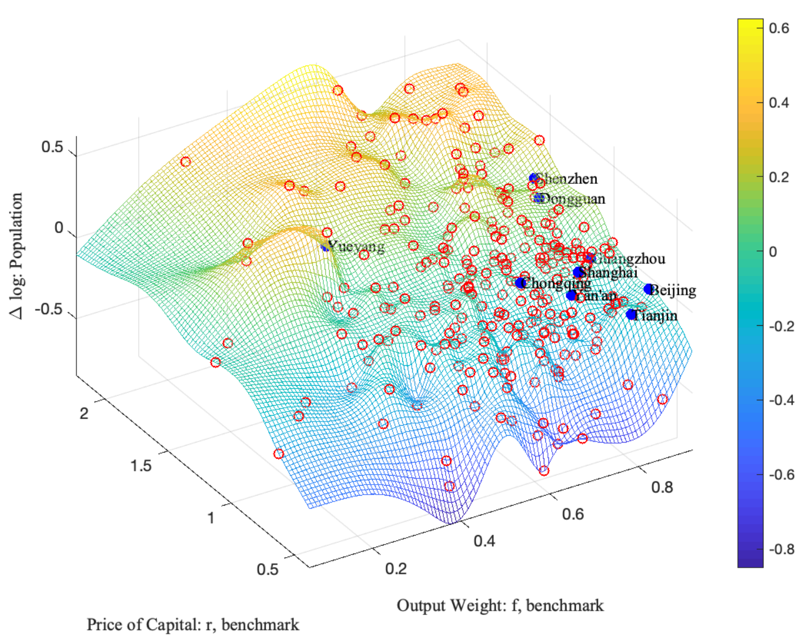


Figure 6. The 3-D representation of population changes

Notes: The two "x"-axes are for the benchmark price of capital and *f*. The vertical axis is the percent change in in the population of CF-3, relative to the benchmark.

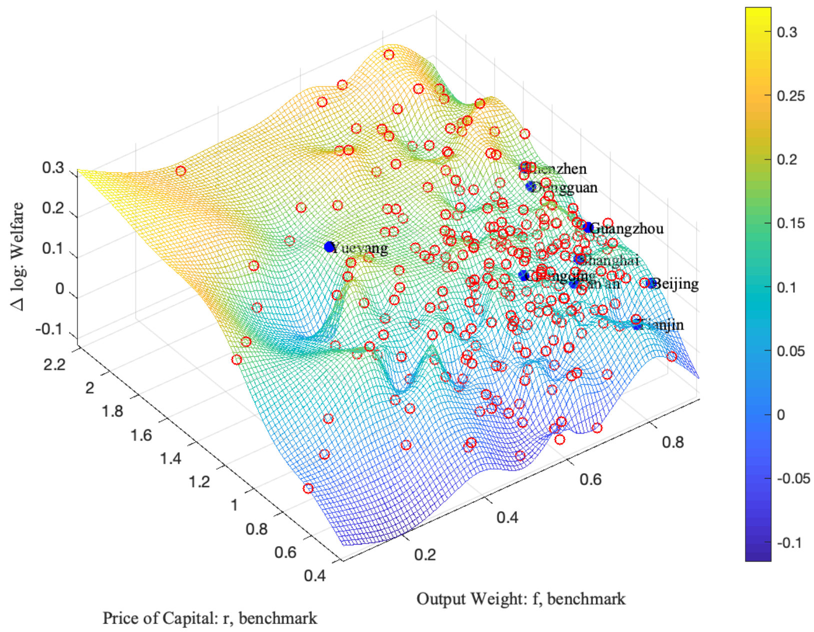


Figure 7. The 3-D representation of consumer welfare changes

Notes: The two "x"-axes are for the benchmark price of capital and *f*. The vertical axis is the percent change in the consumer welfare of CF-3, relative to the benchmark.

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Table 1: Parameters

Name	**Value**	**Notes**	**Source**
β	0.26	Housing spending share	Cao, Chen, & Zhang (2018)
ρ	0.7	Capital share, housing	Tan, Wang, & Zhang (2020)
α_L	0.55	Labor share, Y	Bai & Qian (2010)
α_X	0.07	Land share, Y	Valentinyi & Herrendorf (2008). We increase their USA share of 0.05 to reflect China's greater capital plus land share in production.
α_K	0.38	Capital share, Y	Back out from $\alpha_L + \alpha_K + \alpha_X = 1$
γ	0.06	Government investment productivity	Melo, Graham, & Brage-Ardao (2013) meta study. 0.06 is the mean over all studies and countries. Non-US countries and long run studies tend to average slightly higher γ's. On the other hand, Wang, Wu, & Feng (2019) estimate 0.031 and 0.046 for China for transport and utilities infrastructure respectively.
ϵ	0.04	Agglomeration economies	Rosenthal & Strange (2004); also de la Roca & Puga (2017).
θ, θ_t	4.0	Dispersion parameters, Frechet	θ is based on Bryan & Morten (2018), although higher than their 3.2. θ_t is from Tombe and Zhu, 2019)
ω	4×10^{-8}	Congestion cost parameter	Combes, Duranton & Gobillon (2019) and Wang & Zhang (2022)

Table 2. Regressions for calibrated parameters

VARIABLES	LnA'	Lnc	LnG	f	f
Share of adults (age 19-55) with high school education 2000	4.953*** (0.898)	-1.599*** (0.243)	9.995*** (1.155)	-0.0560 (0.397)	0.0577 (0.413)
Avg. winter temperature, (2014) (www.meteomanz.com)	0.00232 (0.00258)				
Ln distance to nearest of the 9 major seaports	-0.0178 (0.0175)	0.0120** (0.00525)	0.0964*** (0.0261)	-0.0268*** (0.00895)	-0.0288*** (0.00927)
Share employment in manufacturing, 2000	0.787*** (0.201)	-0.337*** (0.0588)	2.281*** (0.270)	0.188** (0.0926)	0.165* (0.0954)
Provincial or sub-prov capital	0.232*** (0.0765)	0.0820*** (0.0227)	0.419*** (0.114)	0.0233 (0.0391)	0.0345 (0.0396)
Ln population 2000 Census	0.215*** (0.0406)	-0.196*** (0.0122)	1.081*** (0.0527)	0.0485*** (0.0181)	0.0528*** (0.0186)
Ln Total FDI, 1996	0.0351** (0.0152)	0.0160*** (0.00454)			
Avg Age of party secretary [PS] (2000-2010)					0.137* (0.0809)
Ave Age of PS Squared					-0.00137* (0.000811)
$ln\bar{Z}$					
Observations Adjusted R-squared	213 0.625	213 0.839	265 0.842	265 0.164	265 0.167

Table 3 Correlations with producer public goods

	(1) No controls		(2) Controlling for $\ln(pop_{2010})$	
	Ln Ave. Inv	Ln cG	Ln Ave. Inv	Ln cG
Ln cG	0.766	1	0.654	1
Ln land revenue	0.769	0.83	0.653	0.684

Table 4. Base results on all counterfactuals relative to benchmark

	Social welfare Eqn. (21) (1)	Total capital income (1000's) (2)	Total G (3)	TFP* (4)	Total effective labor. Eqn. (17) (5)	National sum of y (actual production) (6)	Inequality Eqn. (23) (7)
Benchmark, equilibrium	1.623	199	44191	0.0262	3.460e+09	391421	0.00684
Counterfactual [CF]1: Equalize r	1.672	204	46268	0.0265	3.470e+09	409811	0.0109
CF 2: Equal r & f=0.	1.754	204	44814	0.0265	3.470e+09	396931	0.0112
CF 3: Equal r & f=0 & relaxed public budget.	1.846	204	22676	0.0254	3.470e+09	377932	0.0112

* $TFP_{agg} = \sum_i \frac{y_i}{\sum_{j \in N} y_j} A_i' G_i^{\gamma} L_i^{\epsilon}$, where y_i is the total amount of the intermediate goods produced in city i.

