# The Geographic Bias of Growth and Structural Change*

ECO4060 Second Year Paper

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**Abstract**

Structural change, or the fall in relative employment in agriculture, can concentrate the distribution of economic activity in space insofar as it causes reallocation of workers from the hinterlands to cities. In this paper, I introduce theory and a structural model to assess how important this mechanism was in explaining rapid geographical concentration in China between 2000-2005. I test this mechanism against other salient explanations including falling trade costs, migration costs, and the changing spatial distribution of productivity. I find that this mechanism explains only 5 percent of observed rise in spatial concentration. However, the model captures a small fraction of the observed structural change because it focuses only on the fall in relative agricultural spending. Expanding the model to fit the observed structural change is a clear avenue for future research.

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# 1 Introduction

Contemporary models of spatial equilibrium imply that productivity growth, when uniform across locations, does not change the overall distribution of economic activity in space. In this paper, I argue that this feature masks an important mechanism by which growth concentrates economic activity even when the spatial distribution of productivity remains unchanged.

The theory rests on two ideas. Firstly, growth changes the consumption basket through Engel's Law; shifting expenditures away from food and toward other goods. This manifests in general equilibrium as *structural change*, where agricultural employment falls relative to other sectors as the economy grows. On the other hand, demand for agriculture shapes geography insofar as the returns to concentrating it in space are dwarfed by other sectors. Taken together, these imply that workers leaving agriculture during the structural change process are absorbed by regions with high population density. This reallocation increases the dispersion of population density across space.

This link between structural transformation and urbanization has previously been explored in Michaels et al. (2012). They build a theory and rationalize rising spatial concentration in part by appealing to differences in land intensity across sectors. As a result, population dense regions specialize outside of agriculture under trade and, conditional on specializing, tend to have more dispersion in population densities. I build on this research in two ways. As a small contribution, I provide conditions on the strength of agglomeration and productivity growth and explicitly prove this relationship holds. Secondly, and most importantly, I measure the magnitude of this effect by taking a spatial equilibrium model to Chinese data from 2000-2005. The theory reveals how to make this measurement.

The structural model allows for falling migration, regional trade costs and changing relative productivity as alternative explanations for the reallocation of workers across space. I find that productivity growth, when uniform across locations and set to the inferred average level, accounts for approximately 5 percent of the total rise in population density dispersion observed in the data. This effect is small because falling agricultural spending appears to explain only a small fraction of observed structural change. For future work, I plan on broadening the model to include other forces that cause structural change, including a falling agricultural productivity gap as in Gollin et al. (2013) or Restuccia et al. (2008).

Why study China? During this period, the country saw a massive reallocation of workers toward the population-dense coastal provinces, such as Beijing, Shanghai and Guangdong. Such mobility was and is made exceptionally difficult by a unique institution– the Hukou system (Chan, 2019) (Meng, 2012). However, by the 2000's the Chinese government introduced significant reform, and there is some quantitative evidence that these reforms caused migration inflows (Fan, 2018). At the very least, migration costs (measured by observing spatial differences in real income relative to migration flows) fell significantly during the period (Tombe and Zhu, 2019). These falling migration costs can increase the dispersion of population density as more workers arbitrage away spatial differences in real income. Moreover, Tombe and Zhu (2019) also find that falling trade costs during this period were also significant; and falling trade costs are key in determining the spatial distribution of economic activity in the economic geography literature. How does the impact of the theory stack up against these two variables, which themselves are largely influenced by policy? China provides a unique opportunity to answer this question.

At the same time, China also experienced rapid growth and structural change during this period. These facts alone distinguish it as a country where the geographic bias of growth could play a major role in shaping the population distribution.

The strategy behind calibrating this model starts with the fact that *relative* productivity growth across space is identified using regional trade data and a gravity model. However, this procedure is uninformative about *aggregate* growth– that is, a scale factor that determines productivity in absolute terms. I propose an estimation strategy that disciplines this growth using information contained in falling agricultural spending. First, I estimate income and substitution elasticities over agricultural goods using GDP data and prices inferred from the gravity model. Given these estimates, I choose the level of aggregate productivity growth that matches the fall in average agricultural spending observed in the data.

For other parameters, calibration uses recent methodology in the trade and spatial literature. Trade costs are mapped from provincial trade data and standard estimates of the trade elasticity. Combined with the calibrated productivity, these are used to construct measures of real income per capita implied by the model. Migration frictions are then inferred from the discrepancy between differences in real income and the observed movement of workers from their hukou.

The paper is organized as follows. I review the literature in Section 2, provide a description of the data and some key motivating facts in Section 3, present a theory and prove it can explain these facts in Section 4, and employ the structural model in Sections 5, 6 and 7. Section 8 concludes with avenues for future research.

## 2 Literature

This paper lies at the heart of a budding literature on the interplay between structural change and geographic outcomes. The earliest of these frames structural change as the driver for spatial convergence in US earnings before 2000 (Caselli and Coleman II, 2001), which has subsequently been applied in China after 2000 (Hao et al., 2020). In contrast to these papers, I focus on the population distribution rather than falling inequality. As a result, they do not emphasize the weaker returns to concentrating agriculture in space as I do.

Another strand of literature throws international trade integration into the mix. Gollin et al. (2016) show that specialization in non-industrial sectors under trade lead to higher non-traded goods employment in "consumption cities"; though space is not directly modeled. Fajgelbaum and Redding (2014) show that regions more integrated into world markets exhibit low agricultural employment shares because of both differences in land intensity and rising employment in non-traded sectors. Data limitations do not allow me to consider the Balassa-Samuelson effect central to these papers. In addition, while I don't focus on international trade in the theory, it is empirically a force for suppressing agricultural employment in the coastal provinces because they import a significant amount of food[1].

[1] In the context of China, local specialization under trade is in part determined by proximity to the eastern coast, highlighed in Coşar and Fajgelbaum (2016).

This literature also highlights dynamic productivity diffusion in space as drivers of structural change (Desmet and Rossi-Hansberg, 2014) (Delventhal, 2019). I abstract from the main mechanisms in these papers by using a simple model of local increasing returns.

Of this body of work, the most closely related are Michaels et al. (2012), Murata (2008) and Eckert and Peters (2018), whom explicitly study the effect of structural change on geography. I build on the mechanism driving spatial concentration in the first two by linking theory to a structural model and assessing it quantitatively against competing hypotheses[2]. The third contains a negative result; that the spatial reallocation of workers accounted for essentially zero of US structural transformation since 1880. In contrast, I ask how falling agricultural employment accounts for total spatial reallocation toward dense locales. I also emphasize the link between density and specialization outside of agriculture, which they do not. For this fundamentally different question, I find results of comparable magnitude. Considering that I do not account for falling agricultural productivity gaps as drivers of structural change, the result may change in future iterations.

This paper is nested within the broader literature on structural change, growth and the agricultural productivity gap[3]. The general concern of these papers are macroeconomic outcomes, and use models where there are multiple sectors but no notion of space within countries[4]. However, the models that give rise to structural change are central to the equilibrium geography that I study here. In particular, I use the non-homothetic CES preferences of Comin et al. (2021) and Lewis et al. (2021) and adapt their estimation strategies for use with prices inferred from trade data.

[2]Michaels et al. (2012) uses decomposition methods to show that population growth can be predicted upon past agricultural specialization. They show that this correlation is robust to controlling for highways, county fixed effects, and some other variables. They relegate their prediction about increasing density dispersion to theory and do not explore it empirically. In contrast, I consider a different set of controls in a fully specified general equilibrium model that can specifically deliver predictions about density dispersion.

[3]See Herrendorf et al. (2014) for a recent review of the structural change literature. This includes Ngai and Pissarides (2007), Boppart (2014), Comin et al. (2021), Matsuyama (1992, 2009, 2019), Uy et al. (2013), Bustos et al. (2016), Bustos et al. (2020), Swiecki (2017), Lewis et al. (2021), Cravino and Sotelo (2019) and Duarte and Restuccia (2010).

[4]A notable exception is Karádi and Koren (2017), which links a disaggregated equilibrium in a monocentric city model to the aggregate production function to facilitate development accounting. While the research question is fundamentally different, their model also features a version of the spatial bias of growth – see Proposition 3.

While the model and methodology in this paper may come from elsewhere, I study a central question in economic geography – how is the distribution of economic activity in space determined? I build on the models of Krugman (1991), Puga (1999), Ottaviano et al. (2002), Murata (2008), Davis (1998) and subsequent work to answer this question. I also draw from recent spatial models that are rich enough to have an empirical implementation, including Allen and Arkolakis (2014), Redding (2016), Nagy (2020), Allen and Donaldson (2020), Desmet et al. (2018), Sotelo (2020), Eckert and Peters (2018) and importantly Tombe and Zhu (2019), Hao et al. (2020), Ma and Tang (2020) and Fan (2019) in the context of China. Each employ a scheme to map observed data to unobservable parameters, which I use extensively for productivity, trade and migration costs. In particular, I draw heavily from the methodology and data choices in Tombe and Zhu (2019) and Hao et al. (2020). The point of departure is the use of homothetic preferences[5], so that any spatially uniform scaling of productivity do not change the equilibrium outcomes that I study. I generalize these empirical implementations to a model falling outside this common class.

Surrounding this central question is an empirically oriented literature in which transportation infrastructure is the main dependent variable. These include Baum-Snow (2007), Duranton and Turner (2011), Duranton and Turner (2012), Baum-Snow (2020), Herzog (2021), Faber (2014), Bartelme (2018) and in particular Baum-Snow et al. (2017) and Baum-Snow et al. (2020) in the Chinese context. I compare the magnitude of the spatial bias of growth against the effects of falling trade costs (among other benefits) considered in these papers. Moreover, data constraints force me to consider a large level of spatial aggregation than what is typical. I hope to consider a model with prefectures instead of provinces in future work.

## 3 Data and Facts

The data reveal key features of China's growth that link geographic concentration and structural change. Firstly, I document rising spatial concentration that is *purely* driven by employment growth outside of agriculture. I also show that locations with higher population density tend to have lower agricultural employment shares and a revealed comparative advantage outside of agricul-

[5] With the exception of Hao et al. (2020).

ture in the cross section. These relationships have a clear grounding in the theory I present in the following section.

To construct these facts, I draw on multiple data sources at the provincial level, excluding Tibet. These concern provincial and international trade, migration, agricultural spending and GDP data disaggregated by the primary and non-primary industries. In the Chinese census and China Statistical Yearbooks (CSY), the primary industry is an aggregate of farming, animal husbandry, forestry and fishing. I follow Hao et al. (2020) by defining the primary industry as the agricultural sector, and all other economic activity as an aggregated non-agricultural sector.

I exploit a model of trade to calibrate productivity, which requires provincial and international trade data. These flows come from the 2002 and 2007 regional input-output tables, which are disaggregated by sector. These are the same data used in Fan (2019) and Tombe and Zhu (2019). However, this level of disaggregation comes at a disadvantage. Flows are limited to rail transport, which misses a bulk of trade.

To capture imperfect labour mobility, I use migration data from the 2000 and 2005 Chinese population censuses. These data map individuals residing in a province and sector to their hukou. I measure migration flows as the fraction working in a sector or province different from the hukou, in the same way as Tombe and Zhu (2019) and Hao et al. (2020). Without loss of generality, I use the term "agricultural" in reference to the rural hukou. Interpreting the movement of workers across sectors but not space as migration is not necessary; the model has no notion of space *within* provinces.

Value added and labour employment data come from the CSY. I do not observe good measures of land use, so I infer it as the allocation that equalizes the return to land within provinces. I also assume that the entire official landmass is used for either production or consumption, which is also reported in the CSY.

