The Effect of Migration Policy on Growth, Structural Change, and Regional Inequality in China

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Abstract

China's impressive economic growth since 2000 is well known; its significant structural transformation and regional income convergence is less so. Since 2000, while its aggregate income quadrupled, the inequality across provinces fell by a third and the share of employment in agriculture fell in half. Worker migration is central to this transformation, with almost 280 million workers living and working outside their area of (*hukou*) registration by 2015. Combining rich individual-level data on worker location and occupation decisions from 2000 to 2015 with a spatial general equilibrium model of China's economy, we quantify the size and consequences of reductions in internal migration costs. We find that between 2000 and 2015 migration costs fell in half, with the cost of moving from agricultural rural areas to nonagricultural urban ones falling even more. In addition to contributing to growth, these migration cost changes account for the majority of the reallocation of workers out of agriculture and the drop in regional inequality. We compare the effect of migration policy changes with other important economic factors in China, including change in trade costs, capital market distortions, average cost of capital, and productivity. While each contributes meaningfully to growth, migration policy is central to China's structural change and regional convergence. Finally, we find the slow-down in growth between 2010 and 2015 is associated with smaller reduction in inter-provincial migration costs and a larger role of capital accumulation during this five-year period.

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1 Introduction

China's economic growth since 2000 has been impressive. And although less well known, China's rapid structural change and large regional income convergence across provinces are no less important. Since 2000, the country's aggregate GDP per worker has quadrupled, while the share of employment in agriculture fell in half and the income inequality across provinces fell by a third. Worker migration is central to this transformation. The number of workers who lived and worked outside their area of *hukou* registration increased from around 110 million in 2000 to almost 280 million in 2015, mostly due to changes in policies that reduced internal migration costs. In this paper, we combine rich individual-level data on worker location and occupation decisions from 2000 to 2015 with a spatial general equilibrium model of China's economy to quantify the size and consequences of policy-driven reductions in internal migration costs. We find that between 2000 and 2015 migration costs fell in half, with the cost of moving from agricultural rural areas to nonagricultural urban ones falling even more. In addition to contributing to growth, these migration cost changes account for the majority of the reallocation of workers out of agriculture and the drop in regional inequality. We compare the effect of migration policy changes with other important economic factors in China, including changes in trade costs, capital market distortions, average cost of capital, and productivity. While each contributes meaningfully to growth, migration policy is central to China's structural change and regional convergence. Finally, we find the slow-down in growth between 2010 and 2015 is associated with smaller reduction in inter-provincial migration costs and a larger role of capital accumulation during this five-year period.

For our quantitative analysis, We compile uniquely detailed data on production, capital, employment, trade, and migration in China between 2000 and 2015. In Section 2 we document four facts concerning China's structural change and regional convergence. First, we show that there was significant regional convergence in aggregate GDP per worker in China between 2000 and 2015. The variance of the cross-province log(GDP per worker) declined by a third, from 0.26 in 2000 to 0.18 in 2015. Second, over the same period, there were little convergence in GDP per worker within the agricultural and nonagricultural sectors. For both sectors, the within-sector cross-province variance of log(GDP per worker) in 2000 and 2015 are virtually identical. Third, structural change was an important contributor to growth and convergence. The fraction of employment in agriculture fell from 44% in 2000 to 22% in 2015. The largest changes occurred in provinces with lower initial levels of income, higher initial shares of agricultural employment, and larger gap in labor productivity between the agricultural and non-agricultural sectors. Therefore reallocation of labor from agriculture to nonagriculture resulted in larger increases in aggregate GDP per worker in poor provinces than in richer provinces and contributed signficantlly to the convergence in aggregate income across provinces. A simple accounting exercise, where sector employment shares evolve as in the data but sector real GDP per worker remains at its 2000 levels, suggests 80% of the observed income convergence is due to structural change. Fourth, the structural change is closely related to inter-provincial migration. The provinces with higher shares of employment in agriculture in 2000 had larger inter-provincial rural-urban migration flows. These facts suggest that migration-induced structural change is essential for China's growth and regional income convergence between 2000 and 2015. We bring our data to a rich yet tractable model of China's economy to both measure changes in migration costs and other frictions in China's economy and to quantify their impacts on migration, structural change, growth, and regional income convergence.

Our model builds on recent developments in international trade. In particular, we extend the multi-sector Eaton and Kortum (2002) model as in Caliendo and Parro (2015) to incorporate both imperfectly spatial and sector labour mobility and capital market frictions. Workers choose where to live and work according to real incomes and their idiosyncratic taste for different locations, but face migration costs of living outside their *hukou* registration area. Capital can also reallocate between sectors and regions, but faces frictions in the form of wedges between marginal revenue products. The aggregate supply of labour is fixed, although the aggregate capital stock can change to reflect changes in central government's credit policies. With this rich characterization of factor and product markets, we are able to quantify the effects of changes in migration costs, trade costs, capital market distortions, average cost of capital, and productivity by combining our detailed data with this model. In addition, to better identify inter-sector migration costs, we consider household preferences that are non-homothetic to control for the impact of income growth on rural-urban migration. As there are multiple types of agents (migrants and non-migrants, in different locations), we exploy the Price Independent Generalized Linearity (PIGL) preferences of Muellbauer (1975) and, more recently, Boppart (2014); Alder et al. (2019). These preferences aggregate across heterogeneous individuals and the corresponding model's equilibrium relative changes can be solved as in standard trade and spatial models.[1] Despite the model's complexity, it yields tractable expressions that characterize equilibrium responses to various shocks and matches its initial equilibrium with observable data well. This approach of solving for equilibrium relative changes – the so-called Exact Hat Algebra of Dekle et al. (2007) – eases the calibration and quantitative analysis substantially.

We first use the model to quantify the size of migration costs, trade costs, and capital market distortions and how they change over time. Intuitively, differences in observed real incomes between sectors and locations will imply a certain volume of migration, conditional on an assumed distribution of tastes for locations across workers. Observing less migration than this in the data implies workers face migration costs. We separate these migration costs into two components: first, migrant workers lose access to land and capital returns, which are only enjoyed by non-migrant locals; and second, costs that capture all other migration frictions (preferences, distance, additional costs of living facing workers without local *hukou*, and so on). This approach builds on Tombe and Zhu (2019), although differs due to the non-homothetic preferences we use here. We find migration costs are large but decline significantly between 2000 and 2015. Initially, migration costs effectively shrink real incomes of migrant workers by one-third – over and above the loss of land

[1] Nonhomoethetic preferences as in Comin et al. (2015) aggregate across agents of different income levels, but are not well suited to solving for equilibrium relative changes without a representative agent in each region.

and capital returns that accrue only to non-migrant locals. But by 2015, these costs decline by half. The decline in between-province migration costs within the nonagricultural sector is particularly large, as are the declines observed for moves out of agriculture and into nonagriculture – both types of moves see migration costs fall by three-quarters. These reductions will prove particularly important in driving structural change and regional income convergence.

Our measure of trade costs and capital market distortions are more straightforward. We estimate trade costs by adapting the approach of Head and Ries (2001), adjusting for trade cost asymmetries as in Waugh (2010). This approach presumes a trade-cost elasticity (we use 4) to back-out costs of trading between all possible pairs of regions within China, and between those regions and the rest of the world. We find trade costs decline substantially early in our period of analysis, but remain largely flat from 2007 onward. The contribution to growth and structural change from trade cost reductions is therefore limited in the latter part of our analysis. To be clear, our trade data ends in 2012 – earlier than other data we have available – so our estimates and quantitative analysis with respect to changes in trade costs are less complete. Finally, capital market distortions are inferred as wedges between marginal revenue products of capital in each sector and region. Efficient allocations imply equalized returns, so observed variation implies a misallocation of capital that we model as exogenous wedges. We find the efficiency with which capital is allocated improves from 2000 to 2010 – with the variance of log returns declining over 30%. But by 2015, capital misallocation rapidly increases back to its level in 2000. We also observe a significant decrease in the average cost of capital in China.

Given these estimated costs, and changes through time, we quantify their effect on structural change and regional income inequality through a variety of counterfactual experiments in our model. Specifically, we simulate each measured change one-by-one, holding all other parameters constant, and observe the relative change in various outcomes. We find migration cost reductions contribute significantly to growth – adding 16% to aggregate real GDP by 2015. But more significantly, and the focus of this paper, migration cost reductions lower regional income inequality by over one-third and shift one-sixth of the workforce from agriculture to non-agriculture. Lower costs of switching sectors – moving from rural agricultural areas to urban nonagricultural ones – account for the overwhelming majority of these effects. Changes in capital market distortions, meanwhile, have little effect on growth but exacerbate regional inequality. Increases in aggregate capital, especially after 2010, adds to aggregate growth – boosting real GDP by nearly 12% between 2010 and 2015. Finally, trade cost changes between 2007 and 2012 are modest – and consequently the effect of these changes on growth, structural change, or inequality is negligible.