Table 5: Population and welfare changes for sample cities

City	**Type**	**Initial *r***	**Initial *f***	**Pop change, CF-1 vs. Benchmark**	**Pop Change, CF-2 or CF-3 vs. Benchmark**	**Welfare change, CF-1 vs. Benchmark**	**Welfare change, CF-3 vs. Benchmark (Subtract 5.13% everywhere for CF-2)**
Beijing	High-*f*, Low-*r*	0.694	0.914	-7.73%	-5.39%	-2.37%	3.30%
Dongguan	High-*f* High-*r*	1.366	0.857	10.4%	12.3%	5.10%	10.3%
Kunming	Low-*f* Low-*r*	0.639	0.494	-16.0%	-17.6%	-7.02%	-3.06%
Yueyang	Low-*f* High-*r*	1.490	0.413	14.0%	12.1%	8.35%	12.4%
Tianjin		0.609	0.849	-11.2%	-10.1%	-6.89%	-1.39%
Shanghai		0.927	0.820	-2.23%	-1.82%	1.57%	6.75%
Chongqing		0.975	0.701	-1.72%	-1.90%	2.24%	6.81%
Guangzhou		1	0.870	-4.21%	-2.19%	5.01%	10.2%
Shenzhen		1.484	0.882	12.7%	15.2%	5.14%	10.4%

On-Line Appendices

Appendix A1. Calibration and counterfactual outlines

In this appendix section, we present the strategy for the calibration of our model. We also provide the outlines for how to solve the model numerically in our counterfactual analyses.

A1.1 Calibration outlines

Given the data on $\{\tilde{L}_i, \tilde{L}'_i, Y_i, r_i, P_{X^I i}, P_{X^R i}\}$, the trade cost $\{d_{ni}\}$, the migration cost $\{g_{ni}\}$, and the parameters $\{\beta, \rho, \alpha_L, \alpha_X, \alpha_K, \gamma, \epsilon, \theta, \theta_t, \omega\}$ in Table 1, we can solve the model to back out other model parameters from the equilibrium. The city-specific parameters include $A'_i, f_i, \bar{Z}_i$ and the city land stock $\bar{X}_i$, while the economy-wide parameter is the aggregate capital stock $\bar{K}_{agg}$. We can also recover the equilibrium quantities of endogenous variables in model units: $G_i, X_{Ii,} X_{Ri,} K_{Ii,} K_{Ri}$. More specifically, the calibration procedure can be summarized as follows:

Step 1: Solve for $\{Z_i V_i\}_{i \in N}$ from (10); use the corresponding migration shares M_{ni}; use (12) to pin down the allocation of the effective labor L_i.

Step 2: Solve for the favoritism parameter f_i from (16a), and solve for s_i from (15)

Step 3: Solve for $\{c_i\}$ from (7a).

Step 4: Solve for $\{A'_i\}$, $\{A_i\}$ and $\{G_i\}$ from the following three conditions (see footnote 10, noting $Y = \frac{wL}{\alpha_L}$).

$$Y_i = \frac{w_i L_i}{\alpha_L} = \alpha_L^{\frac{1}{\alpha_L}-1} c_i^{\frac{1}{\alpha_L}} A_i^{\frac{1}{\alpha_L}} L_i^{\frac{\epsilon+\alpha_L}{\alpha_L}} \left(\frac{1}{P_{X^I i}} \frac{\alpha_X}{\alpha_L}\right)^{\frac{\alpha_X}{\alpha_L}} \left(\frac{1}{r_i} \frac{\alpha_K}{\alpha_L}\right)^{\frac{\alpha_K}{\alpha_L}},$$

$$Y_i = [\alpha_X + (1-\rho)\beta(1-\tau_i)\alpha_L + \tau_i \alpha_L]^{\frac{\gamma}{\alpha_L-\gamma}} \left[\left(\frac{\alpha_X}{P_{X^I i}}\right)^{\frac{\alpha_X}{\alpha_L}} \left(\frac{\alpha_K}{r_i}\right)^{\frac{\alpha_K}{\alpha_L}} \left(c_i^{\frac{1}{\alpha_L}} A_i'^{\frac{1}{\alpha_L}} L_i^{\frac{\epsilon+\alpha_L}{\alpha_L}}\right)\right]^{\frac{\alpha_L}{\alpha_L-\gamma}} \cdot c_i^{-\frac{\gamma}{\alpha_L-\gamma}},$$

$$A_i = A'_i G_i^{\gamma}.$$

Step 5: Solve for $\{X_{Ii,} X_{Ri,} K_{Ii,} K_{Ri}\}$ from equations in footnote 10. This also gives $\{\bar{X}_i\}$ and $\bar{K}_{agg}$ by recalling their definitions.

Step 6: Use eqns (2), (8a), (3a) and (1) to derive $P_{hi}, CMA_i\ \ Q_i,$ and V_i .

Step 7: Derive the amenity Z_i from $Z_i = Z_i V_i / V_i$; derive the base amenity $\bar{Z}_i$ from $Z_i = \bar{Z}_i \cdot \exp(-\omega L_i)$.

Step 8: Calculate the welfare and inequality index defined in (19) and (21).

A1.2 Counterfactual outlines

To be as general as possible, we will consider alternative values/rules of the model parameters $\{f\}$, $\{r\}$, $\{g_{ni}\}$ altogether in the following such that all markets clear (including the aggregate capital market).

Notice that we can directly derive the land allocation share s_i from (15) with the new $\{f\}$. Then the land allocation $\{X_I, X_R\}$ for each city is pinned down according to $X_I = (1 - s_i)\bar{X}_i$ and $X_R = s_i \bar{X}_i$. To solve for other endogenous variables, we use the following iterative algorithm:

Step 1: Find a set of $\{Y_i, L_i, r_i\}$ such that (8a) and (13) are satisfied, and r_i's are equalized across cities. Note that in step 1, we do not require the aggregate capital market to clear. The algorithm is similar to the homotopy method.

> More specifically, suppose we have an initial guess of $\{Y_i(0), L_i(0), r_i(0)\}$, which can be the ones derived from the calibration. Let $\overline{r_i(0)}$ be the mean of $\{r_i(0)\}$, and let $r_i(n) = \frac{n}{N} \cdot \overline{r_i(0)} + \frac{N-n}{N} \cdot r_i(0)$ for a large fixed N.[31] Suppose for the (n-1)-th iteration, we already find a set of $\{Y_i(n-1), L_i(n-1), r_i(n-1)\}$ such that (7a) and (12) are satisfied. Now we consider the n-th iteration. With $r_i = r_i(n) = \frac{n}{N} \cdot \overline{r_i(0)} + \frac{N-n}{N} \cdot r_i(0)$, we plug $\{Y_i(n-1), L_i(n-1)\}$ into the right-hand sides of (7a) and (12).[32] The implied $\{Y_i, L_i\}$ can be plugged into the right-hand side of (7a) and (12) again. We can repeat this process until $\{Y_i, L_i\}$ converge. This gives a set of $\{Y_i(n), L_i(n), r_i(n)\}$ satisfying (7a) and (12). Then we can move on to the (n+1)-th iteration. When it comes to N-th iteration, we can automatically have a set of $\{Y_i, L_i, r_i\}$ satisfying (7a) and (12). And it is worth noting that $r_i(N) = \overline{r_i(0)}$ by construction.

