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Land Conversion and Misallocation Across Cities in China

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Abstract

The Chinese government has been using quotas to control the amount of farmland that can be converted for urban uses in different cities every year. Using a sample of more than 1.5 million land-lease transactions during 2007 to 2016, we document facts on land conversion for urban development in China. We present evidence that land conversion quotas have been increasingly misallocated across cities, in that a growing share of land conversion is occurring in less productive cities. A city-level production function is estimated for counterfactual analysis. Based on estimated parameters, we assess the economic losses from misallocation of land conversion quotas across cities in China and calculate the potential gains from reallocating land quotas to regions or cities where urban land is more productive. We also discuss policy options to improve efficiency.

Keywords: land conversion, land quota, misallocation, urbanization, China.

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Land Conversion and Misallocation Across Cities in China

1. Introduction

As part of the rapid urbanization in China, large amounts of farmland at the urban edge are converted for urban use. This occurs in a unique institutional context: The central government specifies the total amount of land to be converted for urban use, both for a long term and for each year; this quota is divided among different provinces, and in turn is allocated to lower level governments. Under this quota system, city governments acquire land from farmers at low costs and convert it for urban use. While some of this land is allocated to building infrastructure and public facilities, the rest is leased to developers and businesses for very long terms (40, 50, or 70 years, depending on the use type). Over the years, local governments have increasingly relied on land lease revenue to finance public spending.

We assembled a large amount of data on land conversion from a government website. Our data contain all land parcels that were converted for urban use in China during 2007-2016. We use these data to describe different aspects of land conversion and land finance in China. We find that among prefectural level cities, land revenue amounts to more than half of local government budget revenue. We show that high-land-productivity regions or cities have a declining share of land converted for urban uses, suggesting that urban land has been increasingly misallocated across cities in China. We also present evidence consistent with misallocation of urban land: First, newly converted urban land has a much higher market value (compared to agricultural land) in coastal than inland provinces. Second, economic gains are substantial if land conversion quotas are reallocated to high-land-productivity regions or cities.

Our study contributes to several strands of literature. First, this paper is related to the literature on land use regulation. Urban land-use regulations are ubiquitous in most countries. They take various forms—such as zoning laws, density restrictions, setback requirements, growth boundaries, etc.—and are extensively studied by urban economists.[1] Yet systematically controlling land conversion with quotas, as the Chinese government does, is very unique. The massive scale of this policy is unprecedented. Its potential impact on the urban system, regional balance, and the efficiency of the whole economy is not well understood. Our paper is among the first to use micro data to document and analyze this type of land use regulation in China.[2]

Second, our paper is also related to the small literature on city size distribution in China. Au and Henderson (2006a) find that Chinese cities are typically smaller than the optimal sizes, presumably due to restrictions on internal migration of population. Chen et al. (2017b) show that political favoritism affects capital prices faced by Chinese cities and in turn leads to growth differentials across cities. Others (Anderson and Ge 2005; Fang et al. 2017) examine the Chinese urban system through the lens of power law distributions and find that city size distribution in China is influenced by government policies. While these existing studies have identified the

[1] See Gyourko and Molloy (2015) for a comprehensive review of the literature on land use regulations.
[2] For studies of other aspects of this policy, see Brueckner et al. (2017), Cai et al. (2017), Chau et al. (2016), and Wang et al. (2017). Lu (2016) provides many insightful observations on this policy.

Hukou system, economic reforms, and urban development policies as the main factors that determine the structural characteristics of Chinese cities, our study considers a more recent urban land quota system that plays a key role in shaping the Chinese urban system.

Third, our findings have potential implications for understanding the recent dynamics of urban housing markets and economic performance of cities in China. In the past two decades, housing supply in larger cities in coastal areas has lagged behind the rapidly rising demand, constantly pushing housing prices to new highs in these cities (Fang et al. 2015; Glaeser et al. 2017; Wu et al. 2016). This has a series of side effects on the Chinese economy, including, for example, reduced firm innovation and decreased female labor force participation (Fu et al. 2016; Han and Lu 2017; Lu 2016). By quantifying the allocation of urban land at the city level, our study helps us better understand the role of the land quota system in explaining cross-city variation of economic development.

And finally, this paper is related to the growing literature on resource misallocation. There have been a large number of studies on misallocation of resources along various dimensions, some of which investigate the role of land misallocation.[3] Duranton et al. (2015) extend the Olley and Pakes (1996) approach and use the covariance between land share and total factor productivity to measure land misallocation among establishments in India during 1989 to 2010. They find that land misallocation plays an important role in explaining the difference of output per worker. Other papers study the effect of land misallocation on agricultural productivity (Adamopoulos and Restuccia 2014, 2015; Adamopoulos et al. 2017; Chari et al. 2018; Chen et al. 2017a; Restuccia and Santaeulàlia-Llopis 2017). All of these studies are conducted at the firm or farm level; in contrast, our analysis is at the city level due to the unique institutional setting in China.[4]

The rest of the paper is organized as follows. Section 2 describes briefly the institutional context. Section 3 introduces data sources. Section 4 reports descriptive statistics on land converted to urban uses. Section 5 explores misallocation of urban land across cities. Section 6 summarizes the results with concluding remarks.

2. Institutional Context

China is experiencing rapid urbanization. In 1982, only 20.9 percent of the Chinese population lived in urban areas; by 2015, this urbanization rate had climbed up to 56.1 percent. At the same time, urban areas expanded at an even faster pace, not only to accommodate the increased urban population, but also to satisfy the rising demand for space by the increasingly richer urban residents. As a result, China's built-up urban area rose from 7,438 square kilometers in 1982 to 43,603 square kilometers in 2011 (Brueckner et al. 2017).

In China, the state, by law, owns all of the urban land; outside urban areas, rural economic collectives own the agricultural land. Thus, the expansion of an urban area involves the urban government acquiring rural land from the local economic collectives and then converting it for

[3] See Restuccia and Rogerson (2013, 2017) and Hopenhayn (2014) for comprehensive reviews of this literature.
[4] There are a few studies of misallocation at the city level, including Albouy (2009), Hsieh and Moretti (2015), Chen et al. (2017b), and Yang et al. (2017), but none of these focus on urban land use.

urban uses either by allocating the land to urban users or transferring the land use rights to developers through leasehold sales. Government regulations require proper compensation for farmers when their land is seized for urban development. However, in reality, because the urban government has the administrative authority over the surrounding economic collectives, the compensation for farmers is always far below the market value of urban land.[5] Therefore, city governments often find it lucrative to acquire land at the urban edge and convert it for urban uses.

Two more institutional factors have provided further incentive for city governments to engage in land conversion. First, in 1994, China implemented a tax sharing system that would divide tax revenues between the central and local governments. This reform favored the central government and increased fiscal stress on local governments. In the following years, local governments throughout China had to look for non-tax revenue sources to help finance their expenditures. Before long, they all realized that selling land leases to developers could generate a substantial amount of revenue. Since then, "land finance"—using extrabudgetary land revenues to fund government spending—has become a prominent feature of local public finance in China (Cao et al. 2008). Second, China has a centralized government personnel system in which local leaders are not democratically elected but are promoted by their superiors based on their performance. There is ample evidence that during the economic reform era, local economic growth is an important factor that determines the probability of a local leader being promoted within the Communist Party's cadre system (Li and Zhou 2005). Consequently, local leaders, such as city party secretaries and mayors, all have strong incentive to develop their local economies. They know that converting and developing land is an important driver of local economic growth: Construction itself contributes to local GDP directly, and better housing and infrastructure attract talents and businesses that lead to long-term growth. For these reasons, local governments have all been actively involved in acquiring and converting agricultural land for urban uses.

Land conversion was occurring at such a large scale and such a fast pace that it alerted the central government of a potential threat to the country's food safety. To balance between the two goals of achieving economic growth and preserving cultivated land, the Chinese government implemented a top-down urban land quota system. The central government formulates the nation's long-term plan to specify the total amount of land that can be used for urban development over a period of time, and then allocates this quota to provincial-level governments (provinces, direct-controlled municipalities, and autonomous regions).[6] The provincial-level government then allocates its land quota to the prefectural cities under its jurisdiction, presumably based on a set of factors similar to those used by the central government. Finally, the

[5] The compensation for farmers is based on the agricultural output of the farmland instead of the opportunity cost or "best use" value of farmland. Land value at the city edge can be 500 times higher than the compensation fees paid to farmers (Wang et al. 2017). Although not our focus here, this low compensation to farmers may also cause welfare loss due to over-conversion of farmland (Tan et al. 2011; Ghatak and Mookherjee 2014).

[6] See, for example, The Outline of the National Overall Planning on Land Use (2006–2020), released in October 2008 (available at: http://www.mlr.gov.cn/xwdt/jrxw/200810/t20081024 111040.htm). It set the goal of preserving 1.8 billion mu of cultivated land nationwide in 2010, and allowed the country's total area of developed land to increase from 31.92 to 33.74 million hectares during 2005 to 2010. This quota of newly developed land is distributed among provincial-level governments based on development level, growth trend, resource and environmental conditions, etc. Whereas the exact quota-allocation formula is not released, the differential treatment is obvious. For example, the allocated quota would only allow the coastal province Shandong to expand its urban areas by 4.15 percent, but would allow the western Ningxia to expand by 10.44 percent.

prefectural city government decides on the scale and location of land conversion and development within the constraints of the land quota it received.

Although the central government has emphasized that an approved land-use plan must be treated as law, in reality it is not as rigid. When the allocated quota becomes binding, local leaders may petition to the upper-level government for some extra quota. Thus, a local leader who is more motivated to develop the local economy or better connected to key decision makers in the upper level government may be able to find a way to raise the allocated quota (Wang et al. 2017; Xie 2015). In addition, starting in 2008, a pilot policy was introduced in some provinces to link the urban land conversion quota to the reclamation of arable land in countryside. For example, if some villagers tear down their single-family houses, move into a high-density building, and consequently increase the village's total area of cultivated land, then they will be awarded some land conversion quota that can be used by the local city government.

Despite these flexibilities, the quota system is believed to have imposed a rather stringent constraint on many local governments, particularly those in the more developed coastal regions.[7] Its side effects have recently drawn the attention of many scholars (e.g., Lu 2016). Since the information on land quota and development at the sub-provincial level is not publicly available, there has never been a systematic examination of what is happening at the city level nationwide. We seek to fill this void in this paper.

3. Data

3.1. China Land Transaction Data

We assembled the China Land Transaction Data by crawling the "China Land Market" website (www.landchina.com), an information portal created and maintained by the Ministry of Land and Resources of China. One of this website's functions is to announce every land-transaction deal in China. As long as a local government handled a parcel of land, whether it is redevelopment of urban land or converting rural land for urban use, it is posted at this website. For each land transaction, the announcement typically contains information on transaction ID, land parcel address, current use, planned use type, transaction method (through negotiation, English auction, two-stage auction, sealed-bid auction, etc.), land area, price, etc. We recorded 1,941,657 land transactions from this website. After deleting duplicates, years with incomplete information, observations with key missing variables, and unreasonable outliers, we constructed an analysis sample of 1,542,283 observations for the period 2007–2016 (see Appendix A for details). Since this is a completely new data source, we assess its reliability by comparing statistics calculated from these data to those from different editions of the China Land and Resources Statistical Yearbook (see Appendix B).

[7] As will become clear below, we study the actual urban land supply at the city level instead of the allocated quota. This actual supply reflects the allocated land quota, quota adjustments obtained through other channels, and quota violations (if there are any).

3.2. China City Statistical Yearbook Data

To obtain other prefecture-level information, we use the 1993–2015 editions of the China City Statistical Yearbook, which contains many city characteristics. Specifically, we collect annual data on city-level GDP, per capita GDP, employment, fixed assets investment, built-up area, budget revenue and population from this Yearbook. Each edition of the yearbook published information from the previous year, thus these variables are used for 1992–2014.