Simulating each counterfactual in a *certerus paribus* manner, while informative, is insufficient to fully decompose changes in growth, inequality, or structural change. All changes together do not capture observed changes in real income, for example. We infer productivity changes by sector, province, and time in order to match (as well as possible) observed changes in real income. In addition, there are interactions between the various counterfactual experiments. That is, the effect of migration cost changes will be different when done in combination with capital market, trade cost changes, or (most importantly) productivity changes. We therefore simulate all possible permutations of counterfactuals, averaging the marginal contribution of each change to growth, inequality, and structural change. We find productivity growth accounts for the bulk of aggregate growth, but migration cost reductions are the second most important factor. From 2010 to 2015, however, growth in aggregate capital accounts for nearly 40% of growth. Structural change, meanwhile, is *fully* accounted for by reductions in migration costs. This matters for inequality, since the greatest moves out of agriculture are found in provinces with lower initial incomes. Specifically, we find lower migration costs, particularly between 2005 and 2015, accounts for over half of the observed reduction in regional income inequality. Productivity growth is also a meaningful contributor to regional convergence, with gains in lower income regions typically exceeding gains in higher income regions from 2005 to 2015. Together, these results demonstrate that multiple factors contribute meaningfully to growth but migration cost reductions were at the heart of China's recent structural change and regional convergence.

Our work contributes to a literature investigating the effect of China's *hukou* system, and recent reforms to it. Most recently, Zi (2019) explores the effect of internal frictions in China's labour market on how trade liberalization improves welfare. In particular, *hukou* restrictions tend to dampen the gains from trade. On the other hand, Tian (2018) finds that the external trade liberalization associated with China's accession to WTO induced some of the migration policy changes and amplified the impact of external trade liberalization on internal migration in China. Estimating *hukou* restrictions at the prefecture-level, Ma and Tang (2019) find significant welfare gains from easing labour mobility restrictions. Importantly, they find positive gains for even destination cities and demonstrate internal trade linkages can spread these gains from migration. Finally, Kinnan et al. (2018) use China's "sent-down youth" program to identify exogenous effect of migration and find migration lowers consumption volatility and asset-holding. Our work is distinct not only methodologically, but also in that we focus on a longer period of time, from 2000 to 2015, and examine the impact on growth, structural change, and regional inequality at the same time in a unified model. We also link the efficiency of labour allocations (through migration restrictions) to both capital allocations (through capital market distortions) and production allocations (through trade).

With also build on a large and growing literature quantifying the effects of internal migration (Caliendo et al., 2017; Schmutz and Sidibe, 2018; Imbert and Papp, 2019; Heise and Porzio, 2019). Most recently, Bryan and Morten (2019) show internal labour migration in Indonesia have significant implications for aggregate productivity there. Reducing migration costs to the U.S. level boosts aggregate productivity by 7.1%. Our work also connects with those investigating the link between migration and trade. Of particular relevance for China, Fan (2019) demonstrates trade may exacerbate inequality. Though there is some overlap, our substantive focus differs with our attention to migration cost changes between 2000 and 2015, rather than the effect of international trade.

We begin our analysis with a detailed review of the data in Section 2, where we also document key patterns in China's growth, structural change, and regional convergence between 2000 and 2015. With that data in hand, we develop a rich model of China's economy that can be brought to this data in Section 3. Various counterfactual simulations of this model reveal the magnitude and consequence of changes in migration costs, trade costs, capital market distortions, and productivity change. We document the results of this quantitative analysis in Section 4 before concluding in Section 5.

2 China's Growth and Migration: 2000-2015

China's economic growth between 2000 and 2015 was significant; so too were its structural changes and regional income convergence. Labour shifted from agriculture to non-agriculture, from rural to urban areas, and from interior to coastal provinces. In this section, we document these shifts. We begin with a brief description of the relevant institutional features of China, and recent changes, before turning to our data and documenting stylized facts.

2.1 Migration Policy in China, 2000 to 2015

The Chinese government formally instituted a household registration or *hukou* system in 1958 to control labor mobility. Chan (2019) provides a detailed and up-to-date discussion of the system and its reforms. Briefly, each Chinese citizen is assigned a *hukou*, classified as "agricultural (rural)" or "non-agricultural (urban)" in a specific location. Individuals need approvals from local governments to change the category (agricultural or non-agricultural) or location of *hukou*, and it is extremely difficult to obtain such approvals. Prior to 2003 workers without local *hukou* had to apply for a temporary residence permit. As the demand for migrant workers in manufacturing, construction, and labor intensive service industries increased, many provinces, especially the coastal provinces, eliminated the requirement of temporary residence permit for migrant workers after 2003. There was also a nation-wide administrative reform in 2003 that greatly streamlined the process for getting a temporary residence permit in other provinces. These policy changes made it much easier for a worker to leave their *hukou* location and work somewhere else as a migrant worker. However, even with a temporary residence permit, migrant workers without local *hukou* have limited access to local public services and face higher costs for health care and for their children's education. In the late 1990s, a few locales began experimenting with eliminating the distinction between local agricultural/nonagricultural populations, providing all local residents with a *resident hukou* entitling them equal access to local public services. This was eventually formalized and extended to the whole nation in 2014. At the same time, however, the government has tighted the requirement for granting *hukou* to migrants in the first- and second- tiered cities. So, over time, it has become easier for a rural migrant worker to obtain *hukou* in a local urban area in lower tiered cities, but it has become harder in recent years for them to move to large coastal cities due to the stricter restrictions there. In our paper, we quantify the various changes in migration costs and the effect of these changes on regional income inequality, structural change, and aggregate economic growth.

2.2 Data on China's Internal Migration, Trade, and Investment

For this analysis, we use the confidential micro data of the 2010 and 2015 population census of China[2], in addition to the 2000 and 2005 census data from Tombe and Zhu (2019). The census data provides detailed information about rural-urban and cross-province migration from 2000 to 2015. In addition, based on the data published by China's National Bureau of Statistics (NBS), we construct provincial GDP, capital and employment for agriculture and non-agriculture for all the years between 2000 and 2015. Moreover, we construct provincial trade flow by provincial input-output table for 2002, 2007 and 2012 from Li (2010), Liu et al. (2012) and Liu et al. (2018). These data allow for a rich investigation of labour allocations and regional inequality in China during the period.

Our data on provincial economic accounts come from a variety of sources. Official statistics published in the annual China Statistical Yearbook (CSY) and statistic books report nominal GDP for each province and by agriculture, industry, and services in each province, which we aggregate to agriculture and non-agriculture. Provincial nominal GDP by sector is then proportionally rescaled such that the sum across provinces equals the national total reported in the 2016 CSY. The CSY also reports both the rural and urban Consumer Price Index (CPI) for each province. Brandt and Holz (2006) constructed rural and urban price levels in 1990 for each province. We combine these 1990 price levels and the published CPI indices to calculate the price levels in other years, and then calculate real incomes by deflating agricultural GDP and non-agricultural GDP with rural and urban price levels, respectively.

Employment data by province also requires some specific adjustments. The CSY provides employment data at the province level by primary, secondary and tertiary sectors. One problem with the official data is that the CSY underestimates the rate of decline in primary sector employment (Rawski and Mead, 1998). An alternative estimate of agricultural employment is constructed from the Rural-Urban employment table:

$$\begin{aligned}\text{Agricultural Employment} = {} & \text{Rural Employment - Township and} \\ & \text{Village Enterprise Employment - Rural Private} \\ & \text{Employment - Rural Self-Employed}\end{aligned}$$

The residual employment is nonagriculture employment. Provincial agriculture and nonagriculture employment is calculated the same way but only up to 2010 because the NBS stops reporting provincial rural-urban employment table after 2010 in almost all published resources. The 2015 provincial employment can only be estimated from yearbooks published by each province. We describe the full estimation procedure in the appendix.

[2]This data is from NBS micro survey database: 2010 China Population Census Mirco-database and 2015 1% Sample China Population Census Mirco-database.

Finally, we estimate investment and capital flows and stocks by province and sector. The CSY reports nominal Gross Fixed Capital Formation (GFCF) and GFCF real growth rate by province for the economy but not by sectors. We construct agricultural GFCF for each province with provincial fixed investment data, which is reported at the provincial and sectoral level in the CSY and Fixed Asset Yearbooks. The real investment is nominal GFCF deflated using the province-specific investment price index reported in the CSY. We construct capital stock with a perpetual inventory method. Assuming a depreciation rate of 7%, average investment growth rates of the first ten years of a province are used to generate initial capital values for 1978. Our estimates of annual real fixed investment are then used to calculate capital stock in subsequent years.

With this data in hand, we can document a number of important – and previously unexplored – stylized facts. We begin with changes in regional income inequality.