Step 2: Find a set of $\{Y_i, L_i, r_i\}$ such that (7a) and (12) are satisfied, r_i's are equalized across cities, and the aggregate capital market clears.

[31] An appropriate choice of N can help to raise the speed of convergence without reducing the probability of convergence.

[32] The terms of $\{V_i, c_i\}$ on the right-hand sides of (7a) and (12) can be written as functions of $\{Y_i, L_i, r_i\}$. To see this, recall that in the calibration stage we show $\{V_i, c_i\}$ are functions of factor prices and L_i. Given we already pin down $\{X_I, X_R, L\}$ in the counterfactuals, we can use Y_i and the expressions for the factor income shares to eliminate the corresponding factor prices.

Start with the results of $\{Y_i, L_i, r_i\}$ derived in step 1. The capital costs $\{r_i\}$ are equalized across cities, but the implied aggregate capital demand $\sum_i K_{I,i} + \sum_i K_{R,i}$ may not be equal to the $\overline{K}_{agg}$.[33] However, if there is excess demand, we can uniformly raise $\{r_i\}$ a bit; if there is excess supply, we can uniformly reduce $\{r_i\}$ a bit. With the small adjustment in $\{r_i\}$, we can find a new set of $\{Y_i, L_i\}$ satisfying (7a) and (12) by following the similar iteration procedure detailed in step 1. With appropriate adjustments in $\{r_i\}$, we can eventually find the right level of $\{r_i\}$ such that the aggregate capital market also clears. To normalize the capital costs such that $r_i = 1$ for Guangzhou, we can rescale $\{Y_i, r_i\}$ by the same constant. Since money is neutral in the economy, the rescaled $\{Y_i, L_i, r_i\}$ still satisfy all the requirements in step 2.

Step 3: Back out all the other endogenous variables. Since we already know $\{Y_i, L_i, r_i, X_{R,i}, X_{I,i}\}$, we can derive the factor prices $\{w_i, P_{R,i}, P_{I,i}\}$ by using the factor income share expressions. Following similar procedures in the calibration outlines, the other endogenous variables can be easily pinned down using these factor prices.

A1.3 Notes on solving the model with *f*=0 and $\tau_i \neq 0$ (comparing CF-2 to CF-3)

Given when *f*=0, τ is the same in all cities in (17), we simply plug in that parametric value of τ and resolve the model as above. Here we show why labor allocations are unchanged when going from CF-2 to CF-3. Recall that the allocation of effective labor given by $L_i = \sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta}} \Gamma(1 - \frac{1}{\theta})$, where $M_{ni} = \frac{(Z_i V_i g_{ni})^{\theta}}{\sum_s (Z_s V_s g_{ns})^{\theta}}$. This suggests that if the base utility V_i changes proportionally, there will not be any changes in populations and effective labor. More specifically, we conjecture that there is no change in the allocation of effective labor L_i. We then show that introducing income tax in addition to CF2 will not change Y_i, which in turn justifies the initial conjecture.

By the definition of CF2, we already solve for the local allocation in X_{Ri} (the optimal allocation of land is independent of taxation), and we impose that the nominal interest rate r_i is the same across cities. We recall that

$$CMA_i = \kappa \sum_{i=n}^{N} (c_i d_{in})^{-\theta_t},$$

where $\kappa \equiv \left[\Gamma\left(\frac{\theta_t + 1 - \sigma}{\theta_t}\right)\right]^{\frac{-\theta_t}{1-\sigma}}$ and c_i is given by

[33] Noticing the Cobb-Douglas structures of the economy, one can write K_I and K_R as functions of $\{Y_i, L_i, r_i\}$ only.

$$c_i^{1-\gamma} = (\alpha_X + (1-\rho)\beta(1-\tau_i)\alpha_L + \tau_i\alpha_L)^{-\gamma}(A'L_i^{\epsilon})^{-1}X_{I,i}^{-\alpha_X}L_i^{-\alpha_L}\left(\frac{r_i}{\alpha_K}\right)^{\alpha_K}Y_i^{\alpha_X+\alpha_L-\gamma}. \qquad \text{(A1.1)}$$

This suggests that given the conjecture of no changes in L_i, ***relative changes in CMA_i across cities*** are purely driven by Y_i. Importantly, the relative changes in CMA_i across cities are not driven by income tax, since all cities have the same income tax in optimization.

According to the trade block, we have

$$(1-\tau_i)Y_i = \sum_n \frac{(c_i d_{in})^{-\theta_t}}{\sum_{i=n}^{N}(c_i d_{in})^{-\theta_t}}(1-\tau_n)Y_n. \qquad \text{(A1.2)}$$

Combining (A1.1) and (A1.2) suggests that there are no relative changes in Y_i across cities, given our conjecture that there are no changes in L_i.

Now we verify that there are no changes in L_i through the migration block. We notice that the base utility is given by

$$V_i = \frac{(1-\tau_i)\alpha_L Y_i}{CMA_i^{-\frac{1-\beta}{\theta_t}}\left[(1-\rho)^{\rho-1}\rho^{-\rho}\left[\frac{(1-\rho)\beta(1-\tau_i)\alpha_L Y_i}{X_{R,i}}\right]^{1-\rho} r_i^{\rho}\right]^{\beta}}/L_i.$$

Given that we have verify that there are no relative changes in Y_i and CMA_i across cities, V_i changes proportionally to income tax (more precisely, $1-\tau_i$). Recall that $L_i = \sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta})$, where $M_{\mathrm{ni}} = \frac{(Z_i V_i g_{ni})^{\theta}}{\sum_s (Z_s V_s g_{ns})^{\theta}}$. We notice that the amenity Z_i's are also unaffected by our conjecture of no changes in the effective labor L_i. Therefore, the proportional changes in V_i due to income tax do no affect the allocation of L_i, since the migration shares are not affected. This justifies our initial conjecture. Hence, the introduction of income tax only rescales c_i and V_i, and therefore does not affect Y_i and L_i.

Appendix A2. Trade costs

In trade framework, the probability that city *n* demands varieties from city *i* by offering the lowest price to city *n* is simply $\pi_{in} = \frac{(c_i d_{in})^{-\theta_t}}{\sum_{i=1}^{N}(c_i d_{in})^{-\theta_t}}$. With the continuum of goods, this probability just equals the fraction of city *n*'s total expenditure on city *i*'s good. The value of total demand for city *i*'s tradable goods is based on the share of labor income spent on tradable goods, the share of labor in output and these π_{in} fractions. The value of total demand is $\sum_n \pi_{in}(1-\beta)(1-\tau_n)\alpha_L c_n y_n = \sum_n \frac{(c_i d_{in})^{-\theta_t}}{\sum_{i=1}^{N}(c_i d_{in})^{-\theta_t}}(1-\beta)(1-\tau_n)\alpha_L c_n y_n$. On the supply side, the value of production is the value of inputs going into traded good production in city *i*. Those inputs are total intermediate good production less inputs into *G* and payments to capital owners, or $c_i y_i - c_i G_i - r_i(K_{Ii} + K_{Ri})$. Substituting for *G* from (6b) and for capital income terms from firms' profit maximization and the demand for housing, the supply of tradable goods in city *i* is $(1-\beta)(1-\tau_i)\alpha_L c_i y_i$. Equating this to the value of demand, we get

$$(1-\tau_i)Y_i = \sum_n \frac{(c_i d_{in})^{-\theta_t}}{\sum_{i=n}^{N}(c_i d_{in})^{-\theta_t}}(1-\tau_n)Y_n.$$