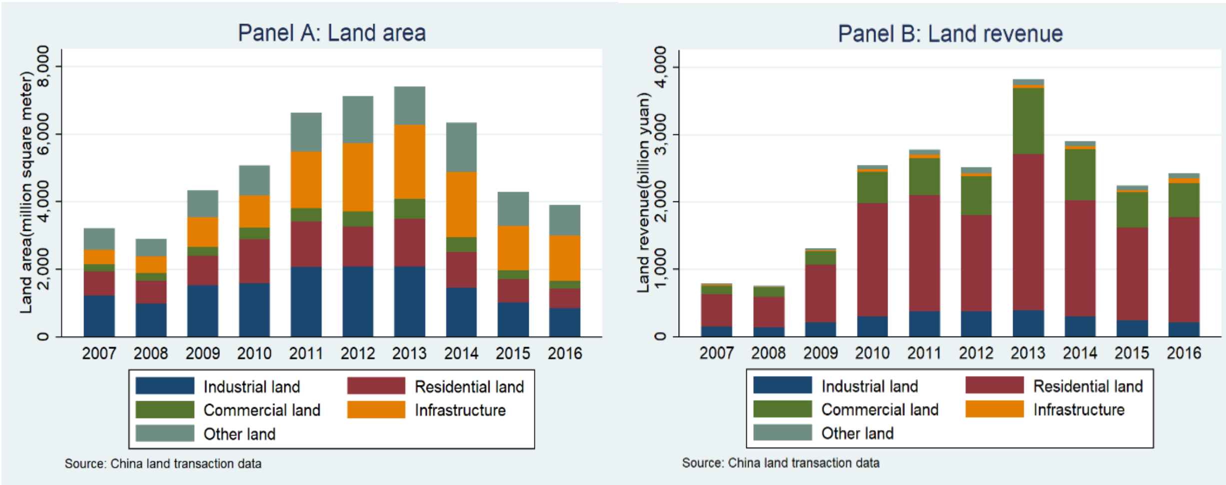
4. Facts on Land Conversion in China

Despite the importance of the land conversion policies in shaping the urban system and the concerns over local governments' reliance on land revenue, little is known about the scale of these issues at the city level. Thus, we start by documenting some stylized facts on land conversion in China. Our China Land Transaction Data contain information on all land parcels for which the local governments granted the leasehold rights to land users, including both the parcels of land newly converted from agricultural to urban uses in the current year and those already in urban uses previously. Although only the newly converted land represents the expansion of urban areas, here we start by examining both kinds of land in order to assess the scale of land finance. During our sample period 2007–2016, newly converted land generally constitutes more than 80 percent of total land area in our sample, except during the global recession period (2007–2008) when this share falls below 70 percent. Newly converted land generates between 51 and 71 percent of total land revenue over different years; this share of land revenue is smaller than the share of land area in every year because newly converted land is at the urban edge and tends to have a lower market value.

4.1. Land Area and Land Revenue in Each Year, by Use Type

Using the land transaction data, we classify land parcels into five different categories based on use type: industrial land, residential land, commercial land, infrastructure land, and other land. Figure 1 presents land area and land revenue for each use type during 2007 to 2016. Notice that residential and commercial land constitutes a relatively small share of the total (converted and redeveloped) land area, yet they generate the bulk of the land revenue in each year. In contrast, industrial and infrastructure land, although it constitutes the bulk of the land area, generates a much smaller share of land revenue for the local government. It is understandable that local governments tend to offer free land for infrastructure construction; after all, it is a kind of public good and local governments are not supposed to profit from it. It is rather interesting to see that industrial land is also quite cheap, suggesting that local governments subsidize factories and compete for industrial plants by providing relatively cheaper land.

Figure 1: Land Area and Land Revenue by Use Type



One might ask why the local government is not allocating more land for residential and commercial uses, given that residential and commercial land is so much more expensive than industrial land. A possible explanation is that upper-level governments tightly control allocation across use types and this leads to misallocation. More plausibly, this is a rational decision by local government officials. The higher price of residential land can be explained partly by its longer lease terms (70 years, as opposed to 50 years for industrial land and 40 years for commercial land). Besides, there are no residential property taxes in China, thus the price of residential land should incorporate all of its use value over 70 years. In contrast, industrial land can be used to lure plants and entrepreneurs and create new jobs. New firms and jobs generate future taxes that can justify the lower price of industrial land. Thus, it makes economic sense to have differential land prices across use types. And finally, there might be inter-governmental competitions for foreign direct investment (FDI) and industrial enterprises (Zhang 2011), which leads to a "race to the bottom" and thus, relatively low prices for industrial land.

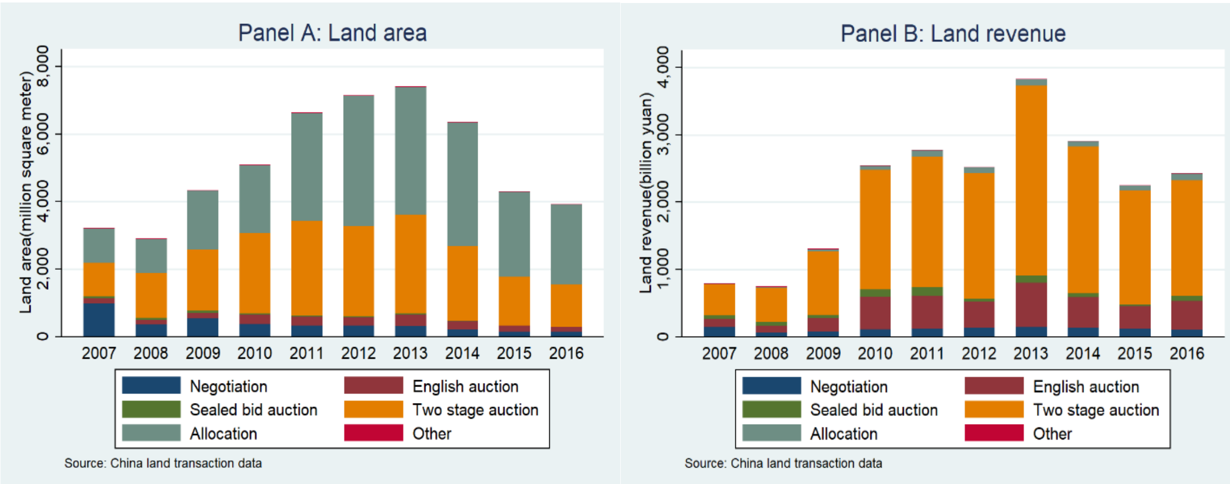
4.2. Land Area and Land Revenue in Each Year, by Transaction Method

By transaction method, we categorize land parcels in the land transactions data into five groups: by negotiation, English auction, sealed-bid auction, two-stage auction, allocation, and other methods.[8] We sum land area and land revenue for all parcels by transaction method in each year, as presented in Figure 2. Two points are worth noting. First, although the two-stage auction only accounts for 31–47 percent of land area, it generates 58–75 percent of land revenue over different years. Many cities in our sample primarily use two-stage auctions to allocate residential and commercial land. Cai et al. (2013) suggest that two-stage auctions are subject to manipulation, and show that these auctions tend to be noncompetitive and result in lower prices.

[8] Negotiation (*xieyi* in Chinese), English auction (*paimai* in Chinese), and sealed-bid auction (*zhaobiao* in Chinese) are standard and straightforward transaction methods. A two-stage auction (*guapai* in Chinese) proceeds as follows: The local government first posts the information about the land parcel for which the leasehold is to be transferred; potential buyers may submit their bids over a specified period of time, which is the first stage; if more than one bidder participated in the first stage, they are allowed to revise their bids in a standard English style auction at the end of the specified period, which is the second stage.

Second, a very large amount of land is transacted by the non-market "allocation" method, mainly for public uses, which hardly generates any land revenue.

Figure 2: Land Area and Land Revenue by Transaction Method

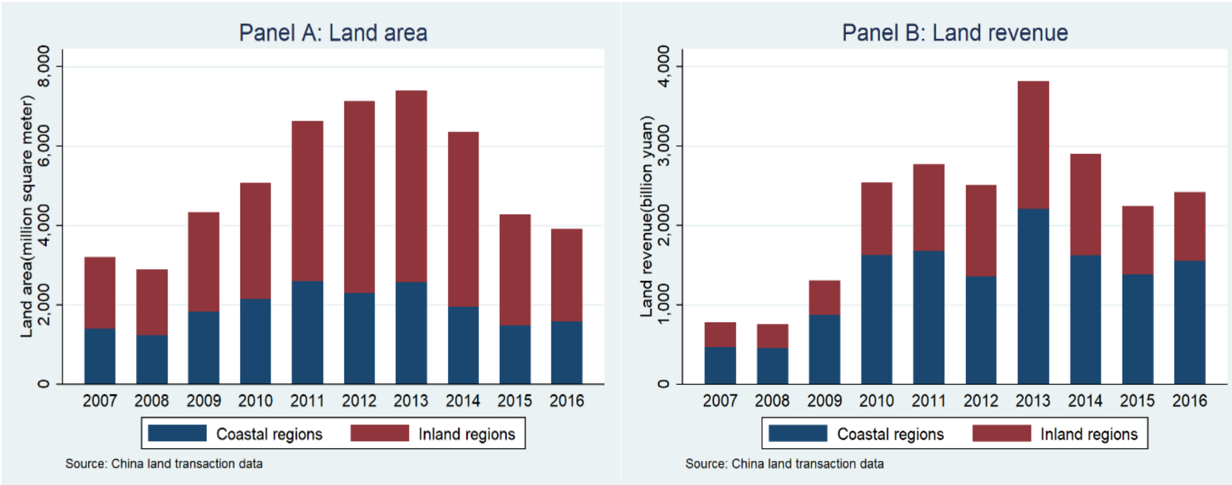


4.3. Land Area and Land Revenue in Coastal and Inland Regions

Following common practice, we define Liaoning, Beijing, Tianjin, Hebei, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan as coastal regions, and the rest of Mainland China as inland regions. Figure 3 graphs total (converted and redeveloped) land area and land revenue for coastal and inland regions in each year. The results show that more land area is converted for urban uses in inland regions even though less land revenue is generated in these regions. This is indicative evidence of land misallocation since more land is allocated to urban use in less productive regions. We will focus more intensively on this issue in section 5.

Note that coastal regions' share of land area (converted and redeveloped) was higher during 2007 to 2009 than in later years. Although there is no reliable micro data prior to our sample period, one can use the officially published provincial-level data to calculate this share in earlier years. Indeed, one only needs to look at the early 2000s to see that coastal regions' share of land area converted used to be much higher than inland regions. As observed by scholars (e.g., Han and Lu 2017; Lu 2016), there was a dramatic change around 2003 when the central government started to allow an increasingly higher share of land converted in inland regions.

Figure 3: Land Area and Land Revenue by Regions



4.4. Land Revenue Compared to Budget Revenue

The China City Statistical Yearbook reports each prefecture's "budget revenue" (mainly from taxes and fees) in each year, for the central city (including city districts only) and the whole prefecture (including city districts, as well as rural counties and county-level cities surrounding the central city). From the China Land Transaction Data, we can calculate the land revenue for each central city or prefecture in each year. Here we present the size of land revenue relative to budget revenue at both levels.

Table 1 reports the summary statistics of land-budget revenue ratio. The sample mean is calculated in two ways: (1) as a weighted average of the ratio in each city-year, using the city's nominal budget revenue in the year as weights; and (2) as a weighted average of the ratio in each city (over 2007–2014), using the city's real budget revenue (over 2007–2014) as weights.[9] It turns out that the sample means calculated in these two ways are almost identical. For central cities (columns (1)–(2)), land revenue on average amounts to 54 percent of the budget revenue. At the whole prefecture level (columns (3)–(4)), the average ratio is 52 percent, implying a slightly lower ratio at jurisdictions outside of the central cities.