2.3 Regional Income Convergence

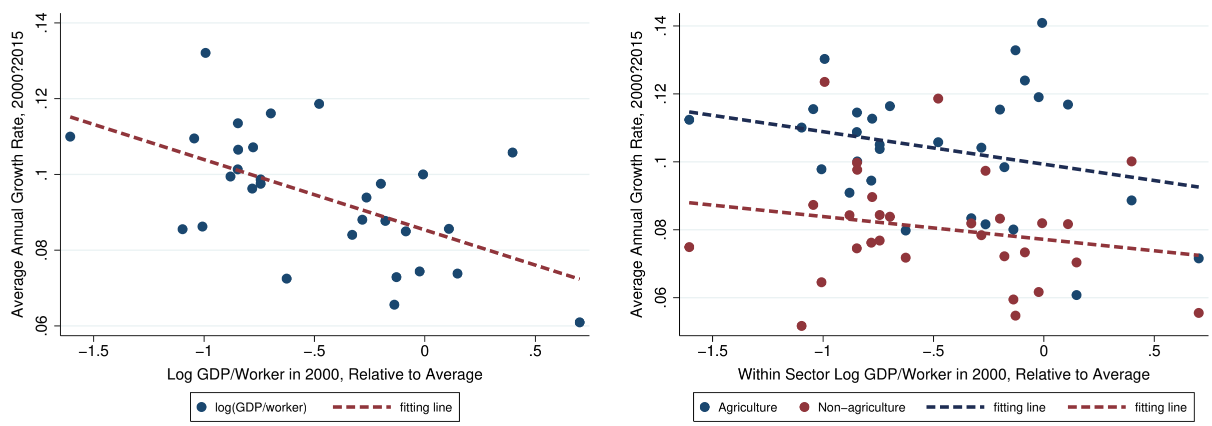
In 2000, cross-province variance of log (real GDP per worker) in China was 0.26. By 2015, this variance declined to 0.18, a 30 percent reduction in regional income inequality. In panel (a) of Figure 1, we display the growth rates of real GDP per worker between 2000 and 2015 of all the provinces against the initial levels of real GDP per worker in 2000. We can see a significant negative relationship between the initial level of income and subsequent income growth, implying strong income convergence over the 15-year period. In panel (b) of Figure 1, we also plot the growth rates of real GDP per worker within the agricultural and non-agricultural sector, respectively. The negative relationship between the growth rates and initial income is much less significant, implying smaller within-sector convergence in real GDP per worker. In fact, the cross-province variances of log (real GDP per worker) within the agricultural and nonagricultural sectors were 0.337 and 0.338, respectively, in 2000, and 0.143 and 0.136 in 2015. In other words, there were little change in within-sector income inequality. This fact suggests that structural change, or reallocation of labor from agriculture to nonagriculture, have to be an important reason for the convergence of aggregate GDP per worker across China's provinces. We next examine the facts on structural change in China.

2.4 Structural Change

In 2000, 56% of China's employment was in non-agricultural activities. This increased significantly by 2015, rising to 78%. Equivalently, the share of employment in agriculture fell by more than half from 44% to 22% over this period. The pace of structural change differed across provinces. The largest reduction in agriculture's share of employment occurs between 2005 and 2010, where it falls from 37% to 26%. In panel (a) of Figure 2, we display the change in non-agricultural employment shares by province between 2000 and 2015. Provinces with relatively small non-agricultural sectors in 2000 saw significantly larger employment shifts into this sector by 2015. On average, the five provinces with the lowest initial non-agricultural share had roughly 30% of their employment shift

Figure 1: Convergence in Provincial Real GDP per Worker, 2000 to 2015

(a) Growth Rate in Total Real GDP per worker (b) Growth Rate in Ag and Non-ag Real GDP per worker



Displays the average annual growth rate in real GDP per worker in total, agriculture and non-agriculture from 2000 to 2015 against each provinceâĂŹs initial real GDP per worker in 2000. The negative relationship implies systematic convergence across provinces, while convergences are much smaller within two sectors.

from agriculture to non-agriculture over this period.

This shift in employment contributes significantly to growth in lower income provinces. This is particularly due to the large labour productivity gap between agriculture and nonagriculture. Tombe and Zhu (2019) document that on average the real GDP per worker of the non-agricultural sector in a province is about 4 times the real GDP per worker of the agricultural sector in the same province. Faster structural change in poor provinces therefore contributes to reductions in regional inequality in China. To visualize this across China's regions, we plot the initial agricultural productivity gap in 2000 by province in panel (a) of Figure 3 and the change in agriculture's share of provincial employment between 2000 and 2015 in panel (b). Interior provinces tend to be lower income relative to coastal ones, and these provinces have both the largest productivity gaps and the greatest structural change. The process of regional convergence in China is one of the interior converging to the coast. Some notable exceptions include the northwest and northeast regions, where agricultural productivity is above average.

One can quantify more precisely the degree to which structural change and the consequent shift of employment from agriculture to non-agriculture is driving convergence between China's provincial economies through a simple decomposition. Changes in the allocation of labour can drive convergence if structural change is larger in lower income regions. We see this in the data. To quantify the effect on convergence, note that aggregate real GDP per worker may be expressed

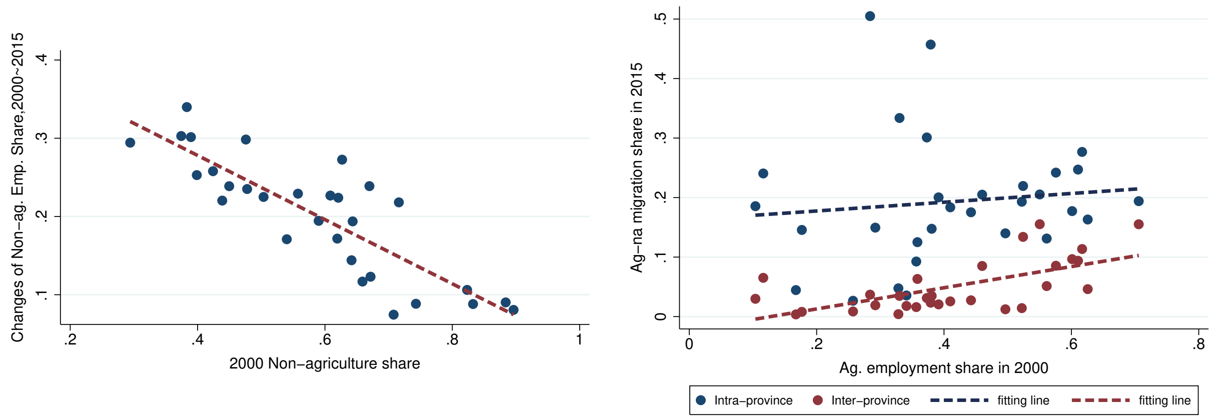
$$y_n = y_n^{ag} + l_n^{na} \cdot \left(y_n^{na} - y_n^{ag}\right), \tag{1}$$

where l_n^{ag} is province n's non-agricultural employment share and y_n^j is the real GDP per worker in sector j in province n. Holding sector real GDP per worker fixed at their 2000 values, we find the variance in $ln(y_n)$ falls by one-quarter when only l_n^{na} is set to its 2015 values. That is, structural

Figure 2: Structural Change in China, 2000 to 2015

(a) Change in Nonag Employment Shares

(b) Ag to Non-ag Migration Share

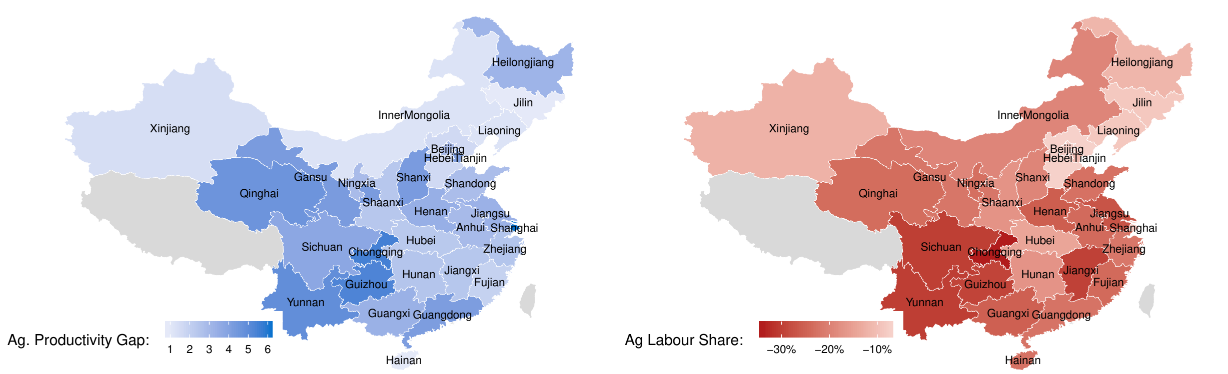


Panel (a) displays the share of employment in non-agriculture, by province, in 2000 and 2015. Panel (b) displays the fraction of workers from rural area working in non-agriculture in provincial registered resident. We distinguish between inter- and intra-provincial migrant workers.

Figure 3: Mapping Structural Change in China

(a) Agricultural Productivity Gap in 2000

(b) Change in Agricultural Employment Share, 2000 to 2015



Panel (a) displays the ratio of real GDP per worker in nonagriculture relative to agriculture. Panel (b) displays the change in agriculture's share of a province's total employment from 2000 to 2015.

change accounts for 80% of the observed convergence between China's provinces. To be sure, this abstracts from many relevant considerations, such as the interaction between labour allocations and capital, internal and external trade flows, and the underlying causes of labour shifting across sectors and regions. To make progress, we next turn to a fundamental driver of changes in labour allocations: migration.