Food spending shares are split by urban and rural areas within each province using data from *China Data Online*. I ascribe rural spending shares to agricultural workers and urban to workers outside agriculture, similarly to Hao et al.

(2020). This is not a perfect match, because workers in rural areas within a province may be employed outside of agriculture. However, it is a sensible one – an overwhelming majority of those holding rural hukou are employed in the primary sector. These food spending shares appear quite large (on average 30 percent in 2000) because I use after tax income. This potentially ignores income effects stemming from the provision of goods and services by the government sector.

### The primary sector and rising spatial concentration

How much has spatial concentration risen from 2000 to 2005? When measuring it as the coefficient of variation of employment density across provinces, it increased from 1.1 to 1.218, representing an approximate 10 percent rise in just 5 years[6]. To put in perspective, I compare this to the US. At the Minor Civil Division level of aggregation, the same statistic increased from 0.3716 to 0.506 from 1880-2000 – representing a growth of 36 percent in a period of *120 years* (Michaels et al., 2012). Extrapolating the observation in China to this longer time period implies a growth of almost 1000 percent[7].

The rising spatial concentration can be illustrated with a regression of employment growth on initial employment density. If employment growth is on average larger for more population dense locations, then population density dispersion will tend to rise. A plot of the regression and the data is reported in Figure 1. The positive coefficient is clearly driven by the inclusion of exceptionally fast growing provinces, like Shanghai, Beijing and Guangdong.

Which sectors are driving the rising concentration? To explore this, I decompose the total employment growth rate $g_i$ into a *agriculture* (a) and *non-agriculture* (n) components. These are related in the following way,

$$g_i = g_{i,a} s_{ia,2000} + g_{i,n} s_{in,2000}$$

[6]When measuring this as employment weighted population density dispersion, it increased from 0.714 to 0.806.

[7]This extrapolation is simply for comparison. The rise in population density dispersion was transitory – it vanished completely from 2005-2010. Explaining this observation is outside the scope of the paper.

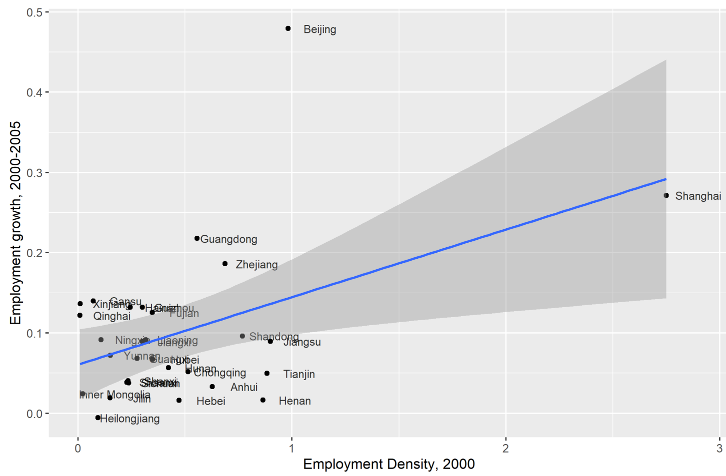


**Figure 1:** Relationship between average employment growth and employment density by Chinese province. Density is measured in millions per 1000 square miles. Slope estimate for unweighted and employment-weighted is 0.0841 and 0.0633, respectively. Unweighted and employment weighted regressions have a p value of $< 0.01$ and 0.08.

where $g_{i,s}$ and $s_{is,2000}$ are the growth rates of employment and the share of employment in 2000 in sector $s$ and province $i$, respectively. I regress both of these components against initial employment density separately[8], noting that the coefficients on each regression must add up to the slope reported in Figure 1. I find that the slope for the agricultural component is negative, implying that the relationship is entirely driven by activity outside of the primary sector. A plot of both regressions is reported in Figure 2.

The facts shown in Figures 1 and 2 are readily explained by the interplay between structural change and the differential returns in space across sectors. Structural change causes outflows of labour from the agriculture, and these outflows tend to have a relationship with population density that is relatively weaker in magnitude[9]. These workers tend to get absorbed in provinces with a comparative advantage outside of agriculture. But, comparative advantage is in part determined by density insofar as the local supply of land in production

[8]This procedure is in a similar vein to that of Michaels et al. (2012), who use historical agricultural employment shares to predict future productivity growth.

[9]The agriculture slope estimate in Figure 2 has less than half the magnitude than that of the non-agriculture component.

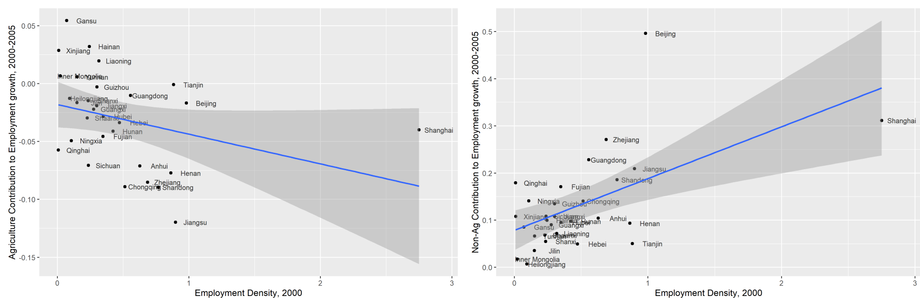


**Figure 2:** Relationship between employment growth by sector and employment density by Chinese province. Density is measured in millions per 1000 square miles. Employment-weighted slope estimates are -0.0593 and 0.1226 for the agricultural and non-agricultural components, with similar magnitudes for the unweighted regressions. Non-ag weighted and unweighted regressions have a p-value of $< 0.01$ and 0.02, respectively.

is inelastic. The question remains – is the relationship between density and comparative advantage a feature of the data? I document below.

Before continuing, I note an additional caveat. These results may appear at odds with the motivating evidence in Eckert and Peters (2018), but I show that they are not. I repeat their additive decomposition of aggregate structural change into ”spatial reallocation” and ”regional transformation” components, defined by

$$s_{a,2005} - s_{a,2000} = \sum_i \left[ s_{ia,2000}(l_{i,2005} - l_{i,2000}) + (s_{ia,2005} - s_{ia,2000}) l_{i,2005} \right] \quad (1)$$

where $s_{at}$ is the aggregate employment share in agriculture at time $t$, and $l_{it}$ the fraction of employment in province $i$ at time $t$, respectively. Intuitively, if the spatial reallocation term $\sum_i s_{ia,2000}(l_{i,2005} - l_{i,2000})$ is relatively large, then most of the structural transformation comprises of workers moving across provinces. I find that the term accounts for only 5 percent of the total change in the share of agricultural employment. This is approximately the same number they find in the US between 1880 and 2000. I reiterate that, while spatial reallocation may not account for much of China's structural transformation, structural transformation may significantly affect spatial reallocation toward dense provinces. This is precisely what Figure 2 suggests.

### Structural change, specialization and comparative advantage

How fast was structural change during this period? The aggregate employment share in agriculture fell from 52.9 percent to 44.8 percent. This decrease is in part reflected in the falling aggregate food expenditure shares implied by the provincial data. Food represented 31.8 percent of the aggregate budget in 2000, and decreased to 28.2 percent in 2005.

How has structural change varied by density, and does this reflect comparative advantage? To examine the relationship in the cross section, I plot the 2000 agricultural employment share against employment density in Figure 7 of Appendix B. The relationship is strong. Each additional million people per thousand square miles is associated with a 0.19 decrease in the share of agriculture employment in the range of densities observed in the data. This relationship remains stable in transition to 2005.

The relation in Figure 7 can be rationalized in the absence of trade. Spatial differences in equilibrium real income could induce this pattern whenever migration is costly. Instead, I consider a more direct measure – the Revealed Comparative Advantage (RCA) as in Balassa (1963). As is well known, it is defined as follows for province $i$ and sector $s$,

$$RCA_{i,s} = \frac{E_{i,s} / \sum_{s' \in \{a,n\}} E_{i,s'}}{\sum_{i' \in \mathbf{P}} E_{i',s} / \sum_{s' \in \{a,n\}, i' \in \mathbf{P}} E_{i',s'}}$$

where $E_{i,s}$ are exports and $\mathbf{P}$ is the set of province indices and a rest-of-the-world aggregate. Exports in this case are defined to include regional trade. In words, RCA measures how intensively a province exports goods in $s$ relative to how intensively that good is exported worldwide. I plot a regression of RCA in agriculture on employment density in 2000, see Figure 3. It reveals that density accounts for about 30 percent of the variation in revealed comparative advantage in the data. In addition, this correlation is supplemented by evidence in Baum-Snow et al. (2020). They show that improved road infrastructure (which presumably increases regional trade integration) caused smaller prefectures to specialize in agriculture.

In short, density matters for trade patterns. Like the previous fact, this is grounded in theory. Chinese agriculture uses land more intensively with a cost share of 0.26 relative to 0.01 in non-agriculture (Hao et al., 2020). If the supply of land for use in agriculture is inelastic and agglomeration forces do not vary too widely by sector, this means that high land prices in dense locations will crowd out agricultural activity.

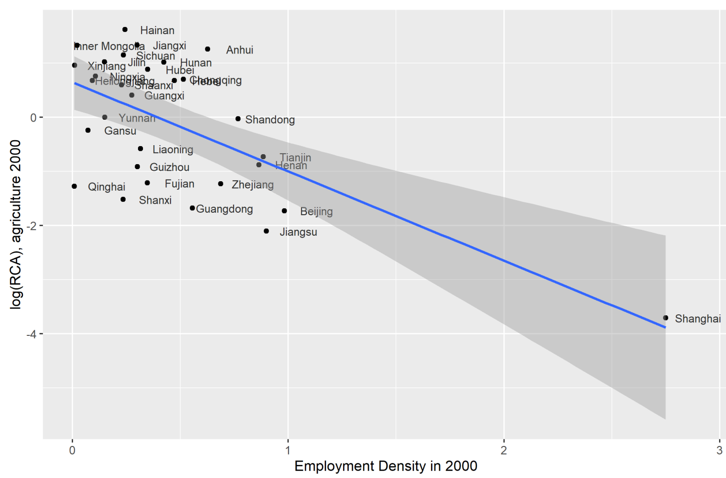


**Figure 3:** Relationship between revealed comparative advantage and employment density by Chinese province. Density is measured in millions per 1000 square miles. The slope estimate is -1.899 with a p-value of $< 0.0001$, and the regression has an $R^2$ of 0.3. Similar results hold in the 2005 cross-section.

# 4 Theory

Explaining these facts and guiding the methodology behind the empirical work, I introduce a theory that captures when and how the geographic bias of growth will occur, and how to measure it. At the heart of this theory is the idea that concentrating agriculture in space comes with a penalty that is larger than other sectors. As a result, the intensity of agricultural consumption (or equivalently, employment in general equilibrium) will inversely affect how concentrated the geography will be. Structural change thus increases concentration.

The theory assumes exogenous spatial variation in productivity. I make this assumption in part because productivity differences are evident, and persist in the time period I study. Moreover, the inferred differences across provinces cannot be explained by population density using typical estimates of the agglomeration elasticity[10]. I use productivity differences solely to generate spatial variation in economic activity. In equilibrium, the location with higher productivity endogenously specializes outside of agriculture.

To this end, define the set of locations $\{1, 2\}$ indexed by $i$, a set of sectors $\{a, n\}$ indexed by $s$, and assume there are a measure $L$ workers to be allocated to each of these sector-location pairs. Locations are ranked by productivity, and are endowed with $H$ units of land that is mobile across sectors but immobile across space. This two location set-up is makes measuring the dispersion in population density simple – it is increasing on the size of the largest location. This is what I show below.