Figure 4 presents the distribution of land-budget revenue ratio, for central cities and for whole prefectures, calculated using method (2). While the average ratio is only slightly higher than 0.5, the distribution has a wide range. Many central cities have a ratio higher than 1. That is, these jurisdictions derived more revenue from land leases than from taxes and fees. They tend to be smaller cities, which have a relatively small influence on the sample mean.

[9] For method (2), we use the consumer price index (CPI) (downloaded from http://www.stats.gov.cn/tjsj/ndsj/) to deflate land and budget revenues. Cities with at least one year of missing data are excluded from this calculation.

Table 1: The Summary Statistics of Land-Budget Revenue Ratio

Statistics	Central Cities		Whole Prefectures	
	Annual land revenue/annual budget revenue	2007–2014 land revenue/ 2007–2014 budget revenue	Annual land revenue/annual budget revenue	2007–2014 land revenue/ 2007–2014 budget revenue
	(1)	(2)	(3)	(4)
Mean	0.5422	0.5421	0.5167	0.5152
Std. Dev.	0.815	0.523	0.541	0.246
Median	0.566	0.6385	0.4803	0.5571
Minimum	0.0006	0.0942	0.0008	0.0946
Maximum	9.110	3.305	17.01	1.422
Observations	2,237	252	2,237	252

Notes: The mean is a weighted average across cities, using each city's budget revenue as weights.

Figure 4: The Distribution of Land-Budget Revenue Ratio

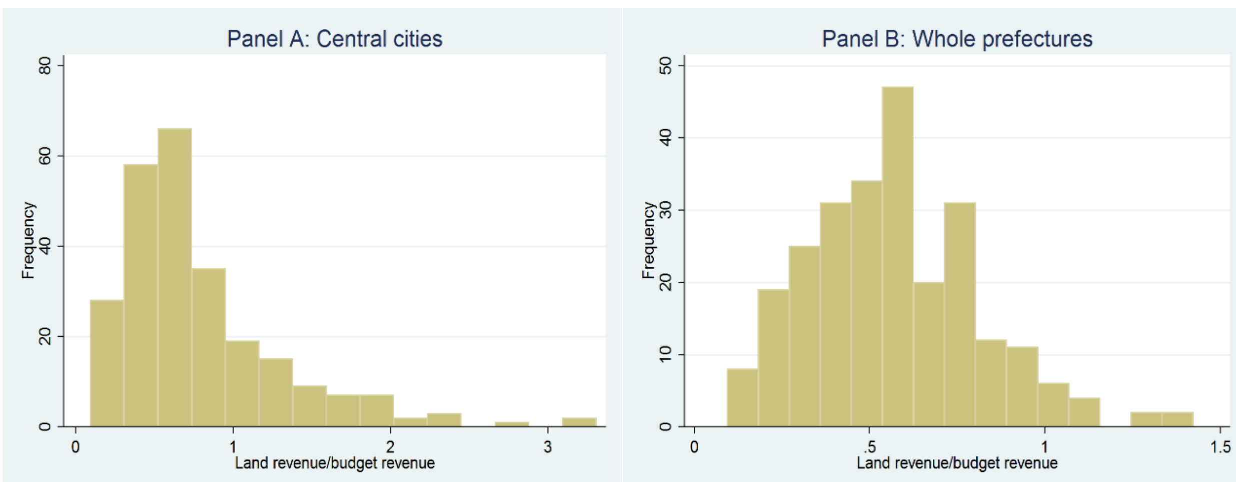
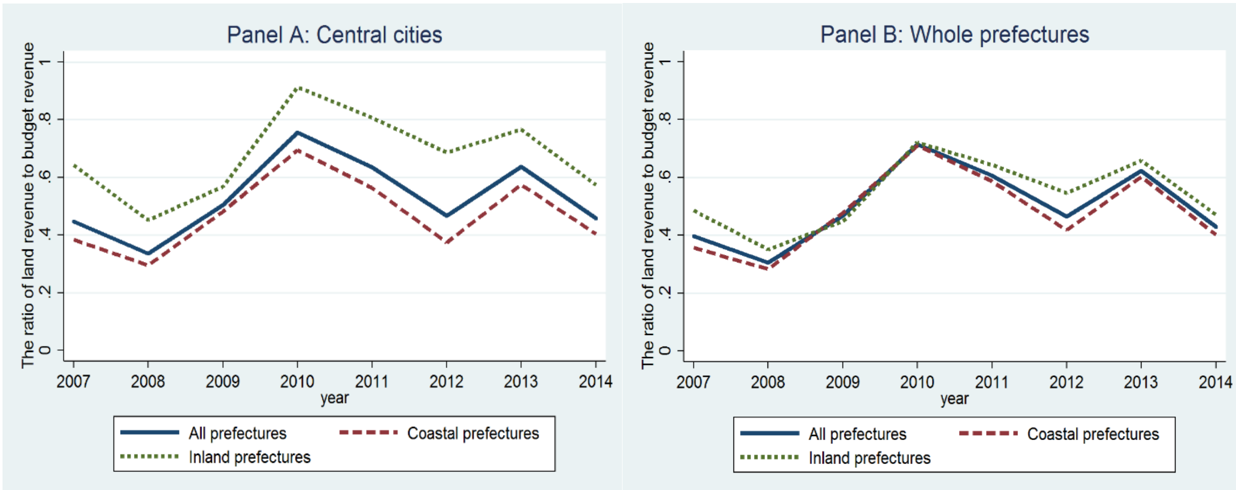


Figure 5 plots the average of land-budget revenue ratio by year, for central cities and whole prefectures. We show the trend for cities/prefectures in the whole sample, in the inland provinces, and in the coastal provinces. For central cities, the ratio is significantly higher in inland provinces than coastal provinces, which is true in every year during 2007 to 2014. Also, this ratio fluctuates substantially from year to year, at both the central city and the whole prefecture levels. For example, the ratio for central cities were only 0.336 in 2008, a year when economic growth slowed down and urban development slacked off amid a global recession; two years later, the ratio jumped to 0.755.

Figure 5: Land-Budget Revenue Ratio Over Time



5. Misallocation of Urban Land Across Cities

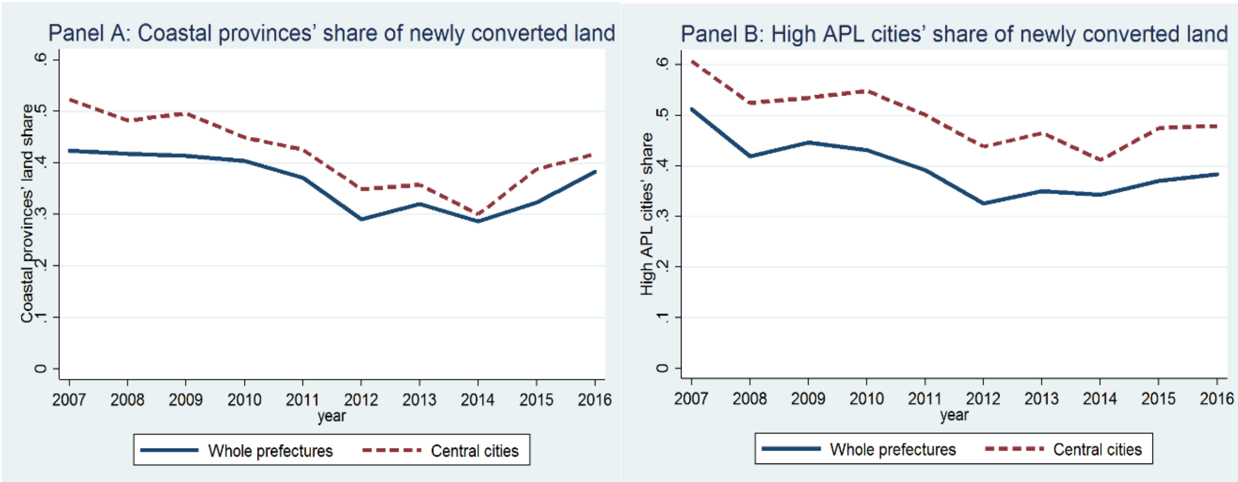
In this section, we first present some indicative evidence of land misallocation across cities in China. We then present a simple graphic model to provide a framework for detecting land misallocation across cities. Using the model as a guide, we present evidence that at the urban edge, the price gap between urban and agricultural land and the marginal productivity gain from converting land for urban uses both vary greatly across cities, implying misallocation of land across cities. We perform some counterfactual analysis to show that the economic gain is substantial if the Chinese government can reallocate some land conversion quotas from low- to high-land-productivity regions/cities. We make two changes to the analysis sample: (1) we drop a land parcel if the information on its price or area is missing; (2) we drop a land parcel if it is urban land auctioned off for redevelopment, thus focusing exclusively on newly converted urban land subject to the annual land conversion quotas.

5.1. Indicative Evidence on Land Misallocation Across Cities

5.1.1. Less Land Quota is Allocated to Regions/Cities with High Land Productivity

Some economists (e.g., Lu 2016) have noted that since 2003 an increasingly smaller share of land conversion quotas has been allocated to coastal provinces. They argue that this is a misallocation because urban land is much more valuable in coastal than inland provinces. Using the China Land Transaction Data, we calculate the share of newly converted urban land for coastal provinces during 2007 to 2016 (Panel A in Figure 6). Indeed, this share was declining during 2007 to 2014 and only started to increase in the last two years. According to Lu (2016) and Han and Lu (2017), who calculated the share using officially published provincial-level data, the declining trend started earlier in 2003. We replicated their calculation using the provincial-level data from the China Land and Resources Statistical Yearbook and confirmed this claim: Indeed, the share of land converted by coastal provinces was rising during 2000 to 2003; it then decreased steadily for a whole decade until 2014.

Figure 6: Share of Newly Converted Urban Land in Coastal Provinces or High Productivity Cities



In Panel B of Figure 6, instead of using the coastal-inland classification, we directly divide cities into high- and low-land-productivity cities, and then examine the share of newly converted land in high-productivity cities. Specifically, we first calculate the average productivity of land (APL) for each city by dividing the city's real GDP by its total land area and averaging this measure over 2007–2014 (the yearbook data were only available up to 2014 when this project was started). Next, we classify all cities into low APL cities and high APL cities by splitting the sample roughly in between (in terms of newly converted land): Starting from the city with the lowest average land productivity, we put each city (one by one) into the group of low APL cities until the share of newly converted land in the central cities during 2007 to 2016 for the low APL cities reaches 50 percent. This approach classified 193 cities into the group of low APL cities and 86 cities into the group of high APL cities. Using the China Land Transaction Data, we calculate the share of newly converted land (in central cities and whole prefectures) allocated to the high APL cities. It appears that these two shares both declined over time, i.e., high APL cities (relative to low APL cities) converted less and less land for urban uses over time, suggesting that land misallocation exacerbated during 2007 to 2016.[10]