2.5 Migration

Workers not only moved across sectors; they moved across provinces and regions. Based on population census data, we report in Table 1 both inter-province and intra-province migration in China for the years of 2000, 2005, 2010, and 2015. The relaxation of Hukou restriction on inter-province migration between 2000 and 2005 documented by Tombe and Zhu (2019) seemed to have continued between 2005 and 2010, with the inter-province migrant workers' share of total employment increased further from 7.2% to 10.5%, and the cross-province rural-urban (or agriculture to non-agriculture) migrant workers' share increased from 5.6% to 8.9%. Between 2010 and 2015, however, the inter-province migration slowed down significantly, and the cross-province rural-urban migrant workers' share of total employment actually declined from 8.9% to 7.7%. Interestingly, this slow-down in inter-province migration is also associated with a slow-down of China's aggregate GDP growth. In contrast, within-province rural-urban migration continued to increase through 2015. These patterns are consistent with policies adopted by the Chinese government after 2010 that have made moving to top tier cities, the destinations of much of the inter-province migration, much harder for people with rural hukou and, at the same time, encouraging local urbanization in poor inland and western provinces. In addition to living outside of one's hukou region, we have found from the census data that for the first time, the share of workers with rural hukou declined significantly from 77% to 66% between 2010 and 2015, mostly due to the government's local urbanization drive after 2010.

To see the impact of migration on structural change, in panel (b) of Figure 2, we plot both the within-province and inter-province agricultural to non-agricultural migration flows in provinces against the provinces' initial shares of employment in agriculture in 2000. We can see that provinces with higher shares of employment in agriculture in 2000 tend to have larger inter-provincial flows of workers out of agriculture and into non-agricultural sector.

Migration across space affects the efficiency with which employment is distributed. To quantify the efficiency in the spatial and sector allocation of labour, we estimate the marginal product of labour by sector and province using data on real GDP and employment. Consistent with the full model to come, we presume observed real GDP includes housing share $(1-\alpha)$ and therefore the production of goods and services is α times observed GDP Y_n^j. Further, if production technologies have an elasticity of substitution of one between all inputs then the marginal revenue product of

Table 1: Worker Migration in China, 2000-2015

	Inter-Provincial				Intra-Provincial			
	2000	2005	2010	2015	2000	2005	2010	2015
Total Migrant Stock	26.5	49.0	76.4	81.5	90.1	120.4	170.0	194.3
Share of Employment (%)								
Total Migrants	4.2	7.2	10.5	11.8	14.3	17.7	23.4	28.4
Ag-to-Nonag Migrants	3.4	5.6	8.9	7.7	13.1	16.4	22.1	26.1

Note: Displays the number of workers living and working outside their area of Hukou registration. The first row is in millions. The last two rows are shares of total employment.

labour is proportional to the average. Specifically,

$$w_n^j = \tilde{\beta}^{j,l} \frac{R_n^j}{L_n^j}, \tag{2}$$

where R_n^j is total sales of sector j in province n, L_n^j is employment there, and $\tilde{\beta}^{j,l}$ denotes labour's (l) share of value-added. We display the dispersion of this measure of marginal labour productivity in Figure 4a. We find that a persistent differences in labour returns, suggesting significant and persistent misallocation of employment. In nonagriculture, however, the distribution becomes somewhat more compressed by 2015. The overall variance in returns is only marginally smaller in 2015 than in 2000 but the inter-quartile range falls 30%.

2.6 Capital Allocation

In addition to labour, we have data on the distribution of capital across provinces and sectors. Capital intensities vary widely. In 2000, for example, the output to capital ratio averages roughly 3.5 in agriculture and 0.8 in nonagriculture. More importantly, there are significant differences across space within sectors. The central, coastal, and northeast regions tend to have higher output to capital ratios than the other regions, for example. This distribution matters for China's aggregate productivity.

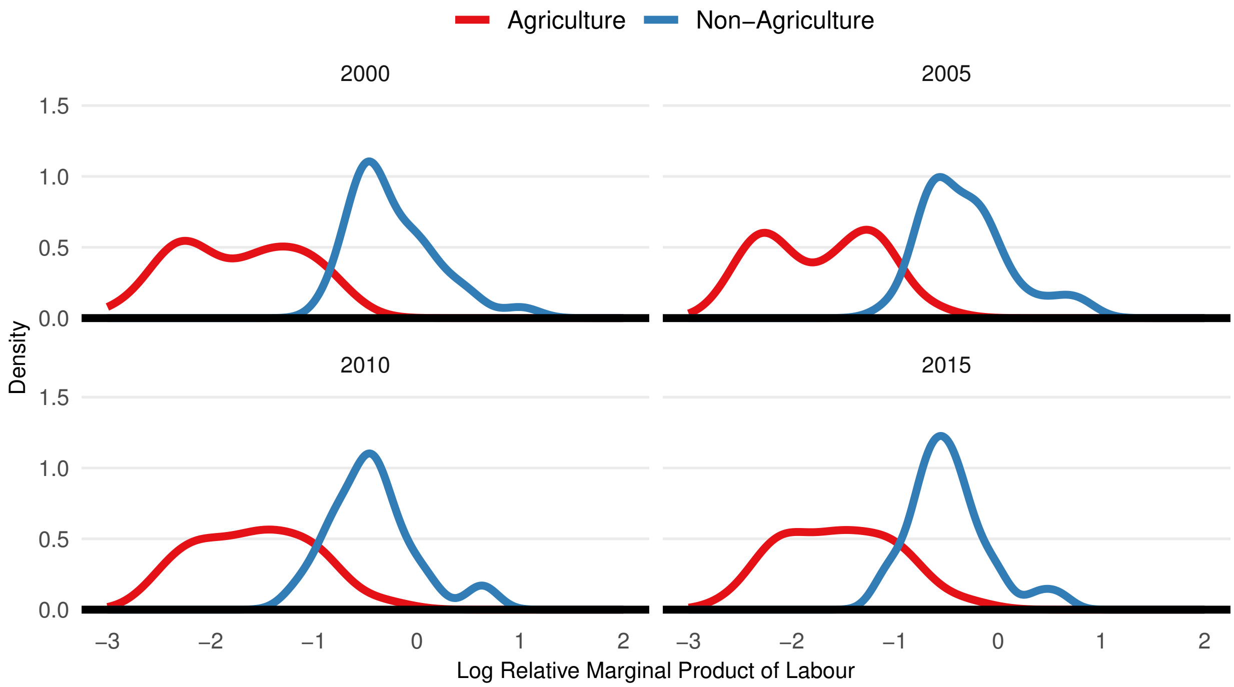
An efficient distribution of capital implies marginal revenue products of capital equalize across space and sectors. In particular, in a competitive market with Cobb-Douglas production technologies, the marginal returns to capital in province n and sector j is

$$r_n^j = \beta^{\tilde{j},k} \frac{R_n^j}{K_n^j}. \tag{3}$$

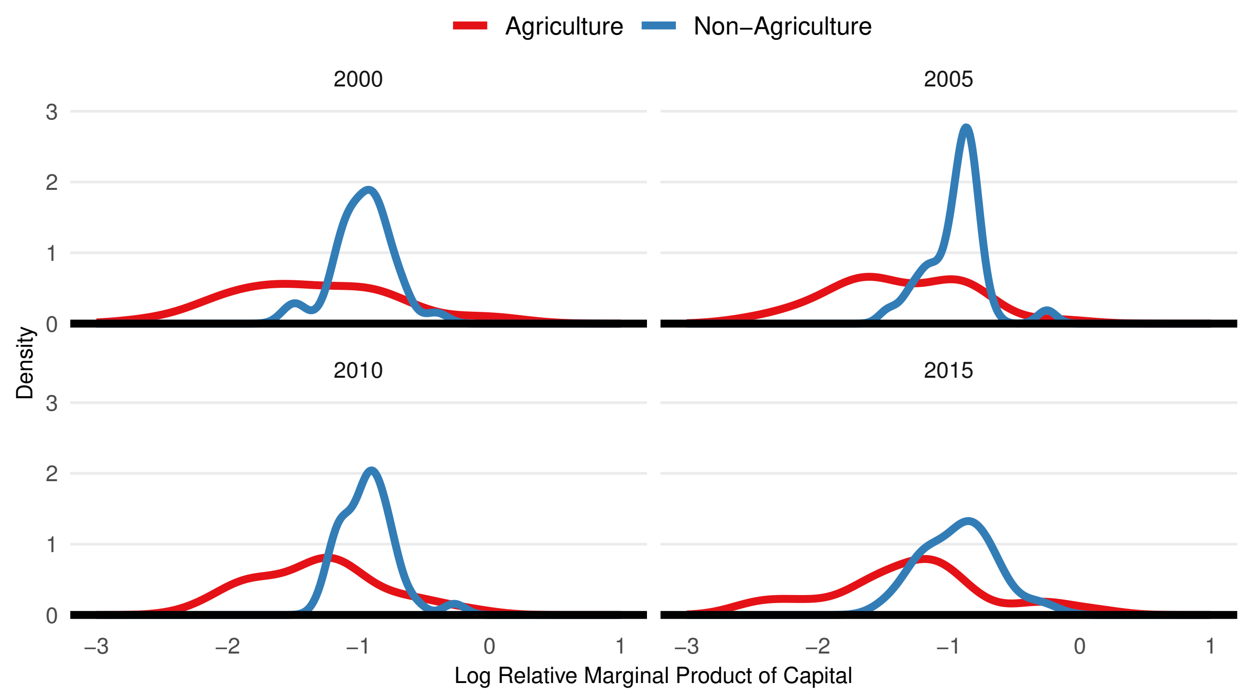
This is similar to the marginal revenue products of labour described in the previous sub-section, but where $\tilde{\beta}^{j,k}$ denotes capital's (k) share of value-added. If the allocation of capital is efficient, then r_n^j will equalize across all sectors and provinces.