## Production

Each sector-location uses a Cobb-Douglas technology

$$Y_{i,s} := A_{i,s} L_{i,s}^{1-\beta_s} H_{i,s}^{\beta_s}$$

where $A_{i,s} := a_{i,s} \left(\frac{L_{i,s}}{H_{i,s}}\right)^{\alpha_s}$ captures economies of density that are not internalized by the representative firm. I assume land is used more intensively in agriculture, $1 > \beta_a > \beta_n > 0$, and positive economies of density $\alpha_s > 0$. To abstract from Ricardian motives for specialization, I assume that location $1$ and $2$ have productivity $ca_s$ and $a_s$ in each sector $s$ and $c > 1$, respectively. In other words, there are no differences in relative productivity across sectors. However, differences in relative marginal costs will arise. This is because location $1$ must have more workers in an equilibrium where mobility is free – and thus produce at a higher density[11].

For simplicity, I assume workers in sector $s$ are paid the rents of all employed factors within their respective location, as in Redding (2016). In other words, leaving the sector or location changes the stock of land that a worker is entitled to earn rents from. I maintain this assumption in the empirical model and defer

[10]See Combes and Gobillon (2015) for a review of the literature on the estimation of agglomeration elasticities.

[11]This assumption mirrors that of larger spatial variance of (log) productivity in non-agriculture used in Michaels et al. (2012). Here, I make the assumption that the spatial variance in productivity are equal across sectors, which is enough to generate the result.

a discussion about its implications. I also assume land are perfectly mobile across sectors within a location. Considering the other extreme of completely immobile land does not change any result.

Abstracting away from perfect labour mobility for now is useful. Let $\phi_{is}$ be nominal output per worker in $i, s$. By properties of the technology, we have that $(1 - \beta_s)\phi_{i,s} = w_{i,s}$, where $w$ are the rents paid to labour. Coupled with perfect land mobility, this means that the allocations of land satisfy

$$\frac{H_{i,a}}{H_{i,n}} = \frac{\beta_a}{\beta_n}\frac{\phi_{i,a}L_{i,a}}{\phi_{i,n}L_{i,n}}$$

and in particular land market clearing implies,

$$H_{i,s} = \frac{\beta_s \phi_{i,s} L_{i,s}}{\beta_a \phi_{i,a} L_{i,a} + \beta_n \phi_{i,n} L_{i,n}} H$$

So that the *employment density* as a function of labour and output per worker satisfies

$$\frac{L_{i,s}}{H_{i,s}} = \frac{\beta_a \phi_{i,a} L_{i,a} + \beta_n \phi_{i,n} L_{i,n}}{\beta_s \phi_{i,s} H} \tag{2}$$

I assume that output markets are perfectly competitive. Prices are then equal to marginal cost, which can easily be shown to satisfy

$$p_{i,s} = (1 - \beta_s)\phi_{i,s}^{1-\Omega_s}\left[\frac{\beta_a \phi_{i,a} L_{i,a} + \beta_n \phi_{i,n} L_{i,n}}{\beta_s H}\right]^{\Omega_s} a_{i,s}^{-1} \tag{3}$$

where $\Omega_s := \beta_s - \alpha_s$ is the negative *effective returns to density* in sector $s$. This describes the penalty (in terms of prices) that arises whenever good $s$ is produced at high density. I make the assumption that $\Omega_a > 0$ and $\Omega_n \leq 0$ so that there are net decreasing returns in the $a$ sector, and weakly increasing returns in $n$. In the empirical model, I use $\beta_a = 0.26$ and $\beta_n = 0.01$ as in Hao et al. (2020). If the returns to scale in both sectors is $\alpha_s = 0.05$, a value that implies an effective agglomeration elasticity of $\Omega_n = 0.04$ which is reasonable given estimates in the literature, then this is easily satisfied. This would only be violated if the spatial returns to agriculture were extremely large.[12]

[12] The assumption that there is increasing returns to scale can be relaxed and replaced with $\Omega_a < \Omega_n$ so that $n$ has increasing returns relative to $a$. This requires an additional assumption to rule out equilibria at extreme parameter values, so I omit it for brevity. I don't view this as an issue– there is overwhelming evidence of agglomeration economies. I stress that agglomeration economies are

**Assumption 1.** $\Omega_a > 0$ *and* $\Omega_n \leq 0$ .

## Regional trade

To make the theory simple, I consider equilibria where there is free trade. Let $\theta > 0$ be the trade elasticity associated with each sector. Prices $P_{i,s}$ are equalized across locations and are assumed to satisfy[13]

$$P_{i,s} = \left[ \sum_{i \in \{1,2\}} p_{i,s}^{-\theta} \right]^{-\frac{1}{\theta}}$$

where $\left[\frac{p_{i,s}}{P_{i,s}}\right]^{-\theta}$ is the fraction of spending in on $s$ goods from location $i$.

## Preferences

Individual preferences are generalized CES as in Comin et al. (2021) and Matsuyama (2019). Utility $U$ as a function of consumption $c_s$ of goods in sector $s$ is implicitly defined by the relation

$$\sum_{s \in \{a,n\}} \gamma_s^{\frac{1}{\eta}} \left( \frac{c_s}{U^{\epsilon_s}} \right)^{\frac{\eta-1}{\eta}} = 1 \tag{4}$$

for $\epsilon_k > 0$ and $\eta \in [0,1) \cup (1,\infty)$. Following these papers, I normalize $\epsilon_n$ and $\gamma_n$ to one as doing so involves a monotone transformation of $U$. Let $\omega_{i,s}$ denote the fraction of income spent on $s$ by workers in $i$ as a function of prices and income. It is well known that $\omega$ satisfies the implicit relation

$$\log(\omega_{i,s}) - \log(1-\omega_{i,s}) = (1-\eta) \log \left[ \frac{P_{i,a}}{P_{i,n}} \right] + (1-\eta)(\epsilon_a - 1) \log \left[ U_{i,s} \right] + \log(\gamma_a) \tag{5}$$

where $U_{i,s}$ is implicitly defined by solving the expenditure minimization problem associated with Equation (4) under prices $P_{i,s}$. Equation (5) is instructive. If $\epsilon_a < 1$ when $\eta < 1$ or $\epsilon_a > 1$ when $\eta > 1$, an increase in the standard of living (measured by the utility function) decreases the agricultural spending share whenever relative prices are fixed. If $\epsilon_a = 1$, the preferences become the standard homothetic CES.

not fundamental to the theory, but factor into it.

[13]This relationship can be derived using an Eaton-Kortum or Armington model. I say nothing about the microfoundations here as it is inconsequential for the spatial bias of growth.

The isoelastic nature of this utility function will also be useful in characterizing how agricultural spending will change as an economy grows. In fact, it only depends on the growth rates of the prices of each sector. (5) can be instead written as

$$\log(\omega_{i,s}) - \epsilon_a \log(1-\omega_{i,s}) = (1-\eta)\log\left[\frac{P_{i,a}}{P_{i,n}}\right] + (1-\eta)(\epsilon_a - 1)\log\left[\frac{\phi_{i,s}}{P_{i,n}}\right] + \log(\gamma_a) \quad (6)$$

Suppose for the sake of this argument that $\phi_i$ is normalized to one. What are the permissible (negative) growth rates of sector prices $g_s$ such that $\omega_i$ must necessarily fall, given that these growth rates must equal across space? It follows directly from (6) that $g_a < \epsilon_a g_n$ when $\eta > 1$ or $g_a > \epsilon_a g_n$ when $\eta < 1$. Intuitively, strong income effects ($\epsilon_a$ is small or large when $\eta < 1$ or $\eta > 1$, respectively) increases the range of growth rates amenable to falling agricultural spending.

In what directly follows, I assume growth rates of the TFP term $a_{i,s}$ are exogenous lie within this range. It is not surprising that this holds in the data, because I estimate $\epsilon_a$ and $\eta$ to partially fit the fall in food spending observed in the data. I also want to stress that the dynamics implicit in this model are not the main focus. Economic growth only acts to decrease agricultural spending shares, and nothing more.

**Assumption 2.** *Let $g_s$ be the growth rate of $a_{i,s}$. I assume $g_a < \epsilon_a g_n$ when $\eta > 1$ or $g_a > \epsilon_a g_n$ when $\eta < 1$.*

## Free trade equilibrium

I now assume perfect labour mobility. I search for a spatial equilibria on the *interior*, that is, where each location is populated and output per worker equalizes. Assuming $1 + \theta\Omega_n > 0$, a lemma in Appendix A shows that all equilibria must be interior whenever there is nonzero total employment in either sector. In other words, the increasing returns in sector $n$ cannot be strong enough to support complete specialization[14]. I abstract away from pathological equilibria where there is no agricultural or non-agricultural production in any location.

[14] Simonovska and Waugh (2014) pin the estimates of the trade elasticity at $\theta = 4$, and there isn't much evidence that it differs in the agricultural sector (Tombe, 2015). Combined with a reasonable value of $\Omega_n = -0.03$, this assumption holds in the structural model.

Free mobility and trade imply that $\omega_{i,s}$ equalizes across locations, and equals the fraction of total employment in agriculture

$$\omega = \frac{L_{1a} + L_{2a}}{L} \tag{7}$$

where I henceforth drop the subscripts from $\omega_{i,s}$ for brevity. The following is derived from goods market clearing

$$\frac{L_{1,s}}{L_{2,s}} = c^{\theta} \left[ \frac{\beta_a L_{1,a} + \beta_n L_{1,n}}{\beta_a L_{2,a} + \beta_n L_{2,n}} \right]^{-\theta \Omega_s}. \tag{8}$$

This equation relates relative employment to the relative density at which production takes place. This implies the following relationship between relative employment in each sector,

$$\frac{L_{1,n}}{L_{2,n}} = c^{\theta \frac{\Omega_a - \Omega_n}{\Omega_a}} \left[ \frac{L_{1,a}}{L_{2,a}} \right]^{\frac{\Omega_n}{\Omega_a}} \tag{9}$$

Equations (7), (8), (9) and labour market clearing define a map between relative employment in 1 and the level of spending $\omega$. Crucially, this means that these variables do not change unless $\omega$ does, so this mechanism cannot be described in a model with exogenous spending shares. Moreover, (9) immediately implies that location 1 is specialized in sector $n$ (has a higher relative employment in $n$) whenever relative employment in agriculture is less than $c^{\theta}$. I defer showing that this condition must hold in equilibrium to the proof in Appendix A. (9) is also instructive about the spatial bias of growth. If there is aggregate disemployment in agriculture and location 1 is specialized in non-agriculture, then it mechanically absorbs a majority of those outflowing workers. This is precisely the story suggested by Figure 2.

There is one minor catch – small changes in productivity, when satisfying Assumption 2, may not decrease the share to total employment in agriculture $\omega$. Instead, it may shuffle around the distribution of workers and employment densities in equilibrium, which additionally affect relative prices. With this in mind, the following proposition *does not* describe a monotone relationship between the population density of location 1 and growth. Instead, I show that the relationship holds *when growth is large enough*. The definition of large is left to empirical work.

**Proposition 1.** *Suppose Assumptions 1 and 2, along with* $1 + \theta\Omega_n > 0$*. Then the following hold:*

1. *The equilibrium path of* $\omega$ *converges to 0, and the population in 1,* $L_{1a} + L_{1n}$*, converges to its maximum possible value in any equilibrium holding* $c$ *constant.*
2. *Location 1 is specialized in sector* $n$*,* $\frac{L_{1,n}}{L_{2,n}} > \frac{L_{1,a}}{L_{2,a}}$ *and has a higher population density* $\frac{L_{1,a}+L_{1,n}}{H}$ *in any of these equilibria.*

*Proof.* See Appendix A. □

How does Proposition 1 guide the empirical work? It tells us that population density dispersion can increase when productivity growth is uniform across space. Moreover, this effect *cannot be described in a model where agricultural spending shares are exogenous.* On this basis, I measure this effect in the data by scaling productivity uniformly and observing how dispersion changes, holding all alternative variables affecting the population distribution fixed. This scaling factor should be some central measure of observed productivity growth across provinces and the rest of the world. In the following sections, I detail a procedure to arrive at it.