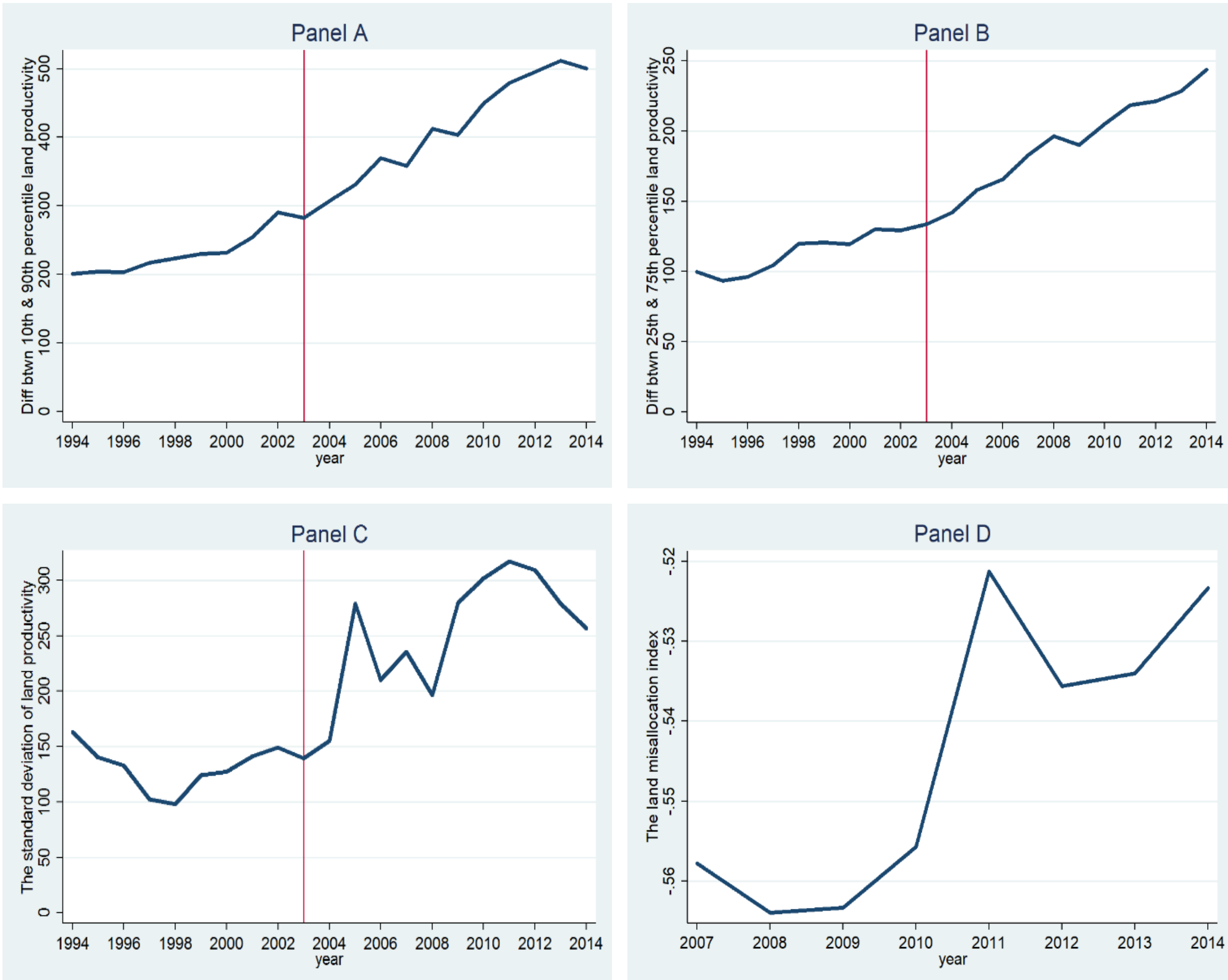
5.1.2. Indicators of Land Misallocation Across Cities

Following standard practice in the literature on misallocation, we next examine a few commonly used misallocation indicators. Using the China City Statistical Yearbook data, we calculate the average productivity of land for all prefectural level cities in each year during 1994 to 2014. We then look at the dispersion of land productivity. Higher dispersion is indicative of land misallocation across cities.[11]

[10] We also tried regressing land converted to urban use on land productivity at the city-year level and find a negative (though not statistically significant) coefficient.

[11] We draw intuition from Hsieh and Klenow (2009), who show that the efficiency of factor allocation across firms is related to the variance of total factor productivity among firms. In our case here, one might argue that the dispersion of marginal (rather than average) productivity of land is a more relevant indicator of misallocation. However, if city production function is of the Cobb-Douglas form, as will be assumed below, then marginal productivity is proportional to average productivity and their dispersions should follow the same trend.

Figure 7: Indicators of Land Misallocation Over Time



Panel A of Figure 7 plots the difference between the 10th and 90th percentile of land productivity among cities over time. Panel B similarly plots the difference between the 25th and 75th percentile of land productivity among cities over time. Panel C plots the standard deviation of city-level land productivity over time. In each panel, we draw a vertical line to indicate the year 2003, when the Chinese government started to allocate more land quotas to cities in inland provinces. Each of the three dispersion measures has an increasing trend, suggesting that land misallocation had become more serious over time. The trend of the standard deviation (Panel C) clearly shows 2003 as a break point.

Instead of the ad hoc productivity dispersion measures, we next look at a regression-based measure of misallocation. Following Duranton et al. (2015), we define misallocation of land across cities in year *t* as follows:[12]

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[12] This measure of misallocation is equal to the difference between the simple and share-weighted average productivity. Olley and Pakes (1996) first used this measure to study firm productivity; Duranton et al. (2015) modified it to measure misallocation along different dimensions.

$$M_t = -n_t * cov(s_{it}, A_{it}), \quad (1)$$

where n_t is the number of cities in year *t*; s_{it} is city *i*'s share of all urban land in year *t*; A_{it} is the total factor productivity in city *i* in year *t*. This measure is very intuitive: if the more productive cities have increasingly larger land shares, then there is little misallocation of urban land; otherwise, if the more productive cities have decreasing land shares, then there is misallocation of land across cities.

Using data from the China City Statistical Yearbook, we obtain each city's built-up area in 2007. From the land transaction data, we calculate the total area of land converted for urban uses in each city in each year. These newly converted land areas are added to the 2007 built-up area to obtain land area in each city in each year, which are then used to calculate each city's land share in each year: s_{it}.[13] To measure the total factor productivity A_{it} for each city, we estimate the following production function for all cities using the yearbook data:

$$\ln Y_{it} = \ln A_{it} + \alpha \ln N_{it} + \beta \ln K_{it} + \gamma \ln L_{it},$$

where Y_{it} is the output level; A_{it} is a productivity parameter; N_{it} is the number of workers; K_{it} is the capital stock; and L_{it} is the quantity of urban land. Total factor productivity for each city in each year is calculated as the residuals not explained by the three factors of production:[14]

$$A_{it} = \ln Y_{it} - \hat{\alpha} \ln N_{it} - \hat{\beta} \ln K_{it} - \hat{\gamma} \ln L_{it}. \quad (2)$$

The misallocation index, plotted in Panel D of Figure 7, also suggests that misallocation has become more serious over time, although the trend is less clear with only seven years of data.

5.2 A Simple Model

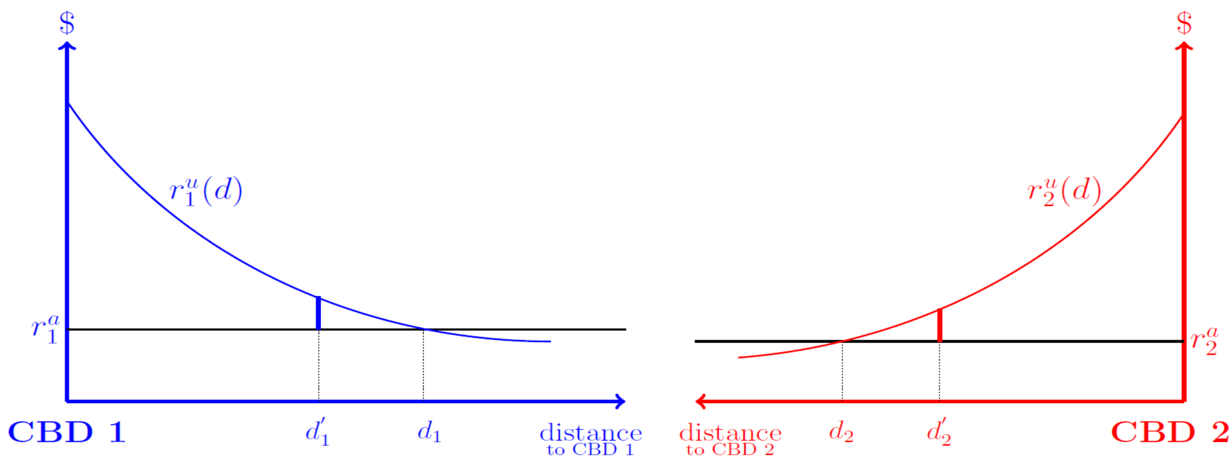
To fix ideas, we present a simple model of land misallocation across cities.

Consider an urban system with two monocentric cities, 1 and 2. In each city, production all happens at the central business district (CBD). Workers live around the CBD, trading off between higher commuting costs and lower land rents. $r_i^u(d), i = 1, 2$, is the bid rent curve in the urban sector, decreasing with *d*, the distance from the CBD. $r_i^a, i = 1, 2$, is the bid rent curve in the agricultural sector, assumed to be constant in either area.

[13] An alternative way to calculate this share is to use each city's built-up area, directly from the yearbook data. However, in recent years many cities expanded by "redistricting": Many small towns in surrounding counties are "acquired" by city districts and become part of the central city. This will introduce artificial changes to the built-up area of a city, making the calculation of the misallocation index imprecise. Thus we do not use the annual data on built-up area from the yearbooks.

[14] We estimate the parameters of the production function in a city-fixed-effects model and use the method pioneered by Levinsohn and Petrin (2003) to control for unobserved productivity shocks, which is detailed in section 5.4.3. The estimates we used to calculate A_{it} are in column (2) of Table 6 below.

Figure 8: A Simple Graphic Model



Without government intervention, in each city, land will be used by the sector that can afford a higher bid rent. Thus, city i ends at d_i, where the urban bid rent equals the agricultural bid rent. Total urban area in this economy is $\pi(d_1^2 + d_2^2)$. Land allocation is efficient in that there is no way to profit from rearranging land use within or across cities.

Suppose that for some reason, the government decides to control urban land supply. Say it only allows $\pi(d_1^2 + d_2^2) - \theta$ units of land to be used by the urban sector, where θ is a predetermined constant. Suppose that the government uses land quotas to end urban development at d_i' so that $\pi[(d_1^2 + d_2^2) - (d_1'^2 + d_2'^2)] = \theta$. In this case, land allocation across cities is efficient under the following condition:

$$r_1^u(d_1') - r_1^a = r_2^u(d_2') - r_2^a. \tag{3}$$

If $r_i^u(d_i') - r_i^a > r_j^u(d_j') - r_j^a$, then the government can reallocate some land quota from city j to city i to improve efficiency.

Let R be the discount rate. At the edge of city i, the price of land in the agricultural sector is $p_i^a = r_i^a/(1+R) + r_i^a/(1+R)^2 + \cdots = r_i^a/R$; similarly, the price of land in the urban sector is $p_i^u = r_i^u(d_i')/R$. Thus, $p_i^u - p_i^a = [r_i^u(d_i') - r_i^a]/R$. That is, if we have land price or rent in both the urban and agricultural sectors at the urban edge, we can test whether land allocation across cities is efficient. In this study, we have land price when it is converted for urban use, and we can estimate land rent in the agricultural sector by its productivity. Thus, we can test efficiency by running the following regression:

$$p_i^u = \delta r_i^a + \kappa_i + \epsilon_i, \tag{4}$$

where the coefficient δ is equal to $1/R$. κ_i is a city specific constant. If κ_i is significantly different across cities, then $p_i^u - p_i^a = [r_i^u(d_i') - r_i^a]/R$ is significantly different across cities, implying inefficient allocation of land across cities.

Alternatively, we can proxy $r_i^u(d_i')$ by the marginal productivity of land in city *i* (MPL_i). If $MPL_i - r_i^a > MPL_j - r_j^a$, then there is misallocation of land across cities and the government can improve efficiency by reallocating some land quota from city *j* to city *i*. For every unit of land quota reallocated, the gain is $(MPL_i - MPL_j) - (r_i^a - r_j^a)$.

5.3. Urban and Rural Land Value Gap: Regional Differences

Guided by the simple model, we detect misallocation of land quotas by testing the equality of the urban-rural land value gap across regions.

5.3.1. Construction of Variables

We use the China Land Transaction Data to calculate the price of urban land (p_{it}^u) for each city in each year as follows:

$$p_{it}^u = \frac{\sum_{k \in B_{it}} Sold\_Price_{itk}}{\sum_{k \in B_{it}} Area_{itk}}, \tag{5}$$

where the subscripts are city *i*, year *t*, and parcel *k*. B_{it} is the set of newly converted land parcels in city *i* in year *t*. That is, for each city-year, we divide the total land revenue by the total land area for parcels newly converted for urban uses.[15] We use the provincial-level urban resident CPI, collected from the China Statistical Yearbook, to deflate land price.