Figure 4: Dispersion in Returns to Labour and Capital in China

(a) Returns to Labour



(b) Returns to Capital



Panel (a) displays the dispersion of returns to labour across provinces, by sector, from 2000 to 2015. Panel (b) displays the dispersion in capital wedges over the same period.

Using data on output and capital in each sector and province, we find that not only is the dispersion of capital returns large but changes through time differently for different sectors. As illustrated in Figure 4b, the dispersion of capital returns in agriculture across provinces was particularly large in 2000. And though the shape of the distribution in agriculture changes, becoming more concentrated in the middle of the distribution, the overall dispersion does not decline. Indeed, it increases in 2015 relative to 2010. The interquartile range, however, declines from 0.93 in 2000 to 0.59 in 2015. For non-agriculture, meanwhile, the dispersion in capital returns declines markedly between 2000 and 2010 before rising again in 2015. Specifically, the variance in log returns falls from 0.26 in 2000 to 0.18 in 2010 but rises to 0.26 by 2015. Government infrastructure and stimulus spending may be contributing to worsening capital allocations in the years to 2015. The gap between the two sectors is also notable, with agricultural returns systematically lower than non-agriculture, suggesting a reallocation of capital from agriculture to non-agriculture would increase overall productivity.

Distortions to the allocation of capital may be modelled as wedges between the cost of capital for a particular region and sector and the overall average cost of capital. Specifically, let capital wedges facing sector j and province n be t_i^j, such that

$$t_n^j = 1 - \bar{r}/r_n^j, \tag{4}$$

where r is the national average return to capital. A region with no capital wedge ($t_n^j = 0$) will have returns equal to r. A region with an over-accumulation of capital will see lower returns relative to other regions, and this will therefore lead to a negative wedge. One could interpret this as reflecting government policies to subsidize or otherwise favour investment in this region over others. The reverse holds for under-accumulation of capital. In the quantitative analysis to come, we explore the implications of moving from $t_n^j \neq 0$ in the observed data to a counterfactual $t_n^j = 0$ for aggregate growth, productivity, migration, regional inequality, and more. More importantly, we also quantity how changes in capital wedges, and therefore the contribution of changes in the efficiency of China's capital market, on observed growth.

To illustrate the pattern of capital distortions across regions and sectors, we report the aggregate measure of capital wedges across fives regions: central provinces, coastal provinces, the northeast, the northwest, and the southwest. In Table 2 we report these estimates and find that nonagriculture systematically has negative wedges (i.e., capital subsidies) while agriculture in higher income coastal and southern regions see the opposite. In lower income regions such as the northwest, we see significant negative capital wedges in agriculture and more moderate negative wedges in the remaining regions.

In addition to the dispersion in capital returns, we measure the economy-wide interest rate $\bar{r}$. By construction, $\bar{r} = (1 - t_n^j)r_n^j$ for all j and n. Competitive markets implies this is merely the national average return to capital. We find this increases from 14% in 2000 to 14.6% in 2005, and to 15% in 2010. By 2015, aggregate capital returns declines significantly to 12%. Central government policies that subsidize or otherwise increase investment – especially following the global financial crisis –

Table 2: Average Capital Wedges Across Broad Regions and Sectors in China

	Agriculture				Nonagriculture			
Region	2000	2005	2010	2015	2000	2005	2010	2015
Central	0.10	0.14	0.08	-0.03	-0.67	-0.75	-0.75	-0.76
Coastal	0.03	0.01	0.12	0.17	-0.66	-0.59	-0.56	-0.50
Northeast	0.12	-0.02	-0.27	-0.17	-0.48	-0.56	-0.77	-0.92
Northwest	-0.77	-0.89	-0.71	-0.70	-1.30	-1.05	-0.99	-1.27
Southwest	-0.10	0.08	-0.04	0.10	-0.79	-1.09	-1.00	-0.91

Notes: Displays the average capital wedge t_n^j for five broad regions of China across agriculture and nonagriculture for 2000 to 2015. Positive numbers imply a capital "tax", or higher marginal returns to capital in a given sector or region relative to the national average. An allocation of capital with no misallocation and equalized returns would have wedges of zero everywhere.

would be consistent with decreasing aggregate capital returns. This decrease is also an important contributor to rising capital-labour ratios and, all else equal, rising real GDP per worker. For clarity, we refer to changes in the aggregate capital-to-output ratio in China instead of changes in interest rates. In the quantitative analysis to come, we demonstrate that decreases in the aggregate cost of capital is a key contributor to China aggregate growth between 2000 and 2015, and especially between 2010 and 2015.

3 Model of Trade, Migration, and Capital Investment

We develop a model of trade, worker migration, and capital investment. We build on a large and growing literature based on the Eaton and Kortum (2002) model of trade. We augment this model as in Tombe and Zhu (2019) to allow for worker mobility decisions and migration costs. Our primary contribution here is to allow for both capital accumulation and distortions to capital markets. The model is rich, yet tractable. In what follows, we describe household preferences, production and trade, worker mobility, and finally capital investment.

3.1 Individual Agents

There are N provinces in China and 1 region representing the rest of the World. There are two types of agents in our model: registered workers with local Hukou, and migrant workers without local Hukou. We denote the number of workers in each province and sector as L_n^j workers and the number of individuals registered in each province and sector as $\bar{L}_n^j$. As workers are mobile, the number of workers in a province need not equal the number of individuals holding a Hukou registration there. The number of Hukou registrants is also fixed.

Following Muellbauer (1975) and, more recently, Boppart (2014); Alder et al. (2019), individual preferences are characterized by the Price Independent Generalized Linearity (PIGL) specification, with indirect utility function

$$V_n^j(q) = \frac{1}{\epsilon}\left[\frac{e_n^j(q)}{\left(P_n^{ag\,\phi} P_n^{na\,1-\phi}\right)^{\alpha} r_n^{j,h\,1-\alpha}}\right]^{\epsilon} - \frac{1}{\gamma}\left(\frac{P_n^{ag}}{P_n^{na}}\right)^{\gamma} - \frac{1}{\epsilon} + \frac{1}{\gamma}, \tag{5}$$

for individuals of type-q (either migrants or non-migrant locals) with earnings $e_n^j(q)$. This general form is useful to aggregate individuals with differing levels of income within each region in a tractable manner. The parameter γ governs the sensitivity of expenditure shares to changes in relative prices and ϵ governs the sensitivity of expenditure shares to changes in income. The implied aggregate share of spending allocated to goods and housing are provided in the following proposition.

Proposition 1. *The fraction of aggregate expenditures allocated to agriculture, nonagricultural, and housing in province n and region j are*

$$\Psi_n^{j,ag} = \alpha\phi + \left(\frac{P_n^{ag}}{P_n^{na}}\right)^{\gamma}\left[\frac{\bar{e}_n^j}{\left(P_n^{ag\,\phi} P_n^{na\,1-\phi}\right)^{\alpha} r_n^{j,h\,1-\alpha}}\right]^{-\epsilon}, \tag{6}$$

$$\Psi_n^{j,na} = \alpha(1-\phi) - \left(\frac{P_n^{ag}}{P_n^{na}}\right)^{\gamma}\left[\frac{\bar{e}_n^j}{\left(P_n^{ag\,\phi} P_n^{na\,1-\phi}\right)^{\alpha} r_n^{j,h\,1-\alpha}}\right]^{-\epsilon}, \tag{7}$$

$$\Psi_n^{j,h} = 1-\alpha \tag{8}$$

where $\bar{e}_n^j = \left[\sum_q e_n^j(q)^{-\epsilon}\omega_n^j(q)\right]^{-1/\epsilon}$ *is the average income across all individuals, and* $\omega_n^j(q) \propto e_n^j(q)L_n^j(q)$ *is the weight of type-q workers in total income in* (n, j).

Proof: See the appendix.

These spending shares imply that as income grows large, the share allocated to the purchase of agricultural goods converges to $\alpha\phi$ from above. Similarly, the share allocated to nonagricultural goods converges to $\alpha(1-\phi)$ from below. And the share allocated to housing is fixed. In certain situations, it is convenient to represent utility as a function of real incomes and expenditure shares. Using equation 6 to substitute for relative prices in equation 5, one can write the utility of an individual with real income $v_n^j(q)$ allocating a share $\psi_n^{j,ag}(q)$ of their income to agriculture goods as

$$V_n^j(q) = \left(\frac{1}{\epsilon} - \frac{\psi_n^{j,ag}(q) - \alpha\phi}{\gamma}\right) v_n^j(q)^{\epsilon} - \frac{1}{\epsilon} + \frac{1}{\gamma}. \tag{9}$$

This expression will prove particularly useful in the calibration and quantitative analysis to come, as it maps directly to data on expenditure shares and real incomes.