Finally, we note the following conventional relations based on the distribution of minimum prices faced by consumers in city *i* for the realized price index in (1) and for city's *i*'s consumer market access (Donaldson and Hornbeck, 2016):

$$Q_i = \left[\Gamma\left(\frac{\theta_t+1-\sigma}{\theta_t}\right)\right]^{\frac{1}{1-\sigma}} \cdot \left[\sum_{j=1}^{N}\left(c_j d_{ji}\right)^{-\theta_t}\right]^{-\frac{1}{\theta_t}} = CMA_i^{-1/\theta_t}.$$

If we define $\kappa \equiv \left[\Gamma\left(\frac{\theta_t+1-\sigma}{\theta_t}\right)\right]^{\frac{-\theta_t}{1-\sigma}}$ and $FMA_i = \sum_n \frac{(d_{in})^{-\theta_t}}{CMA_i}(1-\tau_n)Y_n$ and if we substitute in $c_i^{1-\gamma} = (\alpha_X + (1-\rho)\beta(1-\tau_i)\alpha_L + \tau_i\alpha_L)^{-\gamma}(A_i{}'\mathrm{L_i}^{\epsilon})^{-1}X_{I,i}^{-\alpha_X}L_i^{-\alpha_L}\left(\frac{\mathrm{r_i}}{\alpha_K}\right)^{\alpha_K}Y_i^{\alpha_X+\alpha_L-\gamma}$(using eqn. (3a) and (6b)) and expressions for w and $\mathrm{P_{X_I}}$ from firm optimality conditions), given (8a) we can rewrite (7a) as

$$\begin{aligned}Y_i = {} & (\kappa FMA_i)^{\frac{1-\gamma}{1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma)}} \cdot (1-\tau_i)^{-\frac{1-\gamma}{1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma)}} \\ & \cdot (\alpha_X + (1-\rho)\beta(1-\tau_i)\alpha_L + \tau_i\alpha_L)^{\frac{\gamma\theta_t}{1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma)}} \\ & \cdot \left((A_i{}'L_i^{\epsilon})^{-1}L_i^{-\alpha_L}(r_i/\alpha_K)^{\alpha_K}\right)^{-\frac{\theta_t}{1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma)}} \cdot X_{I,i}^{\frac{\alpha_X\theta_t}{1-\gamma+\theta_t(\alpha_X+\alpha_L-\gamma)}},\end{aligned}$$

which is an alternative form to (7b).

We take trade costs from Baum-Snow, Henderson, Turner, Zhang, & Brandt (2020) and we note some details here. They digitize a large-scale national paper map for 2010 and calculate travel times between each pair of prefecture cities over the highway network. The 2010 map describes limited access highways and two classes of smaller roads, on which we assume travel speeds of 90 kph and 25 kph respectively. This allows them to calculate pairwise travel times between any pair of prefecture cities. For any good arriving in city i from city j we must ship d_{ij} units of that variety. To calculate d_{ij}, they assume $d_{ij} = 1 + 0.004\vartheta(\text{hours of travel from i to j})^{0.8}$ This expression captures both the pecuniary and time (opportunity) cost of shipping. Hummels & Schaur (2013) estimate that each day in transit is equivalent to an ad-valorem tariff of 0.6-2.1%. Limao & Venables (2001) and that the cost of shipping one ton of freight overland for 1000 miles is about 2% of value, or about 1% per day. This expression generates the resulting target with a loss of 1.6-3.1% in value per day, while also incorporating some concavity. Because the transformation from travel time to iceberg cost is necessarily speculative, they checked the robustness of their relevant results to alternative calculations of d_{ij} based on values of ϑ between 0.5 and 2, finding similar results.

To see if what we get is plausible, based on data from Liu, Tang, & Han (2018), we calculate all pairwise import volumes from province *v* to province *u*. We include both intermediate and final goods and restrict the sample to our 26 provinces. The import share from province *v* to province *u* is then calculated as the import volume divided by the total import volume (which includes the import volume from the home province), so that the import shares of province *v* adds up to one. The Rsq of the model prediction as a function of the actual data is 0.68. The two are plotted against each other in Figure A2.1

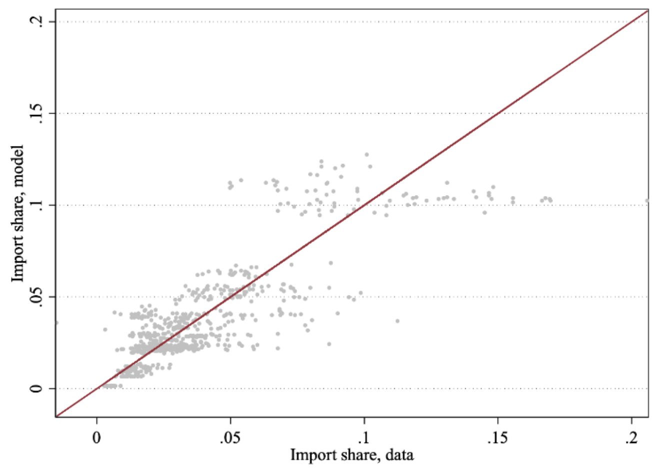


Figure A2.1 Trade flows: Data versus model

Appendix A3. Estimating migration costs

We have 2010 census data on province-to-province moves of people in the last 5 years; for the 10-year period flows we simply double this number. Tombe & Zhu (2019) use 2005 inter-census data which have sampling issues and we wanted more recent data anyway. Based on the model below, we have 24*25 province origin destination pairs to estimate the fixed and variable costs of inter-provincial moves; then we will show how we add in the prefecture-to-prefecture part. We show first how we use this province-to-province information to calculate city-city migration costs. Then we detail the set of assumptions under which our calculations are valid.

A3.1 Province to province costs

Under some suitable conditions as dsicussed in Section A3.2, the province n to province i migration share is given by $M_{ni} = \frac{\tilde{V}_i g_{ni}^{\theta}}{\sum_s \tilde{V}_s g_{ns}^{\theta}}$, where $\tilde{V}_i$ represents destination province's attractivenss and g_{ni} is the province-to-province migration cost. The migration share is aggregated from the city-level migration flow, with further details to be discussed later. For now, we take this as given.