We use the China City Statistical Yearbook data to calculate the value of rural land outside the city as follows:

$$r_{it}^a = \frac{First\_Sector\_GDP_{it}}{Cultivated\_Land\_Area_{it}}, \tag{6}$$

where $First\_Sector\_GDP_{it}$ is the GDP in the agricultural sector in city *i* in year *t*. $Cultivated\_Land\_Area_{it}$ is the total cultivated land area in city *i* in year *t*. From the China City Statistical Yearbook, we have the cultivated land area for each city in 2007. To obtain cultivated land area in each year during 2008 to 2014, we subtract the area of converted land in each year from the previous year's cultivated land area. We also use the provincial-level CPI to deflate the GDP in the agricultural sector. Table 2 reports the summary statistics of urban land price and rural land value. We find that urban land price is about eighty times that of rural land value. Note that urban land price is a transaction price, which should be a sum of discounted revenue streams it can generate over many years; rural land value, however, is calculated based on the value of one year's output, which is more like the rent one needs to pay for using the land in one year instead of the price one pays to acquire the ownership of the land.

[15] Our calculation is based on all land parcels newly converted for urban uses, including those whose leasehold rights are transferred to users at very low prices. One might argue that this measure underestimates the market value of urban land, because local governments have incentives to charge low prices for certain land parcels (e.g., those for industrial uses) in exchange for non-pecuniary gains or future benefits (e.g., employment opportunities or tax revenue). We want to emphasize that this potential underestimation does not affect the validity of our test as long as our measure is proportional to the true market value of urban land.

Table 2: Summary Statistics on Urban Land Price and Agricultural Land Value

Variable	Obs.	Mean	Std. Dev.	Min	Max
Urban land price (yuan/m^2)	2,186	426.6	484.0	3.192	8,966
Rural land value (yuan/m^2)	2,186	5.205	5.134	0.356	114.0

5.3.2. Regression Analysis

Following equation (4), we regress urban land price (p_{it}^{u}) on rural land value (r_{it}^{a}) together with province dummies (κ_n), allowing the urban-rural land value gap to vary across provinces.[16] Specifically, we estimate the following equation:[17]

$$p_{it}^{u} = \delta * r_{it}^{a} + \kappa_n + \varepsilon_{it}. \tag{4'}$$

This generates an estimate $\hat{\delta} = 15.5658$, with a standard error of 1.8696. Figure 9 shows the estimated coefficients for province dummies. Beijing and Shanghai are clear outliers in that urban land is much more valuable than rural land at the edges of these cities. There is substantial variation among other provinces too, and indeed coastal provinces tend to have larger urban-rural land value gaps. To verify this last point, we regress the estimated urban-rural land value gap on coastal- and inland-province dummies:

$$p_{it}^{u} - 15.5658 * r_{it}^{a} = \kappa_C * \mathbf{1}_{Coastal\_provinces} + \kappa_I * \mathbf{1}_{Inland\_provinces} + \varepsilon_{it}. \tag{7}$$

[16] Equation (4) suggests that we should estimate a city-specific urban-rural land value gap. However, we have only a few observations for each city, which doesn't allow for a precise estimation of a city fixed effect. Thus we choose to estimate a province-specific urban-rural land value gap. In an alternative specification, we also tried regressing the ratio of urban land price to rural land value on province dummies. The results are qualitatively identical.

[17] In an alternative specification, we tried regressing the ratio of urban land price to rural land value on province dummies. The results are qualitatively identical.

Figure 9: Variation in Urban-Rural Land Value Gap Across Provinces

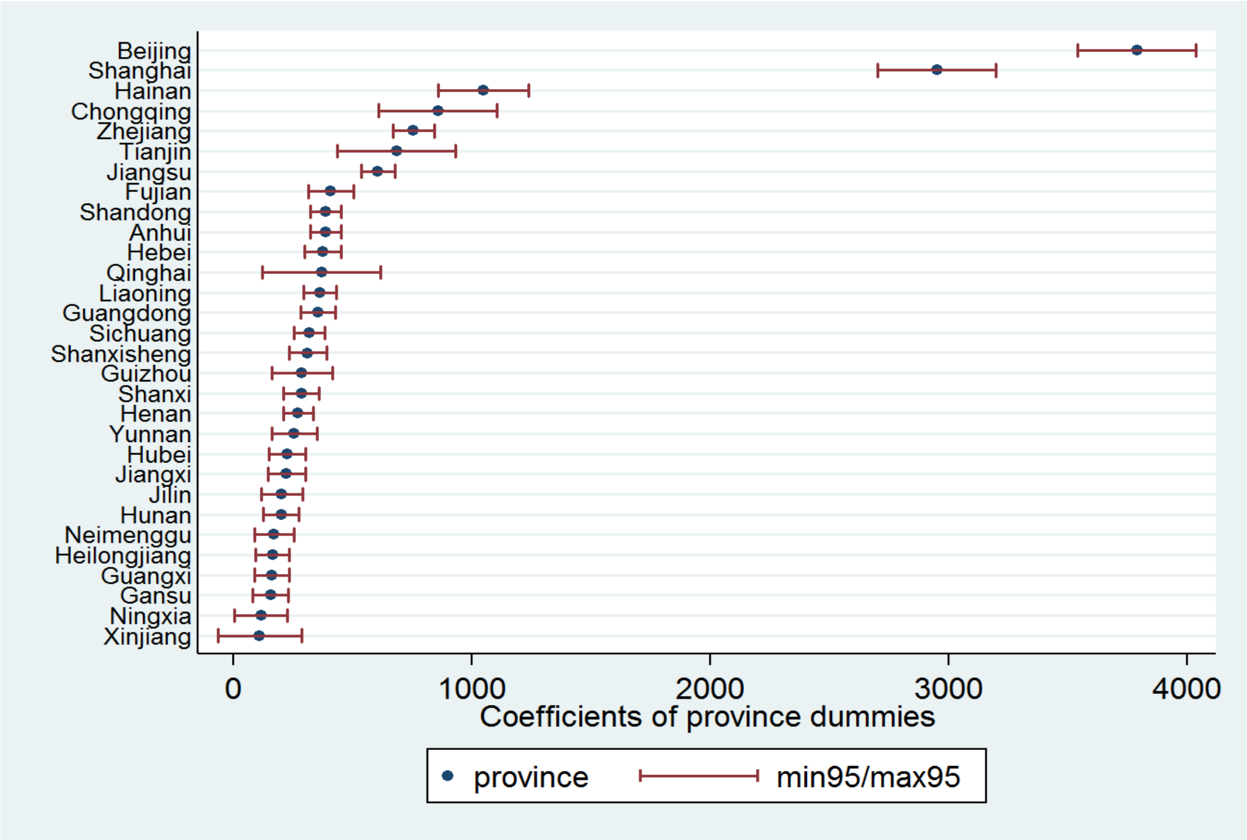


Table 3 presents the results. We estimate the equation in two ways: with or without the two outliers Beijing and Shanghai. The results show that the coefficient for coastal provinces is about twice as big as that for inland provinces. In other words, converting one unit of land for urban uses generates a much larger value premium in coastal than inland provinces, suggesting that land quota puts a more stringent constraint on cities in coastal provinces.

Table 3: Urban-Rural Land Value Gap in Coastal and Inland Provinces

	Dependent variable: $p_{it}^{u} - 15.5658 * r_{it}^{a}$	
	Full Sample	Excluding Beijing and Shanghai
	(1)	(2)
Coastal provinces	528.9***	468.4***
	(16.18)	(11.70)
Inland provinces	246.3***	246.3***
	(11.90)	(8.519)
N	2186	2170
R^2	0.407	0.529

Notes: Standard errors are in parentheses. *** p < 0.0001.

5.3.3. Explaining Urban-Rural Land Value Gap

We further explore what kind of cities tend to have a higher gap. We regress the urban-rural land value gap on city characteristics as follows:

$$p_{it}^{u} - 15.5658 * r_{it}^{a} = \beta * X_{it} + \varepsilon_{it}, \tag{8}$$

where city characteristics X_{it} include provincial capital dummy, population, built-up area, per capita GDP, and per capita government revenue. Table 4 reports the results. We find that the urban-rural land value gap is larger for provincial capitals, cities with more population, cities with larger built-up areas, and cities with higher per capita government revenues. There has been speculation that the Chinese government uses land quotas to control population growth in large cities and balance cross-region inequalities in government revenue. Our regression results are consistent with such arguments.

5.4. Counterfactual Analysis: Potential Gains from More Efficient Land Allocation

In this section, we compute the marginal productivity of urban land based on an estimated city production function and then calculate the potential gains if we reallocate some land conversion quotas from inland to coastal provinces or from low- to high-productivity cities.

5.4.1. Specification

Consider the following city-level production function:

$$Y_{it} = A_{it} {N_{it}}^{\alpha} {K_{it}}^{\beta} {L_{it}}^{\gamma}, \tag{9}$$

where Y_{it} is the output level; A_{it} is a productivity parameter; N_{it} is the number of workers; K_{it} is the capital stock; and L_{it} is the quantity of urban land, all indexed by city *i* and year *t*. Taking log of equation (9), we have:

$$\ln Y_{it} = \ln A_{it} + \alpha \ln N_{it} + \beta \ln K_{it} + \gamma \ln L_{it}. \tag{10}$$

Table 4: Explaining Urban-Rural Land Value Gap

	Dependent variable: $p_{it}^{u} - 15.5658 * r_{it}^{a}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Province capital	564.6***					173.7***	129.0***
	(29.93)					(33.80)	(32.67)
Population		184.3***				154.9***	120.3***
		(14.02)				(15.44)	(16.35)
Built-up area			260.6***			58.26***	42.43**
			(10.26)			(17.91)	(16.48)
Per-capita GDP				239.7***		-97.62***	39.49
				(13.32)		(28.23)	(27.34)
Per-capita government revenue					198.3***	220.5***	94.11***
					(9.065)	(20.10)	(20.48)
Province fixed effect	N	N	N	N	N	N	Y
Constant	284.6***	-735.9***	-783.6***	-2109.2***	-1142.9***	-1491.1***	-73.03
	(9.839)	(82.86)	(45.18)	(136.8)	(68.63)	(196.4)	(238.2)
N	2,184	2,184	2,182	2,184	2,184	2,182	2,182
R^2	0.140	0.073	0.228	0.129	0.180	0.308	0.524

Notes: Standard errors are in parentheses. ** $p < 0.05$; *** $p < 0.01$.

For empirical implementation, we further assume that the total factor productivity can be decomposed as follows: $\ln A_{it} = C_i + \tau_t + \varepsilon_{it}$, where C_i is a city-specific time-invariant component that captures the effect of local fundamentals; τ_t is a year fixed effect that captures common macroeconomic shocks; and ε_{it} is an idiosyncratic error term. Therefore, we have the following empirical specification:

$$\ln Y_{it} = \alpha \ln N_{it} + \beta \ \ln K_{it} + \gamma \ln L_{it} + C_i + \tau_t + \varepsilon_{it}. \qquad (11)$$

We need an estimate of γ, based on which we can perform some counterfactual analysis.

5.4.2. Key Variables

We estimate equation (11) using city level data during 2007 to 2014. For output *Y*, we use city GDP; for labor *N*, we use total employment in the city; both are from the China City Statistical Yearbook.

For capital *K*, we use the perpetual inventory method to estimate it since we only have fixed assets investment data from the China City Statistical Yearbook. Capital is calculated by

$$K_{it} = \sum_{s=1992}^{t} 0.85^{t-s} \, FAI_{is}, \qquad (12)$$

where FAI_{is} is city *i*'s fixed assets investment in year *s*. We assume that 15 percent of the capital in the previous year is depreciated in the current year. To estimate the value of capital in the base year (2007), we use the investment data in the previous 15 years. Note that $(1 - 0.15)^{15} = 0.087$, which means that only 8.7 percent of the capital in 1992 still exists in 2007. So, we simply set the capital in 1992 equal to zero ($K_{i1992} = 0$). Using the fixed assets investment data available in each year after 1992, we calculate capital stock for each city during 2007 to 2014 based on equation (12), which we then use to estimate equation (11).