3.2 Production and Trade

Within each sector, final goods are produced as aggregates over a continuum of individual varieties $\nu \in (0,1)$ according to the CES technology

$$Y_n^j = \left(\int_0^1 y_n^j(\nu)^{(\sigma-1)/\sigma} d\nu \right)^{\sigma/(\sigma-1)}, \tag{10}$$

where σ is the elasticity of substitution across varieties. For each variety, producers use labour, capital, land and a composite intermediate good to produce output using the follow Cobb-Douglas technology,

$$y_n^j(\nu) = z_n^j(\nu) l_n^j(\nu)^{\beta^{j,l}} k_n^j(\nu)^{\beta^{j,k}} h_n^j(\nu)^{\beta^{j,h}} \prod_{s=\{ag,na\}} m_n^j(\nu)^{\beta^{j,s}} \tag{11}$$

where $\beta^{j,l} + \beta^{j,k} + \beta^{j,h} + \sum_s \beta^{j,s} = 1$. This implies the marginal cost of production is inverse proportional to productivity and proportional to the cost of an input bundle

$$c_n^j \propto (w_n^j)^{\beta^{j,l}} (r_n^{j,k})^{\beta^{j,k}} (r_n^{j,h})^{\beta^{j,h}} \prod_{s=\{ag,na\}} (P_n^s)^{\beta^{j,s}} \tag{12}$$

While a sector's composite output is not tradeable, individual varieties are. Trade is costly, however, and τ_{ni}^j units must be shipped for one to arrive at the destination. Trade within a region is costless, and therefore $\tau_{nn}^j = 1$. Together with the marginal costs of production, the price for sector j varieties produced in region i and shipped to region n is

$$p_{ni}^j(\nu) = \tau_{ni}^j c_i^j / z_i^j(\nu) \tag{13}$$

The overall pattern of consumer and business intermediate spending across possible suppliers from either their own region or from others is such that the cost of a sector's aggregate composite good is minimized. As demonstrated by Eaton and Kortum (2002), if productivity is distributed Frechet $F_n^j(z) = e^{-T_n^j z^{-\theta}}$, with variance parameter θ and location parameter T_n^j, then the share of total sector j spending allocated by buyers in region n to producers in region i is

$$\pi_{ni}^j \propto T_i^j \left(\frac{\tau_{ni}^j c_i^j}{P_n^j} \right)^{-\theta}, \tag{14}$$

where the price index P_n^j is given by

$$P_n^j \propto \left[\sum_{i=1}^{N+1} T_i^j \left(\tau_{ni}^j c_i^j \right)^{-\theta} \right]^{-1/\theta}. \tag{15}$$

In both equations 14 and 15 the constant of proportionality is common across all regions and sectors.

Trade shares from equation 14 determine total sales of each sector in all regions. Given total spending X_n^j by consumers and firms in region n on goods from sector j, total revenue is

$$R_n^j = \sum_{i=1}^{N+1} \pi_{in}^j X_i^j, \tag{16}$$

which implies intermediate demand by firms is $\beta^{j,s} R_n^j$. Combined with final demand spending by consumers $\Psi_n^{s,j} \bar{e}_n^s L_n^s$, total spending on good j by consumers and firms in region n is therefore

$$X_n^j = \sum_{s\in\{ag,na\}} \Psi_n^{s,j} \bar{e}_n^s L_n^s + \sum_{s\in\{ag,na\}} \beta^{s,j} R_n^s. \tag{17}$$

3.3 Income from Employment, Land, and Capital

Workers each income from work and, for some, from their claim to land and capital returns. Broadly consistent China's institutional setting, we presume only local non-migrant individuals receive income from land and capital in their region. Thus, the income of migrant workers is only their wage w_n^j while the income of non-migrant locals is $w_n^j \delta_n^j$, where $\delta_n^j > 1$ represents the rebate of land and capital income.

Total rebates in each region combine a number of sources. Total spending on land, for housing by individuals and as an input to production by firms, equals total land rebates. Specifically, if sectoral sales are R_n^j then spending on land inputs is $\beta^{j,h} R_n^j$ and if consumer income is $\bar{e}_n^j L_n^j$ then their spending on housing is $(1-\alpha)\bar{e}_n^j L_n^j$. All together, if total land supply in a given province and sector is $\bar{H}_n^j$ then total land income is

$$r_n^{j,h} \bar{H}_n^j = \beta^{j,h} R_n^j + (1-\alpha)\bar{e}_n^j L_n^j. \tag{18}$$

Similarly, spending on capital by producers is proportional to their total sales $\beta^{j,k} R_n^j = r_n^j K_n^j$. Total income from all sources is therefore

$$\bar{e}_n^j L_n^j = w_n^j L_n^j + \beta^{j,h} R_n^j + (1-\alpha)\bar{e}_n^j L_n^j + \beta^{j,k} R_n^j, \tag{19}$$

which implies average per capita income is

$$\bar{e}_n^j = w_n^j \left(\frac{\beta^{j,l} + \beta^{j,h} + \beta^{j,k}}{\alpha \beta^{j,l}} \right) \equiv w_n^j \lambda^{-1}, \tag{20}$$

where $\lambda = \alpha\beta^{j,l}/(\beta^{j,l} + \beta^{j,h} + \beta^{j,k}) < 1$. Note this follows because a sector's wage bill is a fixed share $\beta^{j,l}$ of its revenue. Conveniently, average per capita income is always a fixed proportion to wages. We also solve for the income premium to non-migrants, captured by δ_n^j, in the following proposition.

Proposition 2. *Given wages w_n^j and migration shares m_{ni}^{js} per capita income of non-migrant local workers* *in province n and sector j is $\delta_n^j w_n^j$ where*

$$\delta_n^j = 1 + \frac{1-\lambda}{\lambda} \frac{L_n^j}{L_{nn}^{jj}} \tag{21}$$

where L_{nn}^{jj} is the population of non-migrant workers.

Proof: See the appendix.
To simplify some of the expressions to come, let δ_{ni}^{js} equal δ_n^j if $n \neq i$ or $j \neq s$ and 1 otherwise.

Finally, capital market clearing is national in scope. That is, total capital demanded by producers in all sectors and provinces must add to the total capital supply $\bar{K}$. As each sector in each region optimally chooses a quantity of capital demanded to equate the marginal revenue product of capital to the cost of capital they face, which reflects the overall cost of capital common to all sectors and the capital wedge facing that particular sector and province. Specifically, define the capital wedge as t_n^j, we have $\beta^{j,k} R_n^j / K_n^j = r_n^j \equiv \bar{r}/(1-t_n^j)$ and therefore

$$\sum_{n=1}^{N} \sum_{j \in \{ag, na\}} \frac{1-t_n^j}{\bar{r}} \frac{\beta^{j,k}}{\beta^{j,l}} w_n^j L_n^j = \bar{K}, \tag{22}$$

since $\beta^{j,l} R_n^j = w_n^j L_n^j$ hold for all n and j. This expression illustrates that, all else equal, a reduction in the national cost of capital $\bar{r}$ reflects a rising aggregate supply $\bar{K}$. This will prove to be an important component of recent growth in China.

To complete the model, we next solve for the equilibrium migration shares m_{ni}^{js} and employment L_n^j in each province and sector.

3.4 Worker Mobility Across Provinces

Workers in China choose where to live (and work) to maximize welfare. Workers are heterogenous in their taste for different regions and sectors, and face costs when living outside their region of Hukou registration. Labour is perfectly mobile across sectors in the rest of the world.

When deciding in which province and sector to work, an individual from province n and sector i compares real incomes in all destinations V_{ni}^{js}, the migration costs between (n, i) and (i, s), and the potential loss of land and capital income reflected in δ_{ni}^{js}. Their indiosyncratic taste for each possible destination z_i^s is distributed identically and independently across workers and follows, as with productivity, a Frechet distribution with variance parameter κ. Workers then choose the destination (i, s) to maximize $z_i^s V_{ni}^{js} / \mu_{ni}^{js}$. Solving for the share of workers that opt to move to each possible destination is straightforward to solve, and we provide equilibrium migration shares in the follow proposition:

Proposition 3. *Given indirect utilities V_{ni}^{js}, migration costs μ_{ni}^{js}, and a Frechet distribution of idiosyncractic preferences $F_z(x)$, the fraction of workers registered in province n and sector j that migrate to province i and* *sector s is*

$$m_{ni}^{js} = \frac{\left(V_i^s / \mu_{ni}^{js}\right)^{\kappa}}{\sum_{s'} \sum_{i'=1}^{N} \left(V_{i'}^{s'} / \mu_{ni'}^{js'}\right)^{\kappa}} \tag{23}$$

where V_i^s is indirect marginal utility from equation 9.

Proof: See the appendix.

This expression for migration shares conveniently summarizes the pattern of interprovincial and intersectoral moves by workers. In addition, the parameter κ governs the elasticity of migration and therefore its value may be determined empirically in the calibration to come. Nonhomothetic preferences mean that an additional dollar of real income affects individual welfare differently depending on the overall level of real income. The expression with homothetic preference in Tombe and Zhu (2019) is nested when the average real income converges to infinite with $\psi_n^{j,ag} = 0$ and $\epsilon = 1$. In either case, migration shares imply total employment in each province and sector is

$$L_n^j = \sum_{i=1}^{N} \sum_{s \in \{ag, na\}} m_{in}^{sj} \bar{L}_i^s, \tag{24}$$

and the number of non-migrant locals is $L_{nn}^{jj} = m_{nn}^{jj} \bar{L}_n^j$.

4 Quantitative Analysis

To quantify the magnitude and consequences of changes in trade costs, migration costs, and capital wedges, we must match the full model to data. In this section, we calibrate the model to reflect changes in trade, migration, capital stocks, real GDP, and more. This provides estimates of trade and migration costs over time, as well as the size and changes in capital market distortions. To quantify their effect on overall economic activity and regional income inequality in China, we simulate the model under various counterfactual experiments detailed below.