Taking logs for M_{ni} and M_{ii} and subtracting gives $ln\left(\frac{M_{ni}}{M_{ii}}\right) = \theta\, ln(g_{ni}) - ln\left(\sum_s \tilde{V}_s g_{ns}^{\theta}\right) + ln\left(\sum_s \tilde{V}_s g_{is}^{\theta}\right)$, where, as conventional, we assume that $g_{ii} = 1$. Migration cost g_{ni} is given by $g_{ni} = t_{ni} * \tilde{t}_i$, where t_{ni}

is variable, time- distance-based part of migration costs where $t_{ni} = t_{in}$, and $\tilde{t}_i$ is a destination sunk cost, based on provincial barriers to entry. Substituting g_{ni} leads to an econometric formulation as follows,

$$ln\left(\frac{M_{ni}}{M_{ii}}\right) = \theta\, ln(t_{ni}) + \theta\, ln(\tilde{t}_i) - ln\left(\sum_s \tilde{V}_s g_{ns}^{\theta}\right) + ln\left(\sum_s \tilde{V}_s g_{is}^{\theta}\right)$$

$$= \delta \cdot dist_{ni} + I_n + J_i. \qquad \text{(A3.1)}$$

$I_n = -\,ln\left(\sum_s \tilde{V}_s g_{ns}^{\theta}\right)$ and $J_i = \theta\, ln(\tilde{t}_i) + ln\left(\sum_s \tilde{V}_s g_{is}^{\theta}\right)$ capture origin and destination fixed effects.[34]

With the estimated coefficients, by recalling $g_{ni} = t_{ni} * \tilde{t}_i$, we have

$$g_{ni} = exp\left(\frac{\delta}{\theta} \cdot dist_{ni}\right) \cdot \exp\left(\frac{I_i + J_i}{\theta}\right)$$

$$= \exp\left(\frac{\delta}{\theta} \cdot dist_{ni} + \frac{I_i + J_i}{\theta}\right). \qquad \text{(A3.2)}$$

By using data, we can estimate δ, I_i and J_i. Therefore, with assumed θ, we are able to derive the easiness-to-access g_{ni} for each migration pair (province-to-province). The distance measure is from Baum-Snow, Henderson, Turner, Zhang, & Brandt (2020), based on inferred driving times between locations over the 2010 road network, where speeds on major highways are set at 90kms/hr and on other roads at 25kms/hr. For the province-to-province times we average all the city pair distances between the two provinces.

To derive city-level migration costs, we assume it has the same structure (variable time-distance-based cost + fixed destination sunk cost) as at the province level. For variable costs, we use the distance parameter from inter-provincial moves and the relevant distances. For fixed costs, for inter-provincial moves we continue to use the associated destination province fixed costs. For the fixed cost for intra-provincial moves, Tombe & Zhu (2019) argue that in general the costs of moving the same distance across provinces is twice within province moves. For the asymmetric case here, accordingly we simple double the $\tilde{t}_i$, correspondingly lowering intra-province migration costs. This assumes that the asymmetric cost pattern for within province moves mirrors the inter-provincial cost pattern across the heterogeneous provinces. Is this warranted? To investigate with available data, we know the extent of total within province moves in the years from 1995 to 2000. Low fractions of moves would suggest high barriers to internal movement. In Figure A3.1, we plot the fraction of within province moves against our estimated $\tilde{t}_i$, indicating the ease of entering a province. There is a strong positive, arguably proportional relationship, which motivates our choice.

[34] The regression includes a constant term, where Guangdong as our base group for the dummies. This implies that the constant term is capturing the $\tilde{t}_i$ of Guangdong.

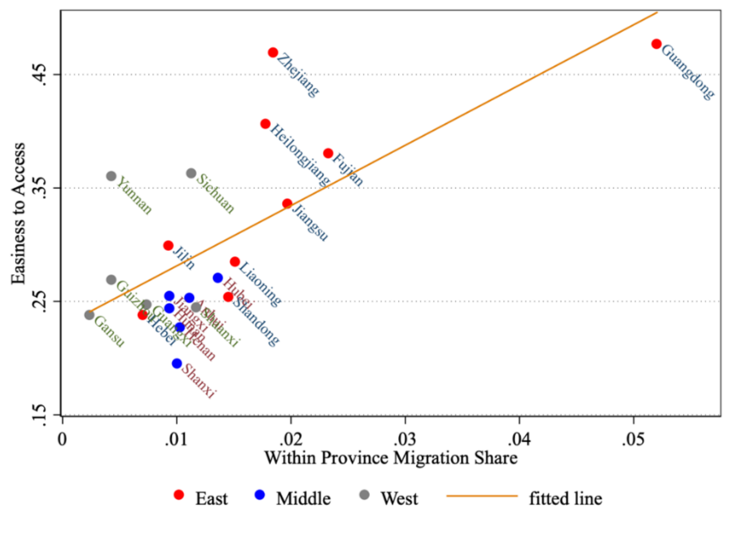


Figure A3.1. Within province flows and ease of entry

A3.2 Inferring city-to-city migration costs from province-to-province data

To see more clearly the aggregation issues in applying between province estimates to the estimation of city-to-city migration costs, we assume worker's productivity draws follow a more general form of Frechet distribution and make key assumptions. In the following, we will first show how to derive the province-to-province migration share in section (A3.1) and then we will also show that the results hold under our text assumptions.

Worker's utility is still given by $U_{ni} = Z_i a_i V_i g_{ni}$, where Z_i denotes the amenity of living in city i; V_i is the base utility of city i that depends on the effective wage rate and housing price of the city. Each worker born in city n gets a random vector of labor productivity draw $(a_1, a_2, \ldots, a_N)$ from a nested Frechet distribution with cdf

$$\Psi(a;n) = exp\left\{-\sum_{P}\left(\sum_{i\in P}\left[(a_i)^{-\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}}\right)^{1-\sigma}\right\},$$

where θ is the parameter that determines how dispersed the distribution is, while ρ and σ are productivity correlation parameters. More specifically, ρ governs productivity correlation within the same province, while σ governs productivity correlation across province. If $\rho = \sigma = 0$, the nested Frechet distribution is reduced to the i.i.d. Frechet distribution in the text.

Following Liu (2019), the migration share from city n to city i is given by

$$\mathrm{M_{n,i}} = \mathrm{M_{i|P}} \cdot \mathrm{M_{P|n}}$$

$$= \frac{(Z_i V_i g_{ni})^{\frac{\theta}{1-\rho}}}{\sum_{i\in\Omega_P}(Z_i V_i g_{ni})^{\frac{\theta}{1-\rho}}} \times \frac{\left[\sum_{i\in\Omega_P}(Z_i V_i g_{ni})^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}}}{\sum_{P\in N}\left[\sum_{i\in\Omega_P}(Z_i V_i g_{ni})^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}}},$$

where $M_{P|n}$ and $M_{i|P}$ are, respectively, the probability of workers born in city n and migrating to province P, and the probability of moving to city i conditional on moving to province P. We also use Ω_P to denote the set of cities in province P.

Since we only have migration flow data at the provincial level, we can derive the migration share at the provincial level as follows

$$M_{P'|P} = \sum_{n\in P} \omega_n M_{P'|n}$$

$$= \sum_{n\in P} \omega_n \frac{\left[\sum_{i\in\Omega_{P'}}(Z_i V_i g_{ni})^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}}}{\sum_{\tilde{P}'\in N}\left[\sum_{i\in\Omega_{\tilde{P}'}}(Z_i V_i g_{ni})^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}}},$$

where ω_n is the population weight of city n in the origin province P.

To use provincial migration flow data to estimate city-by-city migration cost, we have to make a few assumptions.