For urban land area *L*, we combine the China Land Transaction Data with the data from the China City Statistical Yearbook. Specifically, from the China Land Transaction Data, we calculate the total area of land converted for urban uses in each city in each year during 2008 to 2014. For urban land area in 2007, we use the 2007 built-up area in each city from the China City Statistical Yearbook. To obtain a city's land area in each year from 2008 to 2014, we add its total area of newly converted land in each year to its land area in the previous year. Table 5 reports the summary statistics of regression variables.

Table 5: Summary Statistics of Variables for Estimating City Production Function

Variable	Obs.	Mean	Std. Dev.	Min	Max
Log output (ln Y)	2,155	15.08	1.155	12.21	19.06
Log employment (ln N)	2,155	3.331	1.020	0.761	7.339
Log capital (ln K)	2,155	15.80	1.135	12.31	19.43
Log land (ln L)	2,155	4.337	0.813	1.946	7.366

Units of measurement: Output—10,000 yuan; employment—10,000 persons; capital—10,000 yuan; and land—square kilometers.

5.4.3. Estimating City-Level Production Function

To consistently estimate equation (11), we need to confront two types of econometric issues. First, there is potential simultaneity bias. That is, observed inputs (land, labor, and capital) may be correlated with unobserved inputs or productivity shocks. For example, younger mayors may have more incentive to promote growth in their cities in order to be promoted within the Communist Party. They may thus negotiate with upper-level government officials for more land to be converted and, at the same time, use a few other pro-growth measures, consequently introducing a bias in the estimated land coefficient. The city fixed effects specification can be thought of as a partial solution to this simultaneity problem, in that the fixed effect term can absorb the effect of time invariant unobserved inputs or productivity shocks. However, it does not solve the problem if the unobserved shocks vary over time, e.g., with two consecutive mayors having different motives to develop the local economy. Second, there is a measurement-errors problem. All inputs in our city-level production function have measurement errors, which will likely cause attenuation bias, resulting in underestimation of the land coefficient.[18]

We adopt two different strategies to deal with these issues. First, following common practice in the literature (Gandhi et al. 2013), we use one-period lagged input values to instrument for current input values. Second, following Levinsohn and Petrin (2003), we use intermediate inputs (water, gas, or both) to control for unobserved productivity shocks. Table 6 reports the regression results of equation (13). Column (1) is the IV results. Columns (2)-(4) report the results when we use water, gas, or both water and gas to control for unobserved productivity.[19] It is rather remarkable that although the four specifications are based on very different identifying assumptions, the estimated coefficient for log land is very similar, ranging from 0.141 to 0.160. The estimate in column (2), $\hat{\gamma} = 0.159$, is obtained using a sample with the smallest number of missing values. It implies that the marginal productivity of urban land is about one-sixth of the average productivity, which seems reasonable. We will use this estimate for the counterfactual analysis below.

[18] In the empirical industrial organization (IO) literature, where researchers often need to estimate a production function for firms, there is also an "endogenous exit" issue that firms dropping out of the sample are not random. This is not a concern in our context because our sample of cities is rather stable over the relatively short period of time.

[19] Electricity is a commonly used input to control for unobserved productivity in the empirical IO literature. However, there are too many missing values for the electricity variable in the Yearbook data, making it not useful in our case here

Table 6: Regression Results for City-Level Production Function

Dependent variable: Log city GDP (ln Y), 2007–2014				
	IV-lagged inputs	LP-water	LP-gas	LP-water & gas
	(1)	(2)	(3)	(4)
Log Employment (ln N)	0.371***	0.169***	0.180***	0.163***
	(0.0433)	(0.0067)	(0.0489)	(0.0259)
Log Capital (ln K)	0.236***	0.270***	0.280***	0.276***
	(0.0281)	(0.0174)	(0.0170)	(0.0265)
Log Land (ln L)	0.141***	0.159***	0.151***	0.160**
	(0.0375)	(0.0268)	(0.0427)	(0.0622)
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
N	1,850	2,118	1,908	1,907
R^2	0.992	—	—	—

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$. "LP" indicates the use of intermediate inputs (water, gas, or both) to control for unobserved productivity shocks, following Levinsohn and Petrin (2003).

5.4.4. Counterfactual Analysis

A. Counterfactual analysis between coastal and inland provinces: *If the total area of converted land in inland provinces decreases by 30 percent and the total area in coastal provinces increases by the same amount in absolute terms, what are the total gains?*

From the China Land Transaction Data, we calculate the average annual total area of converted land for the whole prefectures in inland provinces and the coastal provinces during 2007 to 2014 to be 337,125 and 200,712 hectares, respectively. Reallocating thirty percent land quotas from inland to coastal provinces is essentially a reversion to the early 2000s situation, which is a rather reasonable scenario.[20]

When we reduce the amount of land converted in inland provinces by 30 percent and reallocate the land conversion quota to the coastal provinces, there are two consequences. First, the converted land in inland provinces decreases by 30 percent, and the converted land in coastal provinces increases by the same amount in absolute terms. Second, agricultural land area in inland provinces increases by the same amount in absolute terms, and agricultural land area in coastal provinces decrease by the same amount in absolute terms. Thus, the total gain in year *t* is as follows:[21]

$$[(MPL_t^C - MPL_t^I) - (r_t^C - r_t^I)] * 0.3 * LC_t^I,$$

[20] We point out here that it is unreasonable to use the condition for efficient allocation in equation (4) as a policy goal. In reality, marginal gains of land conversion may differ across cities for many reasons including, for example, random shocks to land productivity, adjustment costs of land use, and measurement errors of land productivity. These issues are well understood in the literature on resource misallocation among firms (Restuccia and Rogerson 2017).

[21] This calculation assumes that the changes are marginal. While 30 percent of the land converted is not an insignificant amount, it is very small relative to the whole urban area and thus can be considered "marginal." We tried an alternative calculation by continuously adjusting the marginal productivity of land along with reallocation; the results are almost identical.

where MPL_t^C and MPL_t^I are marginal productivity of urban land in year *t* in coastal and inland provinces, respectively; r_t^C and r_t^I are rural land value in year *t* in coastal and inland provinces, respectively; LC_t^I is the total area of land converted for urban use in year *t* in inland provinces. Also, it is important to note that the potential gains (or, in actuality, loss, since the gains were not realized) in each year are not a one-shot deal. We should expect a similar loss in each of the following years due to the original misallocation. Thus, the cumulative gain in year *t* is calculated as

$$[(MPL_t^C - MPL_t^I) - (r_t^C - r_t^I)] * 0.3 * \sum_{i=2007}^{t} LC_i^I.$$

From equation (11), we know that the marginal productivity of land (MPL) in a city is proportional to the average productivity of land (APL):

$$MPL = \frac{\partial Y_{it}}{\partial L_{it}} = \gamma A_{it} N_{it}{}^{\alpha} K_{it}{}^{\beta} L_{it}{}^{\gamma-1} = \gamma \frac{Y_{it}}{L_{it}} = \gamma * APL. \quad (13)$$

From Table 6, we use the estimated land coefficient $\hat{\gamma} = 0.159$. From the China City Statistical Yearbook, we obtain city-level GDP and total urban land area for coastal and inland provinces in each year, so we can calculate the average productivity of land and the marginal productivity of land, presented in Table 7. Note that the differences in marginal productivity of land are much smaller than the differences in average productivity between coastal and inland provinces because the land coefficient γ is much smaller than one.

Table 7: Differences in Urban Land Productivity Between Coastal and Inland Provinces, 2007–2014

Year	Coastal provinces		Inland provinces	
	APL	MPL=$\hat{\gamma} \cdot$ APL	APL	MPL=$\hat{\gamma} \cdot$ APL
2007	735.6989	116.9761	391.3773	62.2290
2008	804.8759	127.9753	448.6968	71.3428
2009	873.5206	138.8898	497.8936	79.1651
2010	974.4478	154.9372	562.8669	89.4958
2011	1085.818	172.6451	537.9908	85.5405
2012	1141.113	181.4370	692.9083	110.1724
2013	1210.919	192.5361	722.5655	114.8879
2014	1196.196	190.1952	746.8965	118.7565

Unit: ten thousand yuan/hectare. $\hat{\gamma} = 0.159$. APL = average productivity of land; MPL = marginal productivity of land.

The difference between the rural land value in coastal and inland provinces is calculated as follows:

$$r_t^C - r_t^I = \frac{\sum_{i=1}^{N^C} First\_Sector\_GDP_{it}}{\sum_{i=1}^{N^C} Cultivated\_Land\_Area_{it}} - \frac{\sum_{i=1}^{N^I} First\_Sector\_GDP_{it}}{\sum_{i=1}^{N^I} Cultivated\_Land\_Area_{it}},$$

where N^C and N^I are the number of cities in coastal and inland provinces, respectively. $First\_Sector\_GDP_{it}$ is the share of GDP in the agricultural sector, collected from the China

City Statistical Yearbook. Also from the Yearbook, we have the cultivated land area in 2007.[22] To obtain the cultivated land area in each year from 2008 to 2014, we subtract the converted land area from the previous year's cultivated land area. Table 8 reports rural land value in coastal and inland provinces and their differences. Note that rural land value is much lower than urban land productivity. As a result, the difference in rural land value is much lower than the difference in urban land productivity. Thus, the gain from reallocation of land quotas will be driven primarily by the difference in urban land productivity between coastal and inland provinces.

Table 8: Differences in Rural Land Value Between Coastal and Inland Provinces, 2007–2014

Year	Coastal rural land value (r_t^C)	Inland rural land value (r_t^I)	Difference
2007	3.5741	1.8965	1.6776
2008	4.4801	2.5988	1.8813
2009	4.8653	2.7377	2.1276
2010	5.6233	3.1251	2.4982
2011	6.4676	3.7359	2.7318
2012	7.0372	4.1496	2.8876
2013	7.6974	4.4726	2.8876
2014	7.8813	4.6983	3.1831

Unit: ten thousand yuan/hectare.

The calculated potential gains are presented in Table 9. We consider two cases: apply the reallocation to all newly converted land in the whole prefectures (columns 1–2) and only to newly converted land in central cities (columns 3–4). In each case, two sets of estimates are calculated, including annual gains and cumulative gains. Estimates in column 1 suggest that the reallocation can generate an annual gain equivalent to 0.06-0.19 percent of the country's GDP. The results in column 2 show that the cumulative effects from a few years of misallocation can be substantial, which might be a reason why the Chinese economy has slowly regressed to "a new normal" in recent years.

[22] For some unknown reason, the cultivated land area after 2007 is not reported in the China City Statistical Yearbook.