4.1 Calibration

To ease the calibration and quantitative exercise, we solve the model in relative changes as in Dekle et al. (2007). This requires a number of equilibrium objects be set equal to data in the initial period equilibrium, which in our case is the year 2000. The key objects here are the initial trade shares π_{ni}^j and migration shares m_{ni}^{jk}. Production function parameters are calculated to match the share of sectoral output going to each type of input, as reported in our Input-Output data. The share of consumer expenditures allocated to housing is set to the average share reported in the China Statistical Yearbook for rural (15%) and urban (11%) households. Agriculture's share of expenditures in the initial equilibrium $\Psi_n^{j,ag}$ is also from the data. We describe each in detail below, and report the relevant values in Table 3.

Table 3: Model Parameters and Initial Equilibrium Values

Parameter	Value	Description
$(\beta^{ag,l}, \beta^{na,l})$	$(0.27, 0.19)$	Labor's share of output
$(\beta^{ag,k}, \beta^{na,k})$	$(0.06, 0.15)$	Capital's share of output
$(\beta^{ag,h}, \beta^{na,h})$	$(0.26, 0.01)$	Land's share of output
$(\beta^{ag,ag}, \beta^{na,ag})$	$(0.16, 0.04)$	Agricultural input's share of output
$(\beta^{ag,na}, \beta^{na,na})$	$(0.25, 0.61)$	Nonagricultural input's share of output
α	0.87	Goods' expenditure share
ϕ	0	Agriculture goods' share in price index
γ	0.30	Price-effect in expenditure shares
ϵ	0.70	Income-effect in expenditure shares
$\Psi_n^{j,ag}$	*Data*	Agriculture goods' expenditure share
θ	4.0	Elasticity of trade
κ	2.14	Heterogeneity in location preferences
π_{ni}^{j}	*Data*	Trade shares
m_{ni}^{js}	*Data*	Migration shares
$\bar{L}_n^j$	*Data*	Initial Hukou registrations

Notes: Displays the main model parameters and the initial equilibrium values for endogenous objects set to match data prior to solving the model in relative changes. See text for details.

Some model parameters correspond to empirical elasticities and other moments in the data. We set their value to correspond to common values from the literature, and explore the sensitivity of our results to alternative values in the appendix. In particular, the sensitivity of migration flows to real income differences $\epsilon\kappa$ is set to match the elasticity of 1.5 estimated by Tombe and Zhu (2019). Given our value for ϵ (described in a moment), this implies $\kappa = 2.14$. The elasticity of trade flows with respect to trade costs θ is set to 4, in line with evidence from international trade. Following evidence from Tombe (2015), we use the same elasticity for both the agricultural nonagricultural sectors. Turning to consumer preference parameters, we set the strength of the income and price effects in consumer expenditure shares to 0.7 and 0.3, respectively. The former is in line with Alder et al. (2019) who finds $\epsilon \in (0.68, 0.76)$ for the United States across different time periods, but the latter is less precise. They also find values for ϵ in the UK (0.76), Canada (0.34), and Australia (1.0). Other research finds lower values, such as Boppart (2014) who finds 0.22 or Eckert and Peters (2018) who find 0.35. In China, although we do not rigorously estimate ϵ here, a regression of log-expenditure shares on log-income suggests a value between 0.8 and 1.0. We opt for 0.7 and explore robustness in the appendix. The value of γ is set to 0.3, consistent with Boppart (2014)'s estimate of 0.41 and Eckert and Peters (2018)'s of 0.32. The range of estimates in Alder et al. (2019) is large. We ensure results are robust to alternative values for γ in the appendix. Finally, the long-run share of spending allocated to agriculture ϕ is set to 0, which simplifies equation 9 with very little quantitative effect on our results, which we demonstrate in the appendix.

4.2 Changes in Migration Costs

With our data on real incomes, employment, Hukou registrations, and migration shares, we infer the full matrix of bilateral migration costs between provinces and sectors. Specifically, we solve for migration costs μ_{ni}^{js} such that equation 23 holds, and therefore

$$\mu_{ni}^{js} = \frac{V_{ni}^{js}}{V_{nn}^{jj}} \left(\frac{m_{ni}^{js}}{m_{nn}^{jj}} \right)^{-1/\kappa} \tag{25}$$

where V_{ni}^{js} are the marginal utility for workers from (n, j) working in (i, s), which combines equation 9 with the the income differences between migrants and non-migrants summarized in Proposition 2. To solve for indirect marginal utilities we use data on employment and Hukou registrations (to determine the rebate adjustment terms), real wages, and expenditure shares. We use data on real GDP per worker by province and sector for real wages, using equation 20. The indirect utility depends on whether one is a migrant or a non-migrant, since only the latter receives land and capital rebates. For this reason, V_{nn}^{jj} reflects non-migrant local utility while V_{ni}^{js} reflects a migrant from (n, j) in (i, s). With these estimates in hand, we report the resulting migration-weighted average migration costs in Table 4.

Migration costs in 2000 were substantial but fell to half its initial value by 2015. Note that migration costs of less than one do not imply migrants earn more than non-migrants, since these costs are net of the foregone land and capital returns due to their living outside their Hukou region. In 2015, the average rebate term δ_{nn}^{jj} across all regions augments non-migrant local workers' wages by a factor of 3.6. The overall cost of moving, averaged across all province-sector migration pairs, is equivalent to half of annual income. In 2000, the overall average cost of moving – inclusive of the foregone returns to land and capital – was equivalent to three-quarters of annual income.

To quantify the effect of these migration cost changes, we solve for counterfactual relative changes in the model where $\hat{\mu}_{ni}^{js}$ are set to their estimated changes and all other model parameters are held constant. Though we report only the average changes in migration costs in Table 4, we simulate the effect of changes across all bilateral province-sector pairs. We report the counterfactual changes in aggregate real GDP, regional income inequality, and structural change in Table 5.

Changes in internal migration costs has significant effects on aggregate economic activity, regional income inequality, and structural change. The first three rows of Table 5 show the effect of all migration cost changes. Aggregate real GDP increases by 16% from 2000 to 2015 as a result. And although the largest gains are found in the five-years between 2000 and 2005, growth in all periods is affected by lower migration costs. We also find lower migration costs significantly reduce inter-provincial differences in real GDP per worker. Overall, the variance in log real GDP per worker across provinces falls by over one-third. We plot the gains across each of China's provinces as a choropleth in Figure 5 to illustrate lower income interior regions gain notably more than coastal ones. This convergence is largely driven by changes in the employment composition of each province's workforce, but within-sector differences in real GDP per worker also result. Within

Table 4: Average Migration Costs in China

Year	Average Cost 2000	2005	2010	2015	Relative to 2000 2005	2010	2015
Overall, Incl. δ_{nn}^{jj}	5.56	4.67	3.53	2.96	0.84	0.64	0.53
Overall, Only μ_{ni}^{js}	2.15	1.77	1.33	1.09	0.82	0.62	0.51
Between Sector μ_{ni}^{js}							
Overall	1.99	1.65	1.22	1.01	0.83	0.61	0.51
Within Provinces	1.72	1.45	1.07	0.87	0.84	0.62	0.51
Between Provinces	6.92	4.65	3.65	3.63	0.67	0.53	0.52
Between Province, Within-Sector μ_{ni}^{js}							
Overall	9.11	6.01	7.07	3.92	0.66	0.78	0.43
Within Agriculture	20.66	20.28	18.07	24.81	0.98	0.87	1.20
Within Nonagriculture	8.29	5.35	6.38	3.41	0.65	0.77	0.41
Agriculture to Nonagriculture μ_{ni}^{js}							
Overall	1.95	1.56	1.09	0.89	0.80	0.56	0.46
Within Provinces	1.63	1.32	0.91	0.74	0.81	0.56	0.45
Between Provinces	6.75	4.54	3.55	3.53	0.67	0.53	0.52
Nonagriculture to Agriculture μ_{ni}^{js}							
Overall	2.15	2.15	2.39	2.15	1.00	1.11	1.00
Within Provinces	2.10	2.09	2.33	2.10	1.00	1.11	1.00
Between Provinces	34.78	23.43	89.64	44.90	0.73	2.58	1.29

Note: Displays the weighted-average migration cost for various years and various types of migration moves. The last three columns display the migration costs in each year relative to 2000. All migration costs displayed are exclusive of the foregone returns to land and capital that accrue only to non-migrant locals, except for the first row that includes this in the average.

nonagriculture, the variance of log real GDP per worker across provinces falls 13%; and within agriculture, 8%. In the data, as reported in Section 2, we find little change in spatial inequality within both agriculture and nonagriculture. As we will see, the reduction in inequality that lower migration costs would have lead to are being offset by other changes – notably changes in trade costs and underlying productivity. Finally, over 16% of employment shifts from agriculture to nonagricultural activities – which accounts for all structural change in the data.[3]

To further illustrate the important role of migration cost reductions in structural change, in Figure 6 we display both the actual changes in non-agricultural employment shares across provinces and the model predicted changes in the shares when there is no migration cost reductions. With-