Assumption 1: *Suppose that the easiness-to-access between city n and city i is given by*

$$g_{ni} = g_{nP} \times g_{PP'} \times g_{p'i},$$

where g_{nP} is the easiness-to-access within province p, $g_{PP'}$ *is the easiness-to-access between province P and province P', $g_{P'i}$ is the easiness-to-access across cities within province P'.*

Therefore, substituting $\mathrm{g_{ni}}$ into $M_{P'|P}$ shows that it can be rewritten as

$$M_{P'|P}$$

$$= \sum_{n \in P} \omega_n \frac{\left[\sum_{i \in \Omega_{P'}} \left(Z_i V_i g_{p'i}\right)^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}} \times (g_{nP} g_{PP'})^{\frac{\theta}{1-\sigma}}}{\sum_{\tilde{P}' \in N} \left[\sum_{i \in \Omega_{\tilde{P}'}} \left(Z_i V_i g_{\tilde{p}'i}\right)^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}} \times (g_{nP} g_{P\tilde{P}'})^{\frac{\theta}{1-\sigma}}}$$

$$= \sum_{n \in P} \omega_n \frac{\tilde{V}_{P'} \times (g_{PP'})^{\frac{\theta}{1-\sigma}}}{\sum_{\tilde{P}' \in N} \tilde{V}_{\tilde{P}'} \times (g_{P\tilde{P}'})^{\frac{\theta}{1-\sigma}}}$$

$$= \frac{\tilde{V}_{P'} \times (g_{PP'})^{\frac{\theta}{1-\sigma}}}{\sum_{\tilde{P}' \in N} \tilde{V}_{\tilde{P}'} \times (g_{P\tilde{P}'})^{\frac{\theta}{1-\sigma}}},$$

where $\tilde{V}_{P'} = \left[\sum_{i \in \Omega_{P'}} \left(Z_i V_i g_{p'i}\right)^{\frac{\theta}{1-\rho}}\right]^{\frac{1-\rho}{1-\sigma}}$ is a term that only depends on destination province P'. Therefore, with $\sigma = \rho = 0$, we have shown that the province-to-province migration share is given by the one in section (A3.1) as long as Assumption 1 is satisfied.

As shown in section (A3.1), to derive the province-level migration cost estimation equation (A3.1) and (A3.2), we only need to assume the following assumption:

Assumption 2: *Suppose that the provincial level migration cost is given by*

$$g_{P^o P^d} = \tilde{t}_{p^d} \times t_{P^o P^d},$$

where $\tilde{t}_{p^d}$ is meant to capture the destination province entry cost, while $t_{P^o P^d}$ is meant to capture the symmetric distance effect.

The estimation procedure in section (A3.1) suggests that

$$t_{P^o P^d} = \exp\left[\frac{\delta}{\theta/(1-\sigma)} \cdot dist_{P^o P^d}\right],$$

$$\tilde{t}_{p^d} = \exp\left[\frac{\left(J_{P^d} + I_{P^d}\right)}{\theta/(1-\sigma)}\right],$$

where I and J are the origin and destination fixed effects in the estimation, respectively.

To derive city level migration cost, we make the following assumption:

Assumption 3: *The city-to-city migration cost has the same structure as the province-to-province migration cost, with* $g_{ni} = \tilde{t}_{ni} \cdot t_i$*. For the variable costs* $\tilde{t}_{ni}$*, the distance parameter is the same as on the province level. For fixed costs* t_i*, for inter-provincial moves we continue to use the associated destination province fixed costs, but for intra-provincial moves we assume that the destination sunk cost is lower.*

Hence, with the estimates of δ, J_{Pd}, and I_{Pd} from the provincial regression, the easiness-to-access from city n to city i is then given by

$$g_{ni} = t_{ni} \times \tilde{t}_i$$

$$g_{ni} = exp\left[\frac{\delta}{\theta/(1-\sigma)} \cdot dist_{ni}\right] \times \left[Adj^{\mathrm{I}_{within}} \cdot \exp\left[\frac{(J_{Pd} + I_{Pd})}{\theta/(1-\sigma)}\right]\right],$$

where $dist_{ni}$ is the city-to-city distance, $Adj^{\mathrm{I}_{within}}$ is an adjustment term depending on whether the moves are within-province or across province.[35] As noted above, based on Tombe & Zhu (2019) and Figure A3.1, we assume that the within province entry cost is lower by taking $Adj^{\mathrm{I}_{within}} = 2$. For inter-provincial moves, we assume the sunk cost is the same as characterized by the provincial level regression so that $Adj^{\mathrm{I}_{within}} = 1$. Figure A3.2 gives the final set of pairwise migration costs

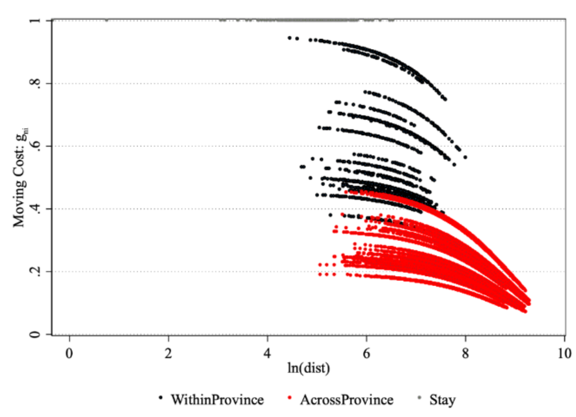


Figure A3.2 City pairwise moving costs: fraction of utility left after moving
Notes: The figure shows the total cost of city-to-city migration as the reverse: ease of migration (income left over after migration), with observations ordered by the (log of) the pair-wise distances.

[35] Here Adj denotes the size of adjustment, while I_{within} is an indicator function with $I_{within} = 1$ if the move is intra-provincial.

A4. Relaxing assumptions that city leaders treat L_i as exogenous

A city leader's optimization in eqn. (13) treats CMA_i, FMA_i, and L_i as exogenous. There are two interrelated reasons for this. First is that there are many cities, and we think, in general, city leaders have naïve or close to naïve expectations. Second, and related to what city leaders would have to calculate if fully rational, is the computation burden of a full solution with rational expectations. A solution would introduce an additional 266 first-order conditions and entail in part simultaneously solving at least 799 nonlinear equations (266 each of local labor market clearing, tradeable good clearing, and best response functions plus one aggregate capital market clearing condition). Note the need to numerically derive the best response functions of the local governments, which are in turn a function of the GE model.

Absent that, we thought of the following experiments relaxing the assumption of exogenous L_i. Suppose city leaders were to try to account for the impacts of s on L, worried about how land allocations might affect their populations, the most likely feature leaders might consider. To derive $dlnL_i/ds$ in the maximization problem in eqn. (13), they would use equation (14), given $M_{ni} = \frac{(Z_i V_i d_{ni})^{\theta_m}}{\sum_s (Z_s V_s d_{ns})^{\theta_m}}$. Under bounded rationality we assume that (a) they see the impact of influencing L on V in the numerator of M_{ni}; (b) they do not try to calculate out changes in the denominator that incorporate national full employment constraints; (c) they do not try to calculate out changes in market access CMA_i, FMA_i resulting from export prices changes. So they see $dM_{ni} = \theta_m M_{ni} dln(Z_i V_i)$. To see the impacts on the effective labor, totally differentiating (12), we get $dL_i = \Gamma\left(1 - \frac{1}{\theta_m}\right) \sum_n \tilde{L}_n \left(1 - \frac{1}{\theta_m}\right) M_{ni}^{-\frac{1}{\theta_m}} \cdot dM_{ni} = (\theta_m - 1)\Gamma\left(1 - \frac{1}{\theta_m}\right) \sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta_m}} \cdot dln(Z_i V_i)$. It follows that

$$\frac{dL_i}{ds_i} = (\theta_m - 1)\Gamma\left(1 - \frac{1}{\theta_m}\right) \sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta_m}} \cdot \frac{dln(Z_i V_i)}{ds_i}. \qquad \text{(A4.1)}$$

To pin down $\frac{dln(Z_i V_i)}{ds_i}$, we can adjust and rewrite (14) (for $\tau_i = 0$) as

$$Z_i V_i \propto (1 - s_i)^{\frac{\alpha_X(1-\beta(1-\rho))}{\frac{1-\gamma}{\theta_t} + (\alpha_X + \alpha_L - \gamma)}} L_i^{\frac{(\epsilon+\alpha_L)(1-\beta(1-\rho))}{\frac{1-\gamma}{\theta_t} + (\alpha_X + \alpha_L - \gamma)} - 1} s_i^{\beta(1-\rho)} \cdot exp\,(-\omega L_i),$$

where we have ignored some multiplicative terms perceived as constants by the local leaders.