Table 9: Gains from Reallocating 30 Percent of Land Quotas from Inland to Coastal Provinces

Year	whole prefectures, newly converted land		central cities, newly converted land	
	Annual	Cumulative	Annual	Cumulative
	Total gains (hundred million yuan)			
2007	197.9432	197.9432	88.1257	88.1257
2008	190.9825	395.1979	83.1630	174.0811
2009	351.7071	767.4475	158.4976	341.6275
2010	458.0830	1296.7640	200.7275	574.0644
2011	893.0699	2631.3275	393.6830	1163.1922
2012	896.3006	3028.7702	343.2460	1285.9155
2013	957.3412	4253.9375	373.4642	1773.0897
2014	802.5075	4703.9012	316.6662	1942.8116
	Total gains as percentage of GDP			
2007	0.0739%	0.0739%	0.0329%	0.0329%
2008	0.0603%	0.1248%	0.0263%	0.0550%
2009	0.1018%	0.2220%	0.0459%	0.0988%
2010	0.1120%	0.3171%	0.0491%	0.1404%
2011	0.1845%	0.5435%	0.0813%	0.2403%
2012	0.1678%	0.5671%	0.0643%	0.2408%
2013	0.1628%	0.7234%	0.0635%	0.3015%
2014	0.1262%	0.7394%	0.0498%	0.3054%

B. Counterfactual analysis between low-productivity and high-productivity cities: *If the total area of converted land in low APL (average productivity of land) cities decreases by 30 percent and the total area in high APL cities increases by the same amount in absolute terms, what are the total gains?*

As already described above, we classify all cities into low APL cities and high APL cities based on the average productivity of urban land. From the China City Statistical Yearbook, we obtain city-level GDP and total urban land area for the high and low APL cities in each year, and calculate the average and then marginal productivity of urban land. Similarly, we calculate the difference in agricultural land values between high and low APL cities in each year. For each year, we then calculate the total gains from reallocation of land quotas as follows:

$$[(MPL_t^H - MPL_t^L) - (r_t^H - r_t^L)] * 0.3 * LC_t^L,$$

where MPL_t^H and MPL_t^L are marginal productivity of urban land in year *t* in high- and low-land-productivity cities, respectively; r_t^H and r_t^L are rural land value in year *t* in high- and low-land-productivity cities, respectively; LC_t^L is the total area of land converted for urban use in year *t* in low-land-productivity cities. We also calculate the cumulative gains for year *t* as follows:

$$[(MPL_t^H - MPL_t^L) - (r_t^H - r_t^L)] * 0.3 * \sum_{i=2007}^{t} LC_i^L.$$

Table 10: Gains from Reallocating 30 Percent of Land Quotas from Low to High APL Cities

Year	whole prefectures, newly converted land		central cities, newly converted land	
	Annual	Cumulative	Annual	Cumulative
	Total gains (hundred million yuan)			
2007	186.6684	186.6684	89.0167	89.0167
2008	235.4717	438.4380	99.9452	196.7339
2009	411.6024	879.3948	194.7435	404.6491
2010	565.1478	1580.7500	231.1090	698.4333
2011	1045.5885	3037.4998	441.1864	1321.2858
2012	1111.4557	3910.3173	429.0643	1646.5446
2013	1209.9409	5313.8410	437.1769	2165.2347
2014	944.4965	6081.7465	378.1434	2471.4224
	Total gains as percentage of GDP			
2007	0.0696%	0.0696%	0.0332%	0.0332%
2008	0.0743%	0.1384%	0.0316%	0.0621%
2009	0.1191%	0.2544%	0.0563%	0.1171%
2010	0.1382%	0.3866%	0.0565%	0.1708%
2011	0.2160%	0.6274%	0.0911%	0.2729%
2012	0.2081%	0.7321%	0.0803%	0.3083%
2013	0.2058%	0.9037%	0.0743%	0.3682%
2014	0.1485%	0.9560%	0.0594%	0.3885%

The results are presented in Table 10. Estimates in column 1 suggest that the reallocation can generate an annual gain equivalent to 0.07-0.22 percent of the country's GDP. This is slightly higher than the gains presented above in Table 9, which is expected because reallocation across cities should be more effective than between inland and coastal regions. The results in column 2 show that the cumulative loss is nearly 1 percent of GDP eight years later.

We need a benchmark to assess whether these potential welfare gains are large or not. One such benchmark is available in the international trade literature. Krugman (1979) builds a model to show that new varieties are an important source of gains from trade. Broda and Weinstein (2006) find the variety gains to be 0.1 percent of GDP in the U.S., and Chen and Ma (2012) show that the welfare gain from new import varieties amounts annually to 0.4 percent of GDP in China. Since the potential welfare gain from land reallocation across cities in China is in the same order of magnitude as these import variety gains, it is quite large and economically significant.

5.5. Why Does the Chinese Government Allocate So Many Land Quotas to Inland Provinces and Low-Productivity Cities?

In this section, we investigate whether cities with higher land price tend to have less land converted from 2007 to 2016. We hypothesize that upper-level governments cannot easily transfer land revenue from one jurisdiction to another, and thus they tend to use land quotas to balance inter-jurisdictional inequalities of land revenue. This implies that if land is expensive in one city, the city tends to receive a lower quota the next time.

From the land transaction data, we obtain land areas converted for urban use (LC_{it}) and land prices for each city in each year (p_{it}). To verify our hypothesis, we regress land area converted on lagged land price at the city level:

$$ln\, LC_{it} = \alpha + \beta\, ln\, p_{it-1} + C_i + \tau_t + \varepsilon_{it}, \quad (14)$$

where C_i is a city fixed effect; τ_t is a year fixed effect; and ε_{it} is the error term.

Table 11: Area of Land Converted and Lagged Land Price

	Dependent variable: Log area of land converted for urban use				
	Full sample	Com., Res. & Ind.	Industrial	Residential	Commercial
	(1)	(2)	(3)	(4)	(5)
Lagged log land price	-0.0123	-0.0538**	-0.0596***	-0.198***	-0.0608***
	(0.0212)	(0.0239)	(0.0196)	(0.0217)	(0.0198)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	5.505***	5.338***	4.803***	5.066***	2.925***
	(0.108)	(0.125)	(0.121)	(0.149)	(0.166)
N	3,123	3,123	3,046	3,012	2,976
R^2	0.302	0.354	0.282	0.270	0.308

Notes: Standard errors are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 11 reports the results. In column (1), we include the full sample of land parcels. In columns (2)–(5), we use the subsamples of commercial, residential, and industrial land, either together or separately. Our results show consistent negative coefficients of lagged urban land price. This is suggestive evidence that the Chinese government is trying to "equalize" government land revenue: If urban land is more expensive in a region/city, less land is converted for urban uses in the following year so that land revenue is not too high relative to other regions/cities.

Another possible reason for land misallocation is that land quotas are used as a policy tool to control population growth in larger cities. The Chinese government has a long-standing policy to control population growth in large cities and at the same time invest more resources in large cities (Xing and Zhang 2017). As a result, land tends to be more productive in larger cities. For example, using data from 2014, the correlation coefficient between city population and average productivity of urban land is 0.405. Given this, if land supply is more tightly controlled in larger cities to contain population growth, it leads to land misallocation across cities. Recall from Table 4 that cities with a larger population size tend to have a bigger urban-rural land value gap, which is consistent with the notion that land quotas are used to control the growth of larger cities.

It is important to figure out the main reason behind the misallocation of land across cities in China, because it has implications for policy solutions to the problem. For example, if indeed the central government allocated more land quotas to inland provinces only to guarantee a certain amount of land revenue for those provinces, then misallocation of land can be easily avoided by some cap-and-trade type of system that allows for buying and selling land quotas among local jurisdictions.[23] However, if the misallocation is a result of controlling growth in larger cities or promoting urbanization in less developed regions, then the welfare loss is inevitable unless the government reverses the policy.

6. Conclusion

Using a large data set of land transactions assembled by crawling a government website, we document various facts about land conversion for urban uses in China. We find that revenue from selling land leaseholds amounts to more than half of local governments' budget revenue during 2007 to 2014. We show that an increasingly larger share of land is converted for urban uses in low productivity regions or cities. There is evidence for land misallocation in this period. We find that the urban-rural land value gap varies substantially across provinces and that the marginal productivity of urban land varies greatly across cities. Our counterfactual analysis shows that the potential gains from reallocating land quotas from low-productivity to high-productivity provinces or cities are economically significant.

Our analysis takes the allocation of other productive factors across cities as given and focuses exclusively on land. It is possible that there are also other sources of misallocation. For example, China has long used the Hukou system to control internal migration. There might be serious misallocation of workers both between rural and urban areas and across cities (Au and Henderson 2006a, 2006b). Moreover, there is also evidence that as a result of political favoritism and place-based subsidies, different cities in China face different prices of capital, leading to a misallocation of physical capital across cities (Chen et al. 2017b; Yang et al. 2017). Solving all of these misallocation problems simultaneously could generate even higher welfare gains.

Finally, we should note that our discussion and calculation has ignored non-market benefits and costs. For example, one might argue that rapid urbanization in coastal regions poses a threat to the environment and that the land quota system helps slow down the development and preserve the ecological balance in such regions. One might also believe that the land quota system helps maintain regional balance in urbanization that is socially desirable. It is a methodological change to incorporate such non-market benefits and costs in our analysis. If, in fact, there are worthy causes for the allocation of more land quotas to inland regions and less productive cities, then our estimated losses should be interpreted as the economic costs of such policy goals.

[23] Indeed, this cap-and-trade type of policy was tried in Zhejiang province during the early 2000s (see Chau et al. 2016). Starting in February 2018, the central government decided to allow trading of land conversion quotas across provinces, which should help alleviate the misallocation problem.

References

Adamopoulos, Tasso, Loren Brandt, Jessica Leight, and Diego Restuccia. 2017. "Misallocation, Selection and Productivity: A Quantitative Analysis with Panel Data from China." NBER Working Paper No. 23039.

Adamopoulos, Tasso and Diego Restuccia. 2014. "The Size Distribution of Farms and International Productivity Differences." *American Economic Review* 104(6): 1667–1697.

Adamopoulos, Tasso and Diego Restuccia. 2015. "Land Reform and Productivity: A Quantitative Analysis with Micro Data." Working Paper. University of Toronto.

Albouy, David. 2009. "The Unequal Geographic Burden of Federal Taxation." *Journal of Political Economy* 117(4): 635–667.

Anderson, Gordon and Ying Ge. 2005. "The Size Distribution of Chinese Cities." *Regional Science and Urban Economics* 35(6): 756–776.

Au, Chun-Chung and J. Vernon Henderson. 2006a. "Are Chinese Cities Too Small?" *Review of Economic Studies* 73: 549–576.

———. 2006b. "How Migration Restrictions Limit Agglomeration and Productivity in China." *Journal of Development Economics* 80: 350–388.

Broda, Christian and David E. Weinstein. 2006. "Globalization and the Gains from Variety." *Quarterly Journal of Economics* 121(2): 541–585.

Brueckner, Jan K., Shihe Fu, Yizhen Gu, and Junfu Zhang. 2017. "Measuring the Stringency of Land-Use Regulation: The case of China's Building-Height Limits." *Review of Economics and Statistics* 99(4): 663–677.

Cai, Hongbin, J. Vernon Henderson, and Qinghua Zhang. 2013. "China's Land Market Auctions: Evidence of Corruption?" *RAND Journal of Economics* 44(3): 488–521.

Cai, Hongbin, Zhi Wang, and Qinghua Zhang. 2017. "To Build above the Limit? Implementation of Land Use Regulations in Urban China." *Journal of Urban Economics* 98: 223–233.

Cao, Guangzhong, Changchun Feng, and Ran Tao. 2008. "Local 'Land Finance' in China's Urban Expansion: Challenges and Solutions." *China & World Economy* 16(2): 19–30.

Chari, A.V., Elaine M. Liu, Shing-Yi Wang, and Yongxiang Wang. 2018. "Property Rights, Land Misallocation and Agricultural efficiency in China." Unpublished manuscript, Department of Economics, University of Houston.

Chau, Nancy H., Yu Qin, and Weiwen Zhang. 2016. "Leader Networks and Transaction Costs: A Chinese Experiment in Interjurisdictional Contracting." IZA Discussion Paper No. 9641.

Chen, Bo and Hong Ma. 2012. "Import Variety and Welfare Gain in China." *Review of International Economics* 20(4): 807–820.

Chen, Chaoran, Diego Restuccia, and Raül Santaeulàlia-Llopis. 2017a. "The Effects of Land Markets on Resource Allocation and Agricultural Productivity." NBER Working Paper No. 24034.

Chen, Ying, J. Vernnon Henderson, and Wei Cai. 2017b. "Political Favoritism in China's Capital Markets and its Effect on City Sizes." *Journal of Urban Economics* 98: 69–87.

Duranton, Gilles, Ejaz Ghani, Arti Grover Goswami, and William Kerr. 2015. "The Misallocation of Land and Other Factors of Production in India." Policy Research Working Paper 7221. The World Bank.