# 5 Extending the model

I extend the theory to allow for multiple provinces, trade and migration frictions, international trade and idiosyncratic productivity differences to accompany a range of alternative explanations for the observed rise in spatial concentration. The end goal is to use a general equilibrium model as an experimental environment. It provides a way infer counterfactual equilibria in 2005 where any combination of these explanatory factors are present. I use these equilibrium outcomes to construct the marginal effects associated with each explanatory factor. Before arriving at this, I complete the set up of the model. Unless otherwise stated, this model shares features from the theoretical one above.

Let $\mathbf{P}$ be the set of provinces and a rest of the world aggregate, indexed by $i$ and $RoW$, respectively. Let $s \in \{a, n\}$ index sectors and $t \in \{2000, 2005\}$ index time. Each province-sector is exogenously endowed with land $H_i$, stock of individuals with hukou status $M_{ist}$[15], and total factor productivity $a_{ist}$. To produce a good, each province-sector combines labour, capital and land with a Cobb-Douglas technology. The technology has cost shares $\beta_s^L$ and $\beta_s^H$ for labour and land, respectively. There are external increasing returns to employment density, measured in workers per unit of land, with elasticity $\alpha_s$. Each of these parameters is assumed time-invariant.

As in Caliendo and Parro (2014), each sector can use goods from other sector-locations in production. A local good in $s$ is a CES aggregate over goods from each $i$ with elasticity of substitution $\theta_s + 1$. Firms in sector $k$ use the local good in each $s$ with cost shares $\beta_{sk}$.

## Preferences

I make an augmentation to the non-homothetic CES preferences above. Recall that $\gamma_a$ in Equation (6) is a preference parameter that increases spending on agriculture independent of real income or relative prices. In order to fit idiosyncratic variation in agricultural spending across provinces, sectors and time, I allow the preference parameter $\gamma_a$ to vary. When migrants leave to a work in a new location or sector, they inherit this $\gamma_a$. I do not interpret this assumption as a literal changing of preferences, rather than a unobserved characteristic of the goods available to workers in that location, sector and year. Lastly, preference parameters $\eta$ and $\epsilon_a$ will remain fixed across time, space and sectors. These will be estimated.

To capture an additional congestion force, I also allow workers to consume land commanding a constant share of income $1 - \nu$. Preferences can then be represented by utility function proportional to

$$U_{i,s}^{\nu}[H_{i,s}^{c}]^{1-\nu} \tag{10}$$

[15] I use the sector subscript $a$ and $n$ for registrant stock $M_{ist}$ simply as notation to refer to those holding a rural or urban hukou, respectively. The stock of hukou registrants $M_{ist}$ are inferred by inverting the migration flow matrix and using the employment data.

where $H^c_{i,s}$ is the consumption of land by workers in $(i, s)$, and $U_{i,s}$ is defined implicity by equation (4) under parameters $\{\gamma_{ist}, \epsilon_a, \eta\}$. In what follows, let $V_{ist}$ be the indirect utility function associated with (10) as a function of income, goods prices and land prices faced by workers in $(i, s)$ at time $t$. Each worker is paid the entire value added in the sector and location for which they work and is also rebated their spending on this local housing, as in Redding (2016).

## Trade

Trade costs take the canonical iceberg form. Shipping one unit of a good from location $i$ to location $j$ in sector $s$ and time $t$ requires producing $\tau_{ij,st}$ units of the good, varying by sector. Within a location, trade is free. Data constraints require me to forgo the cost of shipping food within a location, so that agriculture and non-agricultural workers face the same prices. Trade costs change the price index in Equation (3) to instead satisfy

$$P_{i,st} = \left[ \sum_{j \in \mathbf{P}} \tau_{ji,st}^{-\theta_s} p_{j,st}^{-\theta_s} \right]^{-\frac{1}{\theta_s}} \tag{11}$$

with the share of spending in sector $s$ in $i$ allocated to $j$ satisfying $\pi_{ji,st} = \tau_{ji,st}^{-\theta_s} p_{ji,st}^{-\theta_s} P_{i,st}^{\theta_s}$, which are observed in the data. Since these cost shares do not distinguish firms from consumers, I assume both groups allocate spending in sector $s$ equally to all locations. I normalize $\tau_{ii,st} = 1$ noting that only relative trade costs are identified.

## Land allocation

Lack of data requires me to assign land use. In particular, I assume land $H_i$ is allocated to production in each sector $H_{is}$ and for consumption $H^c_{is}$ to equalize the rate of return on land in each province $r_{it}$. I can drop this assumption in place of zero land mobility, and I find very similar results. I also assume an exogenous total supply of land for production because of data limitations. This is not satisfactory, because the equilibrium level of density is crucial for the mechanism in this paper. I plan to drop this assumption in future iterations.

## Migration

I model costly migration similarly to Tombe and Zhu (2019) and Hao et al. (2020), with some key differences. Each worker is endowed with a hukou status $(j, k)$, and must choose Chinese province-sector pair to work. There is no international migration. The fraction of workers $m_{jkis,t}$ (observed in the data) with hukou status $(j, k)$ who choose to work in $(i, s)$ is given by the constant-elasticity regional supply curve[16]

$$m_{jkis,t} = \frac{(V_{ist}/f_{jkis,t})^{\kappa}}{\sum_{i' \in \mathbf{P} \setminus \{RoW\}, s' \in \{a,n\}} (V_{i's't}/f_{jki's',t})^{\kappa}} \tag{12}$$

where $\kappa > 0$ is the elasticity of migration with respect to (discounted) real income, and $f_{jkis,t}$ are exogenous migration frictions that discount real income earned when migrating. Similar to trade costs, I make the normalization $f_{isis,t} = 1$. This supply curve is useful because the migration flows in 2005 can be written as a function of only the proportional change in real income $\frac{V_{is2005}}{V_{is2000}}$, frictions $\frac{f_{jkis,2005}}{f_{jkis,2000}}$ and initial migration flows $m_{jkis,2000}$, which I use to solve the model.

There is one key issue with using non-homothetic preferences in conjunction with this regional labour supply curve. From Equation (12), the size of differences in real income across space matter for determining migration flows. This implicitly demands a cardinal interpretation of the utility function. In the following section and in Appendix C, I derive a cardinal measure from the compensating variation, rather than using the proportional change in real income measured by the utility function $\frac{V_{is2005}}{V_{is2000}}$. Here, I define compensating variation as the fraction of income deducted in 2005 required to be as well off as in 2000. When preferences are homothetic, this measure corresponds to a transformation of both the equivalent variation *and* the measured growth in the utility function (Samuelson and Swamy, 1974). Unfortunately, this useful property does not hold here.

[16] This regional supply curve can be derived in a model where there are non-pecuniary and idiosyncratic Frechet shocks to real income discounted by the migration friction $f$. See, for example, Redding (2016).

## Solving the model in changes

The objective is to solve for a balanced trade equilibrium in 2005 that can *rationalize the observed population distribution and food spending shares* when accounting for the entire range of forces permitted in the model; that is, trade costs, productivity and migration frictions. I target these moments because they are crucial for controlling predictions on the geographic bias of growth. This can be used to quantify the marginal effects of each of these variables on the population distribution in transition from 2000 to 2005. These equilibria are computed by solving the model in changes using a variation of "hat algebra" as in Dekle, Eaton, and Kortum (2007). Henceforth, I use the conventional "hat" notation. For any quantity $g$, define $\hat{g} := \frac{g_{2005}}{g_{2000}}$ to be its value in 2005 relative to 2000.

There is one key issue in using hat algebra as a definition of equilibrium. The model cannot rationalize the observed population distribution in a balanced trade equilibrium without specifically calibrating values of changes in migration frictions $\hat{f}$. For this reason, I introduce two sets of values of $\hat{f}_{isjk}$ – one that rationalizes the population distribution in 2000, and one that does the same in 2005. I use the $t$ subscripts to make a distinction between them. I do the same for changes in preference parameters $\hat{\gamma_{is}}$ in order to fit food spending shares in 2000 and 2005. Trade costs and productivity are not chosen to target any moments.

The solution takes as given changes in trade costs $\hat{\tau}_{ij,s}$, changes in migration frictions $\hat{f}_{isjk,t}$, preference parameters for food, changes in productivity $\hat{a}_{is}$, hukou registrants $M_{ist}$, and changes preference parameters over food $\hat{\gamma}_{ist}$, as well as initial trade flows $\pi_{ji,s,2000}$, initial value added per worker $\phi_{is,2000}$ and the set of time-invariant parameters $\{\theta_s, \epsilon_a, \eta, \beta_s^L, \beta_s^H, \beta_{sk}, \nu, \alpha_s, \kappa\}$. As a normalization, I set labour and land used internationally to 1 and assume they are completely immobile across sectors. I assume the international aggregate spends a share of income in agriculture equal to world value added – approximately 4 percent and declining slightly between 2000 and 2005. For a formal definition of equilibrium and a proof that these variables identify the set of equilibria, see Appendix C.

Before continuting, I note one caveat of the model. Multiple equilibria cannot be ruled out ex-ante. This is because the model features non-homothetic preferences, increasing returns to scale and potential complementarity between goods from different sectors[17].

The question remains – if changes in costs $\tau$ and $f$, as well as productivity $a$ are not directly observed in the data, how can one compute the counterfactual equilibrium in 2005? I use a model-based approach to infer these quantities. This is the purpose of the following section.

# 6 Calibration

## Trade costs

Making the implicit assumption that trade costs are symmetric across provinces and the rest of the world, I recover them using a simple Head-Riess index. However, the matrix of trade flows in agriculture at the province level is not strictly positive, making the index ill-defined. Following Tombe and Zhu (2019), I aggregate provinces to fall in a set of 9 regions such that the implied matrix is strictly positive. Then, I choose trade costs between provinces $(i, j)$ in sector $s$ to satisfy

$$\tau_{ij,st} = \left[ \frac{\pi_{i'i',st} \pi_{j'j',st}}{\pi_{j'i',st} \pi_{i'j',st}} \right]^{\frac{1}{2\theta_s}} \tag{13}$$

where $i'$ is the region associated with province $i$.

## Productivity

Trade flows are informative about productivity $\hat{a_{i,s}}$. I start by recovering unit costs with the demand system associated with Equation (11). It links observed trade shares, trade costs, and unit costs relative to the rest of the world aggregate (RoW)

$$\frac{\pi_{i,RoW,st}}{\pi_{RoW,RoW,st}} = \left[ \frac{c_{ist}}{c_{RoW,st}} \right]^{-\theta_s} (\tau_{i,RoW,st})^{-\theta_s} \tag{14}$$

[17] The demand system defining general equilibrium in this model does not satisfy any notion of gross substitution, including that of Berry et al. (2013).

for each province $i$, sector $s$ and time $t$. This recovers relative marginal costs $\frac{c_{ist}}{c_{RoW,st}}$ given a pre-specified value of $\theta_s$. I use this procedure because it does not rely on assumptions about trade balance[18], unlike other calibration techniques in the spatial economics literature stemming from Redding (2016). However, this demand system has the property that Equation (14) holds for every combination of locations. In other words, the system is *overidentified*; there are generally no values for cost such that the equation holds for *every* location pair. I choose to solve for costs relative to the rest of the world because the data on international trade flows are non-zero for every province and are likely of higher quality than within-province trade data.