This implies that $\frac{dln(Z_i V_i)}{ds_i} = \beta(1-\rho) \cdot \frac{1}{s_i} + \frac{\alpha_X(1-\beta(1-\rho))}{\frac{1-\gamma}{\theta_t} + (\alpha_X + \alpha_L - \gamma)} \cdot \frac{-1}{1-s_i} + \left(\frac{(\epsilon+\alpha_L)(1-\beta(1-\rho))}{\frac{1-\gamma}{\theta_t} + (\alpha_X + \alpha_L - \gamma)} - 1 - \omega L_i\right) \cdot \frac{dlnL_i}{ds_i}$.

From condition (A4.1), we have $\frac{dL_i}{ds_i} = (\theta_m - 1)\Gamma\left(1 - \frac{1}{\theta_m}\right)\left(\sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta_m}}\right) \cdot \frac{dln(Z_i V_i)}{ds_i}$ *or* $\frac{dlnL_i}{ds_i} = \frac{\Theta_m}{L_i} \cdot \frac{dln(Z_i V_i)}{ds_i}$. Thus

$$\frac{dlnL_i}{ds_i} = \frac{\Theta_m}{L_i} \cdot \frac{\beta(1-\rho)\cdot\frac{1}{s_i} + \frac{\alpha_X(1-\beta(1-\rho))}{\frac{1-\gamma}{\theta_t} + (\alpha_X + \alpha_L - \gamma)} \cdot \frac{-1}{1-s_i}}{1 - \frac{\Theta_m}{L_i} \cdot \left(\frac{(\epsilon + \alpha_L)(1-\beta(1-\rho))}{\frac{1-\gamma}{\theta_t} + (\alpha_X + \alpha_L - \gamma)} - 1 - \varpi L_i\right)} \qquad \text{(A4.2)}$$

where the constant Θ_m is defined as $\Theta_m = (\theta_m - 1)\Gamma\left(1 - \frac{1}{\theta_m}\right)\left(\sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta_m}}\right)$.

We then adjust (A4.2) considering leaders do know that the reality is a fraction of this term in A4.2. This is because they may understand that the denominator of $M_{ni} = \frac{(Z_i V_i d_{ni})^{\theta_m}}{\sum_s (Z_s V_s d_{ns})^{\theta_m}}$ will change and that population changes and hence output changes would affect prices they receive on exports and hence wages. To deal with all this, we experimented with making the magnitude of $dlnL_i/ds$ in (A4.2) a fraction of (A4.2). We tried fractions like 0.20, 0.50, and 0.65. Figure A5.1 shows our text *f*'s versus these new *f*'s for the 0.5 fraction. They are very highly correlated (0.94). However, the problem is that now we get *f*'s in excess of 1, which violates the model. The higher we set the fraction, the greater the proportion of *f*'s that exceed 1, a handful at 0.20 but 91 at 0.50. Given the close correlation, we chose in the text to go with the assumption that $dlnL_i/ds = 0$, which, except for perhaps the very largest cities, seems more reasonable.

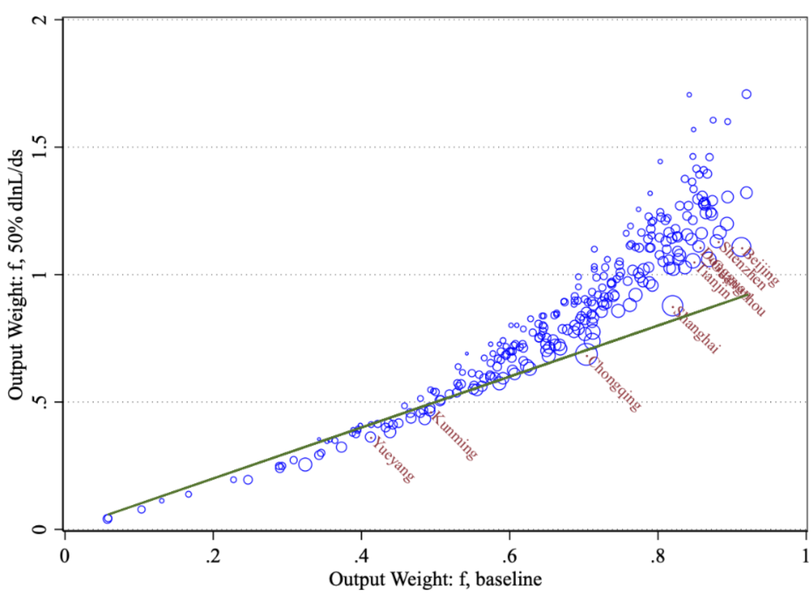


Figure A4.1 *f*'s under an alternative assumption versus the text

Implications of $dlnL_i/ds_i = 0$ and /or $dlnL_i/d\tau_i = 0$ for counterfactuals. Although the calibration of the output weights f is somewhat affected by relaxing the assumption of $dlnL_i/ds = 0$, the counterfactuals considered in CF2 where we set $\boldsymbol{f} = \mathbf{0}$ is not. To see this, we notice that the optimal policy decision of a welfare-maximizing local leader with $f = 0$ are given by the first order condition $dlnZ_iV_i/ds_i = 0$, so that the marginal benefits for local welfare are zero. Combining with condition (A4.1), we notice that the above FOC implies $dlnL_i/ds_i = 0$. Intuitively, when s_i is optimized, its marginal contribution to local welfare is zero, which in turn means no more additional population would be attracted to the city. These equilibrium results coincide with our assumption of $dlnL_i/ds_i = 0$, which is directly imposed in Section 6. It follows that the optimal supply of residential land for the welfare-maximizing leaders is still given by (15), with the results of CF2 being unaffected.

The same logic applies to CF3 where we set $\boldsymbol{f} = \mathbf{0}$ and a local leader optimizes both residential land supply and taxation. The first order conditions are $dlnZ_iV_i/ds_i = 0$ and $dlnZ_iV_i/d\tau_i = 0$. Combining with (A4.1) and a similar condition $\frac{dL_i}{d\tau_i} = (\theta_m - 1)\Gamma\left(1 - \frac{1}{\theta_m}\right)\sum_n \tilde{L}_n M_{ni}^{1-\frac{1}{\theta_m}} \cdot \frac{dln(Z_iV_i)}{d\tau_i}$, we find the above FOCs imply $dlnL_i/ds_i = dlnL_i/d\tau_i = 0$. Intuitively, when s_i or τ_i are optimized, their marginal contributions to local welfare are zero, which in turn means no more additional population would be attracted to the city. These equilibrium results coincide with our assumptions of $dlnL_i/ds_i = dlnL_i/d\tau_i = 0$ in Section 6. It follows that the optimal supply of residential land and the optimal taxation for the welfare-maximizing leaders are still given by (15) and (17), with the results of CF3 also being unaffected.