Fang, Hanming, Quanlin Gu, Wei Xiong, and Li-An Zhou. 2015. "Demystifying the Chinese Housing Boom." in *NBER Macroeconomics Annual*, Vol. 30, ed. Martin Eichenbaum and Jonathan Parker, 105–166. University of Chicago Press.

Fang, Li, Peng Li, and Shunfeng Song. 2017. "China's Development Policies and Urban Dynamics: An Analysis based on the Zipf Law." *Urban Studies* 54(12): 2818–2834.

Fu, Shihe, Yu Liao, and Junfu Zhang. 2016. "The Effect of Housing Wealth on Labor Force Participation: Evidence from China." *Journal of Housing Economics* 33: 59–69.

Gandhi, Amit, Salvador Navarro, and David Rivers. 2013. "On the Identification of Production Functions: How Heterogeneous is Productivity." Working paper. Department of Economics, University of Wisconsin-Madison.

Ghatak, Maitreesh and Dilip Mookherjee. 2014. "Land Acquisition for Industrialization and Compensation of Displaced Farmers." *Journal of Development Economics* 110: 303–312.

Glaeser, Edward, Wei Huang, Yueran Ma, and Andrei Shleifer. 2017. "A Real Estate Boom with Chinese Characteristics." *Journal of Economic Perspectives* 31(1): 93–116.

Gyourko, Joseph and Raven Molloy. 2015. "Regulation and Housing Supply." In *Handbook of Regional and Urban Economics*, Vol. 5, ed. Gilles Duranton, J. Vernon Henderson and William Strange, 1289–1337. Elsevier.

Han, Libin and Ming Lu. 2017. "Housing Prices and Investment: An Assessment of China's Inland-favoring Land Supply Policies." *Journal of the Asia Pacific Economy* 22(1): 106–212.

Hopenhayn, Hugo. 2014. "Firms, Misallocation, and Aggregate Productivity: A Review." *Annual Review of Economics* 6, 735–770.

Hsieh, Chang-Tai and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics* 124(4): 1403–1448.

Hsieh, Chang-Tai and Enrico Moretti. 2015. "Why Do Cities Matter? Local Growth and Aggregate Growth." NBER Working Paper No. 21154.

Krugman, Paul R. 1979. "Increasing Returns, Monopolistic Competition, and International Trade." *Journal of International Economics* 4: 469–479.

Levinsohn, James and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies* 70(2): 317–341.

Li, Hongbin and Li-An Zhou. 2005. "Political Turnover and Economic Performance: The Incentive Role of Personnel Control in China." *Journal of Public Economics* 89(9–10): 1743–1762.

Lu, Ming. 2016. *Great State Needs Bigger City*. Shanghai People's Press.

Olley, G. Steven and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunication Equipment Industry." *Econometrica* 64(6): 1263–1297.

Qin, Yu, Hongjia Zhu, and Rong Zhu. 2016. "Changes in the Distribution of Land Prices in Urban China during 2007–2012." *Regional Science and Urban Economics* 57: 77–90.

Restuccia, Diego and Richard Rogerson. 2013. "Misallocation and Productivity." *Review of Economic Dynamics* 16(1): 1–10.

———. 2017. "The Causes and Costs of Misallocation." *Journal of Economic Perspectives* 31(3): 151–174.

Restuccia, Diego and Raül Santaeulàlia-Llopis. 2017. "Land Misallocation and Productivity." NBER Working Paper No. 23128.

Tan, Rong, Futian Qu, Nico Heerink, and Evy Mettepenningen. 2011. "Rural to Urban Land Conversion in China—How Large Is the Over-Conversion and What Are Its Welfare Implications?" *China Economic Review* 22(4): 474–484.

Wang, Zhi, Qinghua Zhang, and Li-An Zhou. 2017. "To Build Outward or Upward? The Spatial Pattern of Urban Land Development in China." Working paper.

Wu, Jing, Joseph Gyourko, and Yongheng Deng. 2016. "Evaluating the Risk of Chinese Housing Markets: What We Know and What We Need to Know." *China Economic Review* 39: 91–114.

Xie, Zhikui. 2015. *Administration upon Spring: Institutional Analysis of the Land Administration in China*. The Commercial Press.

Xing, Chunbing and Junfu Zhang. 2017. "The Preference for Larger Cities in China: Evidence from Rural-Urban Migrants." *China Economic Review* 43: 72–90.

Yang, Shangming, Yuming Fu, and Yi Lu. 2017. “The Spatial Misallocation of Capital and Labor in China: A Welfare Analysis Based on Urban Accounting.” Working paper. Department of Real Estate, National University of Singapore.

Zhang, Junfu. 2011. “Interjurisdictional Competition for FDI: The Case of China's “Development Zone Fever”.” *Regional Science and Urban Economics* 41(2): 145–159.

Appendix A: Sample Construction Using the China Land Transaction Data

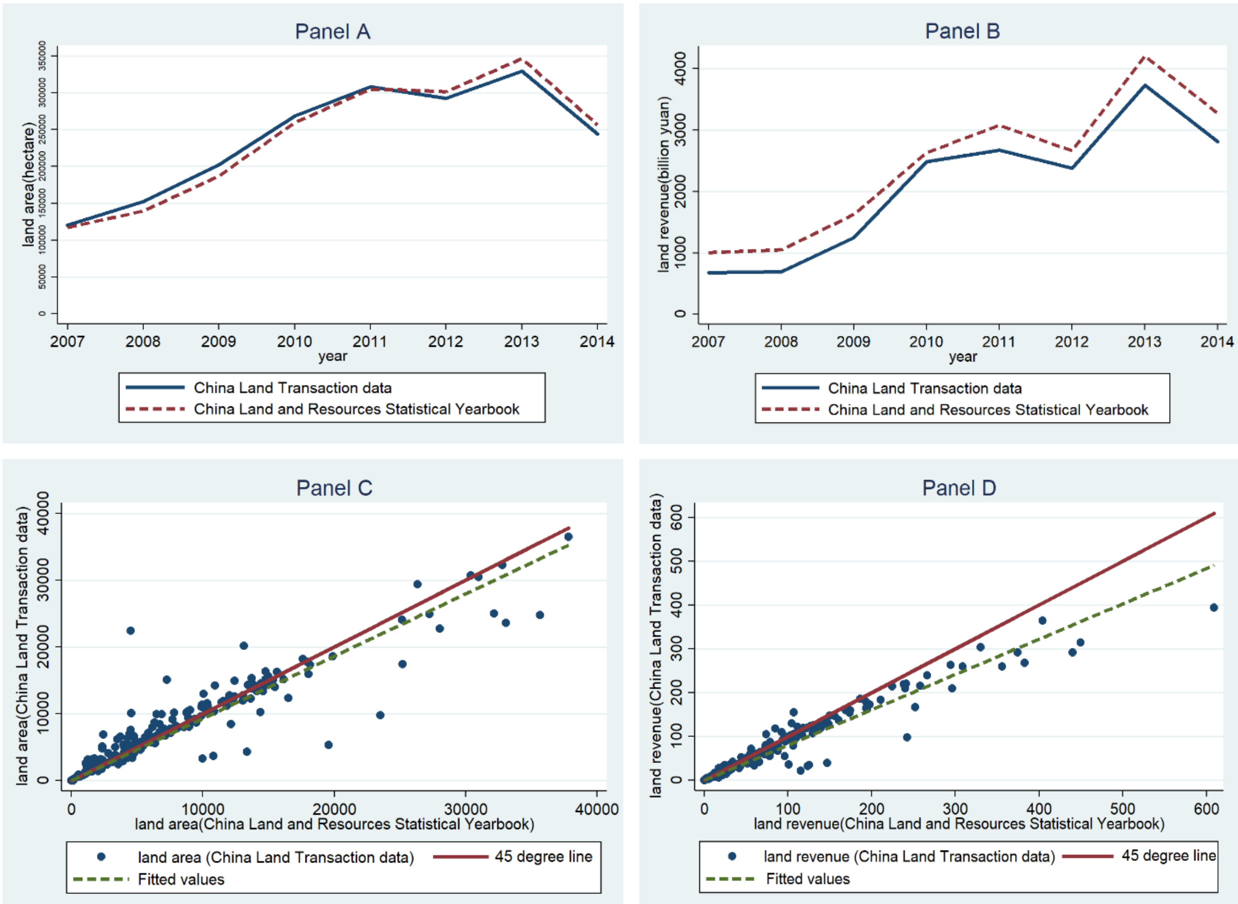
There are 1,941,657 observations in the full sample. Table A.1 describes the steps we followed to create our analysis sample. First, since there are no city-level variables in the land transaction data, we merge it with a data set that contains city characteristics, resulting in 1,914,927 observations. Second, if two observations have identical province, city, district, transaction ID, project name, contract date, land price, and land area, we consider them as duplicates and only keep one observation. Third, we drop 132 observations where the contract year in these observations is missing. Fourth, since the website was launched in early 2008, the coverage of pre-2007 deals is very incomplete; we thus drop all the observations before 2007. Fifth, we drop 401 observations in which price is negative or land area is nonpositive. Sixth, we drop a total of 15,427 top 1 percent outliers based on land price in each city-year. For each city-year, the top 1 percent are separately identified and excluded from our empirical analysis. While this may lead to an underestimation of totals, it is necessary because some prices are unbelievably high (likely a result of incorrect units used in data recording). Seventh, we drop 24 outliers in which price is larger than 500,000 yuan per square meter or land area is larger than 20000 hectares. Finally, we drop 4 more outliers in Xinjiang in 2009 where the land price is unbelievably high (by local standard). We end up with 1,542,279 land transaction deals after these steps.

Table A.1: The Steps to Create Our Analysis Sample

Sample Selection	Number of Obs.
Full sample	1,941,657
Successfully merged with administrative unit identifiers	1,914,927
231,031 duplicate observations deleted	1,683,896
132 observations without contract year deleted	1,683,764
125,629 pre-2007 observations deleted	1,558,135
401 obs. with negative price or non-positive land area deleted	1,557,734
15,427 top 1% outliers in each city-year deleted	1,542,307
28 outliers (price > 500,000 yuan/m^2 or area > 20,000 ha anywhere, or price > 80,000 yuan/m^2 in Xinjiang in 2009) deleted	1,542,279

Appendix B: Assessing the China Land Transaction Data

Figure A.1.: Comparing Land Transaction Data with Alternative Data Source



The quality of the China Land Transaction Data is crucial for the reliability of our empirical findings. Here, we try to assess the data by comparing it with the only alternative data source available: provincial-level data from the China Land and Resources Statistical Yearbook compiled by the Ministry of Land and Resources of China. In Panel A of Figure A.1, we compare total area of land converted for urban uses in each year, from the two data sources. We see that the two series follow the same trend and are very close to each other. In Panel B we compare the total land revenue in each year calculated from the two data sources. They also follow the same trend, but the total from our China Land Transaction Data is always smaller. We suspect that this is a result of dropping top outliers based on price. However, we find that adding back the outliers only makes this difference smaller, but cannot eliminate this difference completely. In other words, our data may underestimate land revenue. In Panels C and D, we compare province-year level land area and land revenue, respectively. Total area or revenue from our China Land Transaction Data is on the vertical axis and the corresponding total from the statistical yearbook is on the horizontal axis. If they coincide perfectly, all of the dots should be on the (solid) 45-degree line. The fitted (dash) line is below the 45-degree line, suggesting that provincial-level total land areas and revenues calculated from the China Land Transaction Data are smaller than the aggregates published by the government. Again, the difference is bigger for revenue data.

Overall, our analysis here indicates that if the aggregate data from the China Land and Resources Statistical Yearbook can be trusted, then the China Land Transaction Data are reasonably good. The data we collected produce identical trends as the publicly available yearbook data; they give very similar aggregate statistics on land area; they may underestimate land price and revenue, which one should keep in mind when interpreting our results.