With relative costs in hand, prices (up to scale) can be recovered with a simple ACR formula (Arkolakis et al., 2012)

$$P_{ist} = \pi_{ii,st}^{\frac{1}{\theta_s}} c_{ist} \tag{15}$$

Then, TFP $a_{ist}$ up to scale can be solved using the marginal cost equation

$$c_{is} = \frac{\phi_{ist}^{v_s} \left[ \frac{L_{ist}}{H_{ist}} \right]^{\Omega_s} P_{iat}^{\beta_{as}} P_{int}^{\beta_{ns}}}{a_{ist}} \tag{16}$$

where $\Omega_s := \beta_s - \alpha_s$. Changes in labour employed $L_{is}$ and GDP per worker $\phi_{is}$ are observed in the data, and $H_{is}$ chosen to equate the return on land within each province given this output and factor data. $v_s$ is the value-added share in sector $s$.

Let's take stock. Relative productivity growth will be useful for determining the endogenous spatial concentration in this model. However, in order to capture the spatial bias of growth, I need to assign a value to that scale factor to measure how much TFP grew in absolute terms. To do so, I exploit information about this growth contained in the observed fall in average agricultural spending. This relationship is mediated by the real income elasticity $\epsilon_a$, and the relative price elasticity $\eta$. It makes sense to estimate them on the same data I use to calibrate the model.

[18]Or allowing for trade imbalances, but forcing them to be exogenous.

The estimation strategy leverages a key fact in the macro-development literature. Variation in real incomes of workers across provinces and sectors is going to be very informative about $\epsilon_a$. This echos the fact that the agricultural sector accounts for a large amount of cross-country variation in real incomes, and that the relative employment in the sector is strongly correlated with real income (Restuccia, Yang, and Zhu, 2008). With this in mind, I use Equations (14) and (15) to construct regional prices in the years 2000, 2005 and 2010, yielding a spatial panel of prices across provinces $P_{ist}$, identified up to a scaling factor $\lambda_{st}$. The true value for prices is thus $\lambda_{st}P_{ist}$.

With the data in hand, I write out a model to estimate $\epsilon_a$ and $\eta$. Manipulating Equation (6), we have a relationship between agricultural spending shares, prices and output per worker

$$\log\left[\frac{\omega_{ist}}{(1-\omega_{ist})^{\epsilon_a}}\right] = \tilde{\eta}\log\left[\frac{\lambda_{at}P_{iat}}{\lambda_{nt}P_{int}}\right] + \tilde{\epsilon_a}\log\left[\frac{\phi_{ist}}{\lambda_{nt}P_{int}}\right] + \log(\gamma_{ist}) \tag{17}$$

where $\tilde{\eta} := 1-\eta$ and $\tilde{\epsilon_a} := (1-\eta)(\epsilon_a - 1)$. Notice how the $\lambda_{st}$ reduce to time and sector varying parameters. I define the time fixed effect $\tilde{\lambda}_t := \tilde{\eta}\log[\frac{\lambda_{at}}{\lambda_{nt}}] - \tilde{\epsilon_a}\log(\lambda_{nt})$. I also introduce an additional fixed effect $\bar{\gamma_a}$ capturing unobserved differences in agricultural spending made by farmers. I assume this additional error term is pure measurement error. These assumptions define a parametric regression model

$$\omega_{ist} = F(\{P,\phi\}_{is,t};\epsilon_a,\eta,\lambda_{2000},\lambda_{2005},\lambda_{2010},\bar{\gamma_a}) + v_{ist} \tag{18}$$

where $F$ is implicitly defined by equation (17) net of the error term[19]. I estimate the model with nonlinear least squares and report along with bootstrapped confidence intervals in Figure 4[20].

Mostly all of these estimates have a grounding in the literature. Firstly, the model fits a declining relationship between real income and agricultural spending (see Equation 5), and does so for all values in their respective 99

[19]The regression error is defined as $v_{ist} = F(\{P,\phi,\gamma\}_{ist}) - F(\{P,\phi\}_{ist})$. This is the difference between the parametric model $F$ when the errors are present relative to where they are not. I implicitly make the assumption on the distribution of $\gamma_{is}$ such that $\mathbf{E}(v_{ist}) = 0$.

[20]The minimization problem associated with this least squares is not globally convergent. For the point estimates, I simulate the result using 50 randomly generated initial conditions, and find that it represents the minimum value of these. However, this is infeasible when bootstrapping. The confidence intervals reported here are constructed using the point estimate as an initial condition.

percent confidence intervals. Secondly, point estimates of the time fixed effects tend to be declining, mirroring the observed fall in agricultural spending (though these are imprecisely estimated). However, I estimate $\hat{\eta} > 1$, and this hypothesis rejects at the 1 percent level. This is at odds with substitution-driven structural change highlighted in Ngai and Pissarides (2007). On the other hand, the relatively small value of $\tilde{\eta}$ suggests that most of the structural change I observe here is through income effects, which is corroborated by Comin et al. (2021)[21]. I also find that the model-implied measures of real GDP per capita under these estimates correlate strongly with those constructed in Tombe and Zhu (2019); see Figure 8 of Appendix B.

| $\epsilon_a$ | $\eta$ | $\lambda_{2000}$ | $\lambda_{2005}$ | $\lambda_{2010}$ | $\bar{\gamma}_a$ |
|---|---|---|---|---|---|
| 2.7538 | 1.216 | -0.149 | -0.108 | -0.3 | -0.226 |
| [1.702, 7.702] | [1.097, 1.398] | [-0.6067, 1.8756] | [-0.2456, 0.0753] | [-0.8887, -0.1055] | [-0.6025, -0.0153] |

**Figure 4:** 99 percent BCa confidence intervals with 1000 repetitions are reported

As an additional robustness check, I estimate $\epsilon_a$ and $\eta$ using a similar procedure to Comin et al. (2021) and observe if $\hat{\eta}$ changes. I report the results in Figure 9 of appendix B. A few additional assumptions are made in their specification, which I also detail in the appendix. I find an even larger value of $\hat{\eta} = 2.266$, which is orthogonal to their robust finding that $\eta < 1$ on international data. I defer a discussion about potential endogeneity issues and explanations of this result for future work.

With these estimates in hand, I detail a procedure to calibrate the scale factor associated with $\hat{a_{is}}$. Taking the time differences between 2000 and 2005 in Equation (17) and rearranging yields, at the point estimates of $\tilde{\eta}$ and $\tilde{\epsilon_a}$,

$$\log\left[\frac{\hat{\omega_{is}}}{(1-\hat{}\omega_{is})^{\epsilon_a}}\right] - \tilde{\eta}\log\left[\frac{\hat{P_{ia}}}{\hat{P_{in}}}\right] - \tilde{\epsilon_a}\log\left[\frac{\hat{\phi_{is}}}{\hat{P_{in}}}\right] = \tilde{\eta}\log\left[\frac{\hat{\lambda_a}}{\hat{\lambda_n}}\right] - \tilde{\epsilon_a}\log\left[\hat{\lambda_n}\right] + \log(\hat{\gamma_{is}}) \tag{19}$$

where $\hat{\lambda_n}$ and $\hat{\lambda_a}$ are precisely the scale factors needed for the calibration. I choose values of $\hat{\lambda_a}$ and $\hat{\lambda_n}$ such that (19) holds on average over provinces and sectors, imposing the moment restriction $\mathbf{E}\left[\log(\hat{\gamma_{is}})\right] = 0$. One problem is that there are multiple choices that satisfy this – there are two parameters and one moment. I look to other data sources for information on average relative prices.

[21]In particular, see the variance decomposition in Table 4 of Comin et al. (2021).

Using the Groningen 10-Sector Database (Timmer et al., 2015), I infer that the aggregate relative price of agriculture in China grew approximately 9 percent in the period, so I choose $\frac{\hat{\lambda_a}}{\hat{\lambda_n}}$ so that the weighted average increase in relative prices match[22]. Then, I choose $\hat{\lambda_n}$ to match the average fall in the left hand side of the equation. This can be used to pin down the scale of both $\hat{a_{in}}$ and $\hat{a_{ia}}$ across provinces.

The implied growth statistics make sense. The geometric average of value added per worker deflated by prices in agriculture and non-agriculture grew approximately 69 and 83 percent, respectively. These are practically identical to official GDP growth in the period, which is pegged at around 80 percent. This estimation procedure does not target any official data on *real* GDP growth, so this is not a trivial result. Interestingly, the same calibration procedure using common values of $\epsilon_a = 0.1$ and $\eta = 0.3$ in the literature yields the extraordinarily low growth projections of 24 and 34 percent for agriculture and non-agriculture. I take these two results as lending credibility to the methodology.

## Migration costs and preference parameters

The calibration of $\hat{a_{is}}$ allows for the construction of changes in welfare across locations and sectors. Coupled with observed migration flows, these can be used to measure how costly migration must be. Recall that I measure the change in welfare deriving from the compensating variation. Let $\hat{W_{ist}}$ be this change in welfare rationalizing the observed population distribution at time $t$. Using Equation (12) and some hat-algebra, the following holds

$$\frac{m_{isjk,2005}}{m_{isis,2005}} = \left[\frac{\hat{W}_{jk,2005}}{\hat{W}_{is,2005}}\right]^{\kappa} \left[f_{isj\hat{k},2005}\right]^{-\kappa} \frac{m_{isjk,2000}}{m_{isis,2000}} \tag{20}$$

which determines the value of $\hat{f}$ given constructed welfare changes and observed migration flows in each year[23]. I define $\hat{W_{is}} := \frac{1}{1-CV_{is}}$, where $CV_{is}$ is the fraction of income deducted in 2005 required to make a worker in $(i, s)$ as well off as they were in 2000. Using the expenditure function associated with

[22] I weight by 2000 observed GDP in each sector because it does a better job of fitting the fall in aggregate spending share on food, which is roughly 3 percent.

[23] Recall that I choose migration costs to target both the 2000 and the 2005 population distribution separately for the counterfactual. To rationalize the employment distribution in 2000 as a balanced trade equilibrium, I use a the same relation replacing $m_{isjk,2005}$ with $m_{isjk,2000}$, and $\hat{W}_{is,2005}$ with $\hat{W}_{is,2000}$ to calculate $\hat{f}_{isjk,2000}$.

the utility function in Equation (10), this can be shown to solve

$$\hat{W_{is}} = \frac{1}{1 - CV_{is}} = \frac{\hat{\phi}_{is}}{\left[\sum_{k\in\{a,n\}} \omega_{is,2000}^{k} \hat{P}_{ik}^{1-\eta}\right]^{\frac{\nu}{1-\eta}} \hat{r_i}^{1-\nu}} \tag{21}$$

where $\hat{r_i}$ is the change in the price of land in $i$. Making this monotone transformation is useful because the welfare index $\hat{W_{is}}$ looks identical to the homothetic CES index with elasticity of substitution $\eta$. This justifies the use of the income elasticity of migration $\kappa$ estimated in Tombe and Zhu (2019), who also use a homothetic welfare index. See Appendix C for a derivation. Lastly, preference parameters $\hat{\gamma}_{ist}$ are chosen in a similar way – so that agricultural spending shares $\omega_{ist}$ are equal to observed levels in a balanced trade equilibrium.

# 7 Counterfactuals

I allow for four different explanations behind the rise in population density dispersion – falling migration costs, falling trade costs, spatial variation in productivity growth and finally spatially uniform productivity growth. The theory directly speaks to the last of these forces. To measure the contribution of each effect to the rise in density dispersion, I calculate an equilibrium population density dispersion where any combination of each of these variables are present and set to their calibrated values. I ascribe to each variable its Shapely value, which is the unweighted average of these marginal effects relative to the total contribution.