Appendix A5: Additional calibration checks

This section shows additional model inferred outcomes versus actual data. We start with land area. Figure A5.1 shows the correlation between model inferred total land ($\bar{X}_i$) and total built upon area of the prefecture for 2010. Figure A5.2 shows the correlation between model housing prices and data on housing prices.

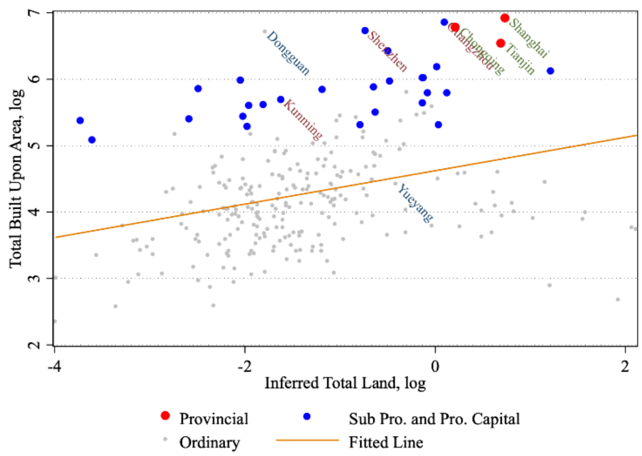


Figure A5.1 Built areas

Notes: On the x-axis is the model inferred values of total land, $\bar{X}_i$. On the y-axis is total built area of the prefecture in 2010 from the China Urban Construction Statistical Yearbook 2010**.**

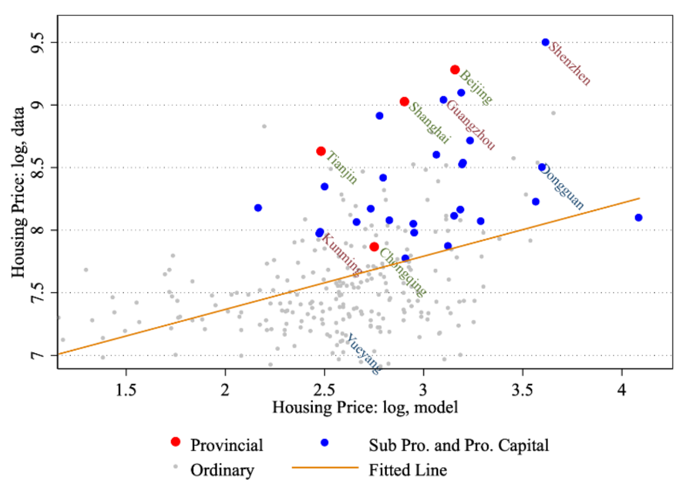


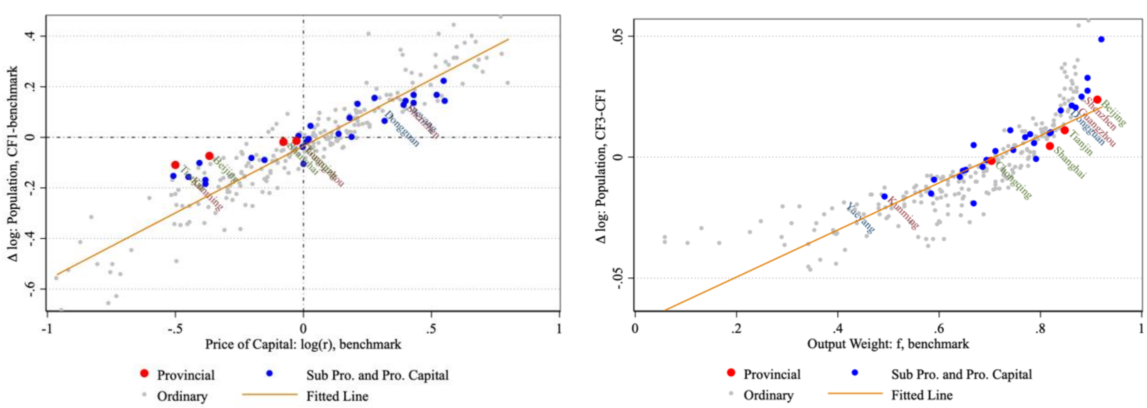
Figure A5.2 Housing prices

Notes: On the x-axis is the inferred housing price from the model. On the y-axis are housing prices for year 2010 from China Regional Statistics Yearbook.

A6. Additional Results

A6.1 Population losses or gains in going from the benchmark to CF-1 and from CF-1 to CF-3

Figures A6.1a and A6.1b illustrate the population gains and losses in two steps: the huge gains or losses which can result in going from the benchmark to CF-1 and then the smaller impacts in going to CF-3 (or CF-2) from CF-1. In A6.1a, the x-axis has the benchmark price of capital relative to Guangzhou (=1 or log at 0); and the y-axis has the changes in population which are centered around no change, with losing cities below the 0-line and gaining cities above. In Figure A6.1a, in going to CF-1, cities like Beijing and Tianjin which are currently heavily favored in capital markets experience large population loses of 7.73 and 11.2%. This suggests that part of the very high population growth of these cities since migration restrictions were eased in the early 2000's has been driven by capital market favoritism. Cities that currently face discrimination gain population, with the example of Shenzhen at a 12.7% increase. Figure A6.1b looks at population changes from CF-3 *compared* to CF-1, as graphed against the *f*'s solved in the benchmark case (and held fixed in CF-1). Here the population changes are much more modest than in Figure A6.1a. While cities with high *f*'s like Beijing or Tianjin experience modest gains relative to CF-1, overall, *relative to the benchmark*, they still have net population losses in CF-3 of 5.39 and 10.1% respectively.



a. CF-1 versus benchmark **b. CF-3 versus CF-1**

Figure A6.1. Population changes

Notes: On the y-axes are the percent changes in population. In part a, the x-axis shows the initial capital prices in the data. In part b, the x-axis gives the baseline *f*'s. Note the huge scale differences in the y-axis in part a versus part b.

A6.2 Table related to Section 6.3

Table A6.1: Population changes for sample cities

City	Type	Initial *r*	Initial *f*	Pop change, CF-2 or CF-3 vs. benchmark	Pop change, CF-3 plus reduced migration costs vs. benchmark
Beijing	High-*f*, Low-*r*	0.694	0.914	-5.39%	-8.51%
Dongguan	High-*f* High-*r*	1.366	0.857	12.3%	10.6%
Kunming	Low-*f* Low-*r*	0.639	0.494	-17.6%	-22.9%
Yueyang	Low-*f* High-*r*	1.490	0.413	12.1%	15.3%
Tianjin		0.609	0.849	-10.1%	-13.2%
Shanghai		0.927	0.820	-1.82%	-3.85%
Chongqing		0.975	0.701	-1.90%	-10.2%
Guangzhou		1	0.870	-2.19%	-3.89%
Shenzhen		1.484	0.882	15.2%	13.5%

Additional References

Hummels, D. L., & Schaur, G. (2013). Time as a trade barrier. *American Economic Review*, *103*(7), 2935-59.

Limao, N., & Venables, A. J. (2001). Infrastructure, geographical disadvantage, transport costs, and trade. *The world bank economic review*, *15*(3), 451-479.

Liu, C. (2019). *Modes of Entry, Correlated Productivity, and the Global Impacts of US Immigration Reform*. mimeo NUS.

Liu W.D, Tang Z.P., Han M.Y. (2018) *The 2012 China Multi-Regional Input-Output Table of 31 Provincial Units.* Beijing: China Statistics Press.