I define ”relative” and ”uniform” productivity growth as follows. When both are present, productivity growth are equal to its calibrated value. When only relative growth is present, I scale TFP growth down by the world average in each sector, preserving relative differences. When only uniform growth is present, TFP growth are set to the world average in each sector. I report the results in Figure 6 and a description of the additional calibrated parameters in Figure 5.

The results suggest that the spatial bias of growth matters slightly, but pales in comparison to other forces. It accounts for 5 percent of the observed rise in population density dispersion, which is under half than the contribution ascribed to changing trade costs. However, the fall in agricultural spending appears to explain little of the observed fall in the agricultural employment share–and structural change is the key mechanism that causes increased density dispersion. The model predicts that agricultural employment falls by roughly 1 percent, at odds with the observed fall of over *8.1 percent* over the period. Accounting for other forces that correlate structural change with economic growth is thus a next step for thinking more broadly about this geographic bias. Constructing parameters that can independently account for the entire structural change could uncover something more interesting than what is contained here.

The other explanatory factors also behave as expected. Falling migration costs (in part a manifestation of the hukou reforms) increased the relative size of population dense regions by making spatial arbitrage easier. The magnitude of this force is relatively massive and directly reflects the magnitude of migration in this period. Falling trade costs also increased density dispersion, which reflects one view in a contested literature. This result appears to be in line with empirical evidence in Baum-Snow et al. (2020), who show that primate prefectures uniquely benefited from railroad investment. The contribution of relative growth is large and negative, suggesting considerable spatial mean reversion in productivity disproportionately benefiting workers in hinterland provinces. This mean reversion is not enough to overpower the other three forces.

| Parameter | Value | Source |
|---|---|---|
| $(\beta_a^L, \beta_n^L)$ | $(.33, .34)$ | Hao et al. (2020) Labour share of income |
| $(\beta_a^H, \beta_n^H)$ | $(.26, .01)$ | Hao et al. (2020) Land share of income |
| $(\beta_{aa}, \beta_{na})$ | $(.16, .25)$ | Hao et al. (2020) Agriculture input shares |
| $(\beta_{an}, \beta_{nn})$ | $(.04, .61)$ | Hao et al. (2020) Non-agriculture input shares |
| $\nu$ | 0.87 | Tombe and Zhu (2019) Share of expenditure on goods |
| $\epsilon_a$ | 2.75 | Section 6 |
| $\eta$ | 1.22 | Section 6 |
| $\kappa$ | 1.5 | Tombe and Zhu (2019) income elasticity of migration |
| $\hat{a_{is}}$ | Multiple | Section 6 |
| $\hat{\tau_{ij,s}}$ | Multiple | Section 6 |
| $\hat{f_{isjk,t}}$ | Multiple | Section 6 |
| $\hat{\gamma}_{is,t}$ | Multiple | Section 6 |
| $(\theta_a, \theta_n)$ | $(4, 4)$ | Tombe (2015) Trade elasticity |
| $(\alpha_a, \alpha_n)$ | $(0.04, 0.04)$ | Combes and Gobillon (2015) To match $\beta_n^H - \alpha_n = -0.03$ |

**Figure 5:** Calibrated parameters.

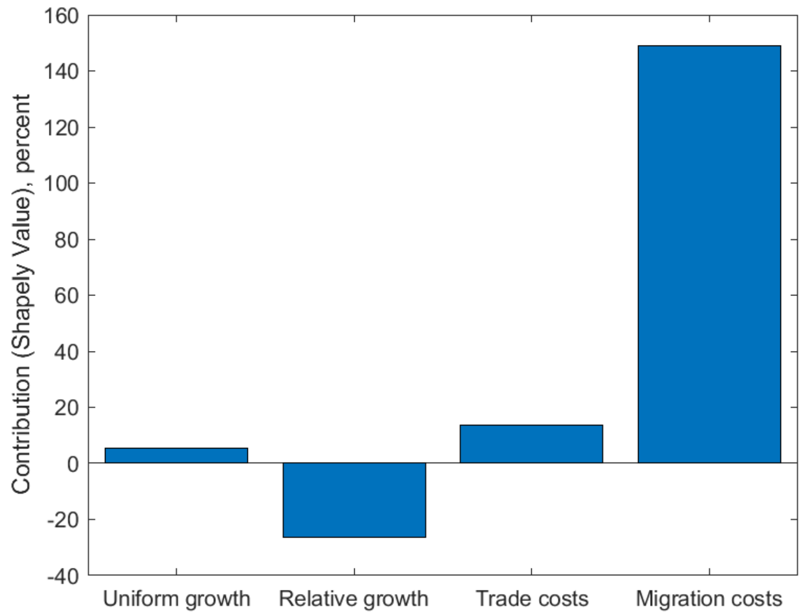


**Figure 6:** Shapely decomposition of the rise in density dispersion (relative to mean density). All values do not add up to 100 percent, because preference parameters and hukou registrants also affect the equilibrium population distribution, and they are omitted here. Growth in TFP and capital per worker, when uniform across provinces and set to the observed sector average, accounts for approximately 5.25 percent of the total observed change in population density dispersion.

How robust are the results of this counterfactual to specific model parameters? Firstly, the assumption of a particular value of the agglomeration elasticity may be driving some or all of the increased dispersion observed. I show that this is far from the case. I repeat the analysis, replacing the agglomeration elasticity in non-agriculture $\alpha_n$ to be zero. I find that the same uniform growth component accounts for approximately 4.98 percent of the observed rise, in comparison to the 5.2 percent above. Secondly, the equilibrium employment density is a key outcome for this mechanism, and in turn, employment density depends on land supply. The restrictive assumption about perfect land mobility might be driving the results. I repeat the counterfactual under the assumption that land is completely immobile across sectors, and find a similar value of 4.75 percent.

### The geographic bias over longer time horizons

How does the strength of the mechanism fare when considering a longer history of Chinese growth? I now consider a similar counterfactual in the particularly transformative period between 1985-2000. According to official statistics, growth over this horizon was approximately threefold, and the employment share in agriculture fell from 63.1 percent to 52.9 percent. To perform the counterfactual, I choose uniform productivity growth from 1985-2000 to match the agricultural spending share moment in Equation (19) under the assumption that the relative price of agriculture remains constant[24]. Due to lack of trade flow and migration data, I ignore changes in relative productivity growth, trade costs, and migration costs, and hukou registrants. They remain at values that rationalize a balanced trade equilibrium with the observed population distribution and agricultural spending in 2000.

Not surprisingly, the results are more poignant. Employment density dispersion increases by by 0.021, representing about 21 percent of the total rise from 2000-2005. Mostly all of the reallocation of workers in this counterfactual are toward Beijing, Shanghai and Guangdong, whom tend to be the provinces with a larger degree of specialization outside of agriculture. Each of these provinces grew approximately 3.5 percent in population. Similar to the main counterfactual, falling agricultural spending explains less than a third of the entire structural change observed in the period.

## 8 Conclusion

In this paper, I argue that the process of structural change and the concentration of economic activity in space are inalienably linked through salient patterns of regional comparative advantage. To do so, I present motivating empirical evidence, and a theory that informs how to measure this geographic bias in a structural model. The model allows for competing hypotheses that also give rise to spatial concentration. I apply this structural model to a particularly transformative period in Chinese history, where millions moved to the population-dense provinces along the eastern coast. I find that productivity growth, which causes structural change through declining spending on agricultural goods, accounts for only 5 percent of the total rise in spatial concentra-

[24]In particular, weighted by 2000 GDP in each sector.

tion. Because the theory can only explain a small fraction of structural change, future work needs to be done to broaden the scope of the theory to incorporate other explanations, like falling agricultural productivity gaps (Gollin et al., 2013)[25]. There are a few interesting avenues that have also been suggested to improve this paper.

Firstly, this paper relies on the assumption that all productivity differences observed are Hicks neutral. However, factor biased technical change, either capital biased in the agricultural sector or labour biased in non-agriculture are likely causing some structural change[26]. This may be compounded by the possibility that this factor biased structural change has a *spatial gradient* – that is, it may be correlated with population density. A similar story could be ideated with high and low skill labour. Skill biased technical change combined with increasing shares of high skill could benefit non-agriculture relatively more, and thus benefit population dense locations. High skill labour locating in cities causing endogenous patterns of comparative advantage could also play into this story by providing another reason for cities to specialize in non-agriculture (Davis and Dingel, 2020).

Secondly, I abstract away from all investment in the current framework and impose balanced trade. Capital outflows from rural areas toward non-agricultural firms have been shown to follow periods of high agricultural productivity growth in Brazil (Bustos et al., 2020). This process might have additional implications for the geographic bias in a dynamic setting.

Lastly, recent advances in the urban economics literature stress the importance of endogenous amenities in compounding the effects of exogenous shocks in shaping geographic outcomes (Diamond, 2016). Endogenous amenities could strengthen this geographic bias. Economic growth could also endogenously affect the demand for amenities through non-homothetic preferences if these amenities are produced in the service sector. Since services are growing fast in Chinese cities, it also makes sense to disaggregate non-agriculture into services moving forward.

[25]It is currently not obvious to me how to exogenously narrow the agricultural productivity gap without also affecting migration costs at the spatial level. This is because the agricultural productivity gap could be modeled as a cost to move across sectors. Solving this issue would yield a clear counterfactual analysis on a similar level to what is done in this paper.

[26]The former has some strong empirical evidence in Bustos et al. (2016).

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# A Proofs of Propositions

## Proof of Proposition 1

I start by showing that employment in both locations must be positive if there is positive employment in both sectors under Assumption 1 and $1 + \theta\Omega_n > 0$. As mentioned before, I abstract away from equilibria where there is zero total employment in either sector.

**Lemma A.1.** *Assume 1 and $1 + \theta\Omega_n > 0$. Consider the set of equilibria where there is positive total employment in both sectors. Then employment is positive in all sector-locations and nominal output per worker equalizes across space.*

*Proof.* Note that $1+\theta\Omega_a > 0$ holds by these assumptions. Market clearing when nominal output per worker is $\phi_{i,s}$ implies, as an analogue to equation (8),

$$\frac{\phi_{1,s}L_{1,s}}{\phi_{2,s}L_{2,s}} = c^{\theta}\left[\frac{\phi_{1,s}}{\phi_{2,s}}\right]^{-\theta(1-\Omega_s)}\left[\frac{\beta_a\phi_{1,a}L_{1,a}+\beta_n\phi_{1,n}L_{1,n}}{\beta_a\phi_{2,a}L_{2,a}+\beta_n\phi_{2,n}L_{2,n}}\right]^{-\theta\Omega_s} \tag{22}$$

for every $s$. Define $Y_{i,s} = \phi_{i,s}L_{i,s}$. Fix any sequence of $\phi_{i,s} > 0$ and $Y_{i,s} > 0$ such that (22) holds and $\frac{Y_{1,s}}{Y_{2,s}} \to 0$ for at least some $s$. Also assume without loss that $\sum_{i,s} Y_{i,s} = 1$. I will show that this implies that relative nominal output per worker $\frac{\phi_{1,s}}{\phi_{2,s}}$ grows without bound, making a spatial equilibrium impossible. (22) can be rewritten as

$$\left[\frac{\phi_{1,s}}{\phi_{2,s}}\right]^{1+\theta(1-\Omega_s)} = c^{\theta}\left[\frac{\beta_aY_{1,a}+\beta_nY_{1,n}}{\frac{Y_{1,s}}{Y_{2,s}}(\beta_aY_{2,a}+\beta_nY_{2,n})}\right]^{-\theta\Omega_s}\left[\frac{Y_{1,s}}{Y_{2,s}}\right]^{-(1+\theta\Omega_s)} \tag{23}$$

The second term $\left[\frac{\beta_aY_{1,a}+\beta_nY_{1,n}}{\frac{Y_{1,s}}{Y_{2,s}}(\beta_aY_{2,a}+\beta_nY_{2,n})}\right]$ on the right hand side of this equation defines a sequence bounded within some interval $(0, b)$ for $a > 0$ and $b$ finite. Since $\Omega_a > 0$ this implies that relative wages in the agricultural sector diverge as relative employment $\frac{Y_{1,a}}{Y_{2,a}} \to 0$. What remains is to show that relative wages in the $n$ sector also behave in this way if $\frac{Y_{1,n}}{Y_{2,n}} \to 0$. The second term in (23) for the $n$ sector can be written as

$$\frac{\beta_a}{\beta_a+\beta_n\frac{Y_{2,n}}{Y_{2,a}}}+\frac{\beta_n}{\beta_a+\beta_n\frac{Y_{2,a}}{Y_{1,a}}\frac{Y_{1,n}}{Y_{2,n}}}$$

Suppose for contradiction that $\frac{\phi_{1,n}}{\phi_{2,n}}$ remains bounded. A necessary condition is then that this term to tends to 0. But the only way that this is possible is if $\frac{Y_{1,a}}{Y_{2,a}} \to 0$ which we have already ruled out as supporting a spatial equilibrium. Hence, there is positive output in each sector-location. Under free mobility, this means that nominal output per worker equalizes across all sector-locations. $\square$

In what follows, I search for equilibria that are interior, so that output per worker is equal across space and sectors and is normalized to 1.

I solve equations (7), (8), and (9) to arrive at a map between relative employment in each sector as a function of total agricultural employment $\omega$. Let $\frac{L_{1,a}}{L_{2,a}} = x$. Then the equilbrium level of $x$ is implicitly defined by the relation

$$x = c^{\theta}\left[\nu(x,\omega)x + (1-\nu(x,\omega))c^{\theta\frac{\Omega_a-\Omega_n}{\Omega_a}} x^{\frac{\Omega_n}{\Omega_a}}\right]^{-\theta\Omega_a} \tag{24}$$

where $\nu(x,\omega)$ is the share of land in agriculture in location 2. Define the function $E(x,\omega)$ as the right hand side of the equation. Then the equilibrium value of $x$ given $\omega$ is a fixed point of $E$ given $\omega$. Moreover, it can be shown that this relation defines $x$ as a continuous function of $\omega$. It can also be shown that, when $x \in [0, c^{\theta}]$, $E(x,\omega)$ is bounded by the functions

$$c^{\theta(1-\theta(\Omega_a-\Omega_n))}x^{-\theta\Omega_n} \leq E(x,\omega) \leq c^{\theta}x^{-\theta\Omega_a} \tag{25}$$

Since $\Omega_a > \Omega_n$. The set of fixed points of $E$ must then be bounded by the minimum fixed point of $c^{\theta(1-\theta(\Omega_a-\Omega_n))}x^{-\theta\Omega_n}$ and the maximum fixed point of $c^{\theta}x^{-\theta\Omega_a}$ provided these fixed points occur in the interval $[0, c^{\theta}]$. These correspond to the unique fixed points $c^{\frac{\theta(1-\theta(\Omega_a-\Omega_n))}{1+\Omega_n\theta}}$ and $c^{\frac{\theta}{1+\Omega_a\theta}}$, respectively, which both occur in the interval under the maintained assumption that $1+\Omega_n\theta > 0$. This leads to the following lemma.

**Lemma A.2.** *Suppose Assumption 1 and $1+\Omega_n\theta > 0$. Then $\frac{L_{1,n}}{L_{2,n}} > \frac{L_{1,a}}{L_{2,a}}$ in every equilibrium, and in all of such equilibria, $\frac{L_{1,a}}{L_{2,a}}$ lies in the interval $\left[c^{\frac{\theta(1-\theta(\Omega_a-\Omega_n))}{1+\Omega_n\theta}}, c^{\frac{\theta}{1+\Omega_a\theta}}\right]$. Lastly, $\frac{L_{1,a}}{L_{2,a}}$ attains this lower bound when $\omega = 0$.*

*Proof.* The second statement follows from the arguments above. The first follows from the fact that $c^{\theta\frac{(\Omega_a-\Omega_n)}{\Omega_a}} x^{\frac{\Omega_n}{\Omega_a}} > x$ if and only if $x < c^{\theta}$. See Equation (9).

Lastly, $\omega = 0$ implies that $\nu(x, \omega) = 0$ and thus $E(x, \omega) = c^{\theta(1-\theta(\Omega_a - \Omega_n))} x^{-\theta \Omega_n}$, whose fixed point in $x$ attains the lower bound. $\square$

We can use the lemma to bound the possible densities that can occur in equilibrium, which bound the permissible prices, to show that $\omega$ must lie on the interior of $[0, 1]$. To this end, density in sector-location $1, s$ can be written as, for $x = \frac{L_{1,a}}{L_{2,a}}$

$$d_{1,s}(\omega) = \frac{\beta_a \frac{x}{x+1} \omega + \beta_n \frac{l(x)}{l(x)+1} (1 - \omega)}{\beta_s} \frac{L}{H} \tag{26}$$

where $l(x) = c^{\theta \frac{(\Omega_a - \Omega_n)}{\Omega_a}} x^{\frac{\Omega_n}{\Omega_a}}$ as in Equation (9). This expression must lie in some strictly positive compact interval for every $\omega \in [0, 1]$ by the previous lemma. The same argument holds for location 2. Thus the set of permissible equilibrium log-price indices $log(P_s)$ are bounded, as they are continuous functions of density in both locations on some strictly positive compact interval. This means that some value of $\omega$ must exist that solves Equation (6) by the Intermediate Value Theorem. This must be the equilibrium $\omega$.

**Lemma A.3.** *There exists an interior equilibrium.*

With these caveats out of the way, I can finally show that growth in the TFP terms $a_{i,s}$ tend the equilibrium level of $\omega \to 0$. To this end, the equilibrium level of $\omega$ can be written as the solution to Equation (6)

$$\begin{aligned} &log(\omega) - \epsilon_a \log(1 - \omega) = -(1 - \eta) \log(a_a) + (1 - \eta) \epsilon_a log(a_n) + \\ &-(1-\eta) \frac{1}{\theta} \log \left[ c^\theta d_{1,a}(\omega)^{-\theta \Omega_a} + d_{2,a}(\omega)^{-\theta \Omega_a} \right] + (1-\eta) \epsilon_a \frac{1}{\theta} \log \left[ c^\theta d_{1,n}(\omega)^{-\theta \Omega_n} + d_{2,n}(\omega)^{-\theta \Omega_n} \right] \end{aligned} \tag{27}$$

where the density terms on the second line are bounded over all $\omega$. By Assumption 2, the terms $-(1 - \eta) \log(a_a) + (1 - \eta) \epsilon_a \log(a_n)$ decrease without bound with respect to time. This immediatley implies that all possible $\omega$ solving (27) must lie in some interval $(a, b)$ where $a \to 0$ and $b \to 0$.

**Lemma A.4.** *Suppose Assumption 2 holds. Then the set of possible equilibrium $\omega$ lie in the interval $(a, b)$ where $a \to 0$ and $b \to 0$.*

I can now prove the entire proposition. Total employment in location 1 can be written in terms of $x$ and $\omega$,

$$L_{1,a} + L_{1,n} = \left[\frac{x}{x+1}\omega + \frac{l(x)}{l(x)+1}(1-\omega)\right]L \tag{28}$$

I will show that this term approaches a maximized value when $\omega \to 0$. Lemma (A.2) implies that $x$ attains its minimum value when $\omega = 0$ and also implies $l(x) > x$. Assumption 1 implies that $l(x)$ is strictly decreasing in $x$, and thus reaches its maximum value when $\omega = 0$. Let $x_{min}$ a be the minimum possible value of $x$ given by the interval in Lemma (A.2). Then the following set of inequalities holds

$$\frac{x}{x+1} < \frac{l(x)}{l(x)+1} < \frac{l(x_{min})}{l(x_{min})+1} \tag{29}$$

for every $\omega \in (0,1)$ and so

$$\left[\frac{x}{x+1}\omega + \frac{l(x)}{l(x)+1}(1-\omega)\right]L < \frac{l(x_{min})}{l(x_{min})+1}L \tag{30}$$

for every $\omega \in (0,1)$. Since the implicit function $x(\omega)$ is continuous in $\omega$, $L_{1,a} + L_{1,n}$ approaches this maximum value $\frac{l(x_{min})}{l(x_{min})+1}L$ as $\omega \to 0$. This completes the proof.

# B Additional Figures and Tables

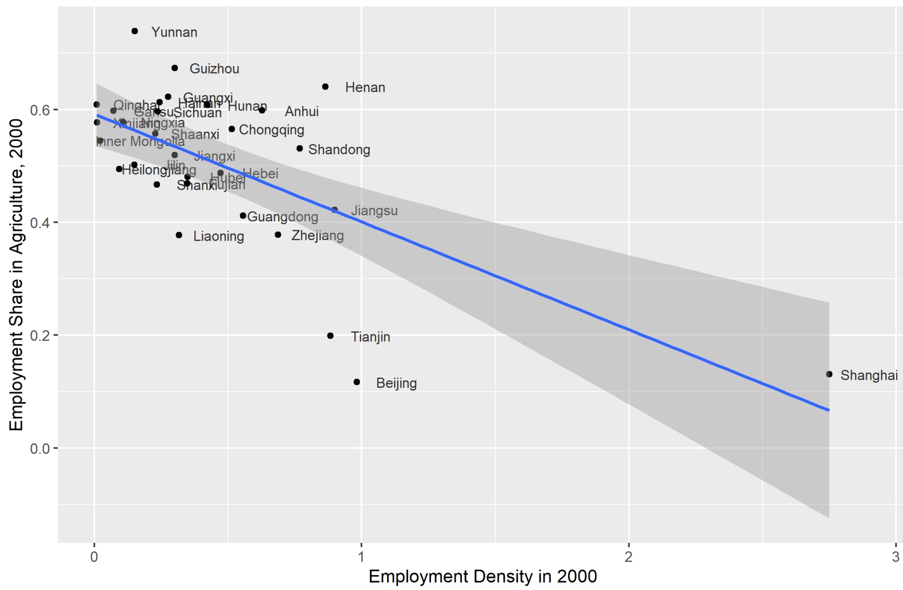


**Figure 7:** Relationship between primary sector employment and initial employment density by Chinese province. Density is measured in millions per 1000 square miles. The model explains greater than 45 percent of the variation in agriculture employment shares. Similar results hold for the 2005 cross section.

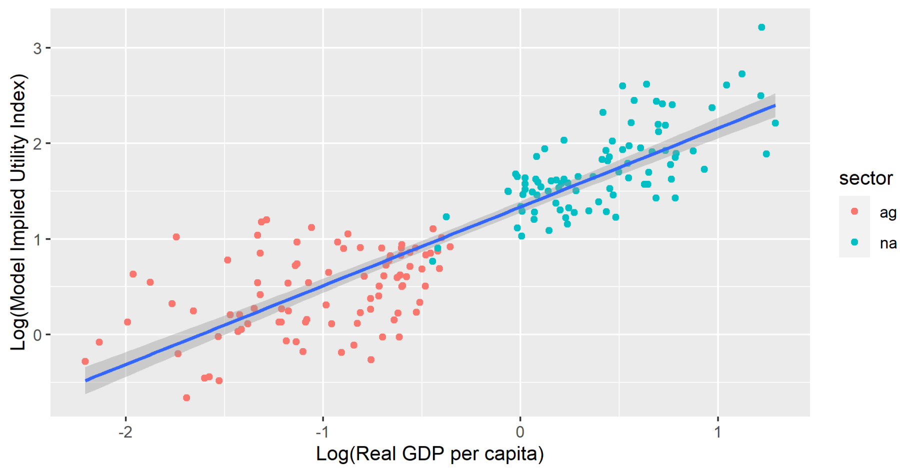


**Figure 8:** Relationship between model implied real GDP of goods consumption against real income per capita constructed in Tombe and Zhu (2019). Sector "ag" corresponds to agricultural workers. The model implied index is constructed using the relation $\log(U_{ist}) = \log(\phi_{is,t}) - \log(P_{in,t}) + \frac{1}{1-\hat{\eta}} \log[1 - \omega_{is,t}]$ implied by Equation (6). $R^2$ of the regression is over 75 percent.

| $\epsilon_a$ | $\eta$ | $\lambda_{2000}$ | $\lambda_{2005}$ | $\lambda_{2010}$ |
|---|---|---|---|---|
| 1.837 | 2.266 | 0.158 | -0.12 | -0.153 |
| [1.436, 2.703] | [1.719, 3.09] | [-0.1551, 0.6144] | [-0.4141, 0.1577] | [-0.5071, 0.1778] |

**Figure 9:** Estimates under the specification used in Comin et al. (2021). Assuming perfect mobility within locations but not across them, as well as no trade, their estimating equation is instead $log\left[\frac{L_{iat}}{L_{int}}\right] = (1-\eta)log\left[\frac{P_{iat}}{P_{int}}\right] + (1-\eta)(\epsilon_a - 1)log\left[\frac{\phi_{ist}}{P_{int}}\right] + (\epsilon - 1)log(1-\omega_{ist}) + \sum_t \lambda_t + log(v_{ist})$. I do not introduce sector trade controls that they do, and these do not affect their estimates. 99 percent BCa confidence intervals are reported. This equation is estimated using only the non-agricultural subsample because there is no within-province variation in the dependent variable. These results imply that the entire fall in spending shares can be explained by substitution effects.

# C Equilibrium Description

## Definition

In this appendix, I detail the system of equation that is used to construct the counterfactual equilibria. All variables are defined in Section 5, which I repeat here for convenience. As is standard notation, variables with hats denote values in 2005 relative to values in 2000. The endogenous variables determined in equilibrium are output per worker $\hat{\phi_{is}}$, change in employment $\hat{L_{is}}$, marginal costs $\hat{c_{is}}$, price indices $\hat{P_{i,s}}$, housing production and consumption allocations $\hat{H_{is}}$ and $\hat{H_{is}^c}$, and rental rates $\hat{r_i}$, and spending shares on sector $k$ goods $\omega_{is}^k$ and migration flows $m_{isjk}$. I start with the marginal cost pricing condition, for location $i$ and sector $s$,

$$\hat{p_{is}} = \hat{c_{is}} = \frac{\hat{\phi_{is}}^{v_s}\left[\frac{\hat{L_{is}}}{\hat{H_{is}}}\right]^{\beta_s^H}\hat{P_{in}}^{\beta_{ns}}\hat{P}_{ia}^{\beta_{as}}}{\hat{a_{is}}\left[\frac{\hat{L_{is}}}{\hat{H_{is}}}\right]^{\alpha_s}} \tag{31}$$

where $v_s$ is the value added share in sector $s$. We have the price index equation, which can be written in hat-algebra form

$$\hat{P_{is}} = \left[\sum_{j\in\mathbf{P}} \pi_{ji,s2000}\hat{\tau_{ji,s}}^{-\theta_s}\hat{c_{js}}^{-\theta_s}\right]^{-\frac{1}{\theta_s}} \tag{32}$$

and a system of equations that implies the goods market clearing and balanced trade, represented in hat-algebra form for all $i$ and $s$,

$$\hat{\phi_{is}}\hat{L_{is}}\frac{\phi_{is,2000}L_{is,2000}}{v_s} =$$

$$\sum_{j\in\mathbf{P},k\in\{a,n\}}\left[\omega_{jk}^s + \beta_{sk}\frac{1}{v_k}\right]\left[\hat{\phi_{jk}}\hat{L_{jk}}\phi_{jk,2000}L_{jk,2000}\right]\frac{\pi_{ij,s,2000}\hat{\tau_{ij,s}}^{-\theta_s}\hat{c_{i,s}}^{-\theta_s}}{\sum_{l\in\mathbf{P}}\pi_{lj,s,2000}(\hat{\tau_{lj,s}})^{-\theta_s}\hat{c_{l,s}}^{-\theta_s}} \tag{33}$$

where $\phi_{is,2000}$ is the observed output per worker, with $L_{is,2000}$ and $\pi_{is,2000}$ being employment and trade flow data in 2000, and $\omega_{is,2000}^k$ the observed spending share in sector $k$ in 2000.

Agriculture spending shares in China are determined by the equation

$$\log \omega_{is}^{a} - \epsilon_a \log(1-\omega_{is}^{a}) = (1-\eta)\log\left[\frac{\hat{P_{ia}}}{\hat{P_{in}}}\right] + (\epsilon_a - 1)(1-\eta)\log\left[\frac{\hat{\phi_{is}}}{\hat{P_{in}}}\right] + \log \omega_{is,2000}^{a} - \epsilon_a \log(1-\omega_{is,2000}^{a}) + \log(\hat{\gamma}_{is}) \tag{34}$$

where the international spending share remains exogenous at world value added. Migration flows, as a fraction of total hukou registrants in $(j,k)$, can be described as follows (in hat algebra form),

$$m_{jkis} = \frac{(\hat{W_{is}}/\hat{f_{jkis}})^{\kappa}}{\sum_{i' \in \mathbf{P}\setminus\{RoW\}, s' \in \{a,n\}} (\hat{W_{i's'}}/\hat{f_{i's'is}})^{\kappa} m_{i's'is,2000}} \tag{35}$$

where $m_{isjk,2000}$ are migration flows in the data. The welfare index $\hat{W_{is}}$ satisfies

$$\hat{W_{is}} = \frac{\hat{\phi_{is}}}{\left[\sum_{k\in\{a,n\}} \omega_{is,2000}^{k} \hat{P}_{ik}^{1-\eta}\right]^{\frac{\nu}{1-\eta}} \hat{r_i}^{1-\nu}} \tag{36}$$

labour market clearing in 2005 implies

$$\hat{L_{is}} L_{is,2000} = \sum_{i' \in \mathbf{P}\setminus\{RoW\}, s' \in \{a,n\}} m_{i's'is} M_{i's'} \tag{37}$$

where $M_{is}$ is the inferred stock of individuals with the corresponding hukou, which is exogenous. Finally, $\hat{r_i}$ is determined by the unique land allocation $\hat{H_{is}}$ and $\hat{H_{is}^{c}}$ that equates marginal products with the price of land in consumption.

An equilibrium allocation is defined as a solution to each equation in the endogenous variables as a function of $\hat{a_{is}}$, $\hat{f_{is,jk}}$ and $\hat{\tau_{ij,s}}$, $M_{is}$ and $\hat{\gamma}_{is}$. Marginal effects are constructed from observing how the equilibrium defined above varies as a function of these parameters. To fit the population distribution and agricultural spending in 2000 and 2005, $\hat{f_{is,jk}}$ and $\hat{\gamma}_{is}$ are set to particular calibrated values detailed in Section 6.

## Derivation of Welfare Index

I define $CV_{is}$ as the fraction of income deducted in 2005 in order for a worker in $(i,s)$ to be as well off as in 2000. Let $E_{is}(P,V)$ denote the minimum expenditure required to achieve consumption level $V$ at prices $P$ for workers in $(i,s)$.

This is derived from the utility function in Equation (10) with preference parameters $\gamma_{is}$ allowed to vary. Then, $C\tilde{V}_{is}$ is defined by the equation

$$(1 - CV_{is})\frac{\phi_{is,2005}}{1-\nu} = E(P_{is,2005}, V_{2000}) \tag{38}$$

where $V_{2000}$ is the utility achieved in 2000 under time-invariant preferences, $\phi_{is,2005}$ value added per worker in 2005 (in this case proportional to nominal income because land spending is rebated and preferences over housing are Cobb-Douglas) and $P_{is,2005}$ are the prices faced by workers in 2005. Define $\mathbf{P}_{is}(P,V) = \frac{E_{is}(P,V)}{V}$ as the *price index* associated with the level of utility $V$ and prices $P$. Also note by duality, $\phi_{is,2005} = E(P_{is,2005}, V_{2005})$. Then (38) can be re-written as

$$\frac{1}{1 - CV_{is}} = \frac{\hat{\phi_{i,s}}}{\hat{\mathbf{P_{is}}}(V_{2000})} \tag{39}$$

Where $\hat{\mathbf{P_{is}}}(V_{2000})$ is the proportional change in the price index *holding utility constant at 2000 levels*. If preferences are homothetic, this change in price index is constant in $V$ and so (39) reduces to the proportional change in utility $\hat{V}$ (Samuelson and Swamy, 1974). However, since preferences are not homothetic, the price index will depend on the initial level of utility $V_{2000}$ which breaks the connection with $\hat{V}$.

I now derive the price index $\hat{\mathbf{P_{is}}}$. To do this, I need to define a second price index associated only with goods consumption, with the measure of goods consumption coming from the non-homothethic CES in Equation (4). Call this index $\mathbb{P}_{is}(P,U)$ associated with prices $P$ and goods consumption level $U$. The connection with $\mathbf{P_{is}}$ and $\mathbb{P}_{is}$ is derived, noting that preferences over goods and housing is Cobb Douglas,

$$\mathbf{P_{is}} = \mathbb{P}_{is}(P,U)^{\nu} r_i^{1-\nu} \tag{40}$$

and so

$$\hat{\mathbf{P_{is}}}(V_{2000}) = \hat{\mathbb{P}_{is}}(U_{2000})^{\nu} \hat{r_i}^{1-\nu} \tag{41}$$

It remains to solve for $\hat{\mathbb{P}_{is}}(U_{2000})$, which is the change in the goods price index holding the measure of goods consumption $U$ at 2000 levels. This can be written directly as (via the solution to the consumers problem)

$$\hat{\mathbb{P}_{is}}(U_{2000}) = \frac{\left[\sum_{k\in\{a,n\}} U_{2000}^{(\epsilon_k-1)(1-\eta)} P_{ik,2005}^{1-\eta}\right]^{\frac{1}{1-\eta}}}{\left[\sum_{k\in\{a,n\}} U_{2000}^{(\epsilon_k-1)(1-\eta)} P_{ik,2000}^{1-\eta}\right]^{\frac{1}{1-\eta}}} \tag{42}$$

However, solving the consumers problem also implies $\omega_{is,2000}^{k} = \frac{U_{2000}^{\epsilon_k(1-\eta)} P_{ik,2000}^{1-\eta}}{\left[\frac{\phi_{is,2005}}{1-\nu}\right]^{1-\eta}}$, which coupled with the definition $\left[\sum_{k\in\{a,n\}} U_{2000}^{(\epsilon_k-1)(1-\eta)} P_{ik,2000}^{1-\eta}\right]^{\frac{1}{1-\eta}} = \frac{\phi_{is,2000}}{U_{2000}(1-\nu)}$ and subbing both into Equation (42) yields the index measure

$$\hat{\mathbb{P}_{is}}(U_{2000}) = \left[\sum_{k\in\{a,n\}} \omega_{is,2000}^{k} \hat{P}_{ik}^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{43}$$

Substituting (43) into (41) and then into (39) yeilds the welfare index formula used in (36).