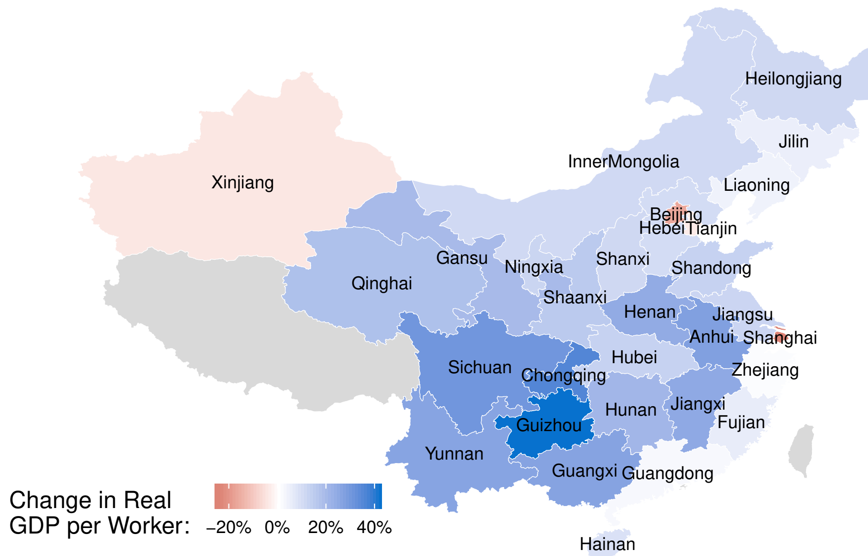
[3]This 16 percentage point reduction in agriculture's share of employment is different from the 22 points found in the raw data on account of our quantitative analysis holding the distribution of Hukou registrants $\bar{L}_n^j$ fixed at their 2000 level. That is, all structural change here is due to changes in m_{ni}^{js}.

Table 5: Effect of Lower Migration Costs, 2000-2015

Counterfactual	Five-Year Growth (%) for Year Ending 2005	2010	2015	Cumulative Effect	Homothetic Preference
Aggregate Real GDP Growth	6.8	4.4	4.2	16.2	7.6
Provincial Inequality	-20.0	-3.8	-13.0	-33.2	-34.1
Agricultural Employment Share	-4.6	-6.6	-4.6	-15.8	-9.6
Changes in Between-Sector Migration Costs					
Aggregate Real GDP Growth	5.9	5.1	2.6	14.2	6.7
Provincial Inequality	-15.5	-8.1	-6.6	-27.5	-27.8
Agricultural Employment Share	-4.5	-6.6	-4.1	-15.2	-9.4
Changes in Between-Sector, Within-Province Migration Costs					
Aggregate Real GDP Growth	2.4	3.4	2.0	8.1	1.7
Provincial Inequality	-2.8	-3.9	-2.5	-8.9	2.3
Agricultural Employment Share	-2.6	-4.9	-3.7	-11.2	-5.7
Changes in Between-Sector, Between-Province Migration Costs					
Aggregate Real GDP Growth	4.0	2.2	0.9	7.2	5.5
Provincial Inequality	-13.7	-5.3	-5.3	-22.6	-31.4
Agricultural Employment Share	-2.3	-2.2	-0.7	-5.2	-4.7
Changes in Within-Sector, Between-Province Migration Costs					
Aggregate Real GDP Growth	1.4	-0.5	1.5	2.3	1.9
Provincial Inequality	-8.0	3.1	-5.8	-10.7	-15.2
Agricultural Employment Share	-0.1	0.0	-0.4	-0.4	-0.1

Note: Displays the effect of changing migration costs in each of the three five-year periods ending 2005, 2010, and 2015. The cumulative effect is reported in the final column. Changing between-sector migration costs affects move between agriculture and nonagriculture only. This is further decomposed into its within-province and between-province components. Changing between-province, within-sector migration costs affects moves from one province to another within agriculture or within nonagriculture. The change in regional inequality is reported as the change in the variance of log real GDP per worker across provinces. The change in agriculture's share of national employment is reported as the percentage point change.

Figure 5: Real GDP/Worker Gains from Lower Migration Costs, 2000 to 2015



Displays the gains in provincial real GDP per worker, across all sectors, in response to changes in migration costs between 2000 and 2015. Blue illustrates increases while red illustrates decreases.

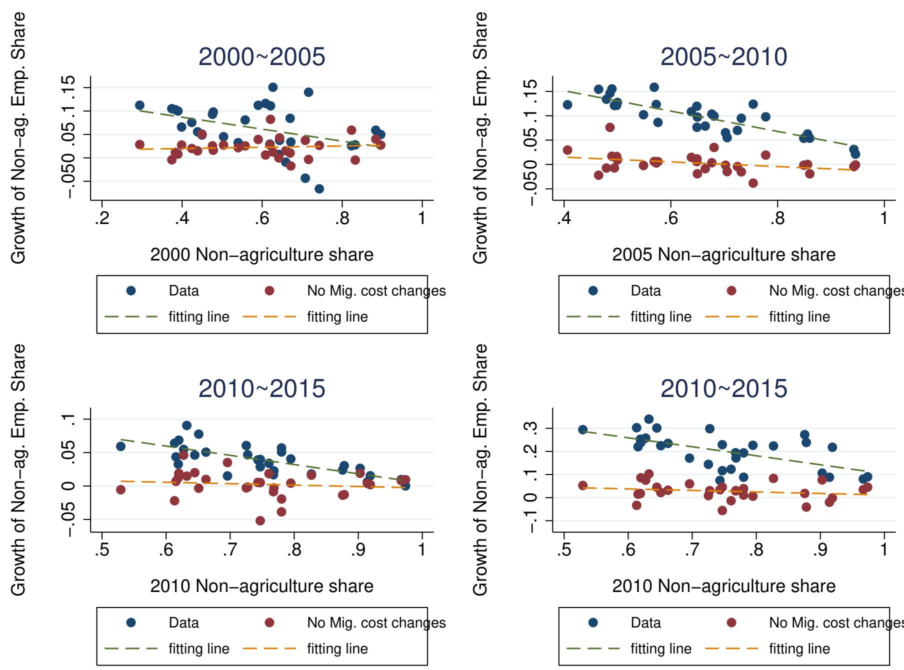
out the migration cost reductions, the average change in the non-agricultural employment share is close to zero and has no systematic relationship with initial economic structure. That is, without migration cost reductions, we would see no overall structural change nor convergence in economic structure.

Changes in the cost of migrating between sectors is particularly important. To show this, we separate estimate counterfactual relative changes when $\hat{\mu}_{ni}^{js}$ only for province-sector pairs where $j \neq s$. These results are reported in the middle panel of Table 5. We find aggregate real GDP in China increases by nearly 14% due to within-sector migration cost changes, and regional inequality falls by over 29%. And with over 15% of employment shifting to nonagricultural activities, these reductions in the cost of switching sectors fully accounts for the observed structural change in our data. Lower migration costs between provinces but within the same sector, meanwhile, account for only 2.6% cumulative growth from 2000 to 2015, a 13% reduction in regional income inequality, and only modest structural change in the 2010 to 2015 period. These are reported in the bottom panel of the table.

4.3 Effect of Capital Wedges and Aggregate Cost of Capital

As documented in Section 2, China experienced notable changes in the efficiency with which capital is allocated across space and sectors in recent years. The widening dispersion of capital returns between 2010 and 2015 suggests the potential for misallocation and lower aggregate TFP.

Figure 6: Structural Change without Migration Costs Reduction, 2000 to 2015



Displays the structural change in data and counterfactual results without migration costs reduction.

To quantify the effect of both changes in capital wedges – that is, capital market distortions – and aggregate costs of capital, we simulate counterfactual equilibria where $\hat{t}_n^j$ and $\hat{\imath}$ changes are set to their estimated levels holding all other parameters constant. We do each separately and together and report the results in Table 6. Overall, the increasing capital market distortions reported in Section 2 subtracted 0.4% from aggregate real GDP growth. A modest, though negative, effect. But while the aggregate effect is negative, it contributed to a 9% increase in regional income inequality across China. This is almost entirely accounted for by changes in non-agricultural capital wedges.

In addition to changes in the efficiency with which capital is allocated across regions, our analysis suggests China experienced a significant decrease in the aggregate cost of capital. We simulate the effect of falling aggregate cost of capital by simulating a counterfactual equilibrium where only $\bar{r}$ changes in each of the five-year periods, holding all other parameters constant. We report the results in Table 4b. We find the lower capital costs between 2010 and 2015 increased aggregate capital accumulation and this resulted in real GDP per worker rising by over 12%. With modest reductions in the years 2000 to 2015, the overall effect over the entire period was just over 8%.

To complete our analysis of capital market distortions in China, we explore fully eliminating the capital wedges. We find that this will boost China's aggregate economy, but at the cost of widening regional inequality. Specifically, we quantity the effect of counterfactual changes in wedges such that $t_n^j = 0$ for all n and j. Starting in year 2000, for example, eliminating capital wedges by 2005

Table 6: Effect of Capital Market Changes, 2000-2015

Counterfactual	Five-Year Growth (%) for Year Ending 2005	2010	2015	Cumulative Effect	Homothetic Preference
Capital Wedge Changes					
Aggregate Real GDP Growth	0.8	0.0	-0.4	0.5	0.2
Provincial Inequality	1.3	5.7	1.9	9.0	12.9
Agricultural Employment Share	0.0	0.0	-0.0	0.0	0.2
Aggregate Capital Cost Changes					
Aggregate Real GDP Growth	-2.0	-1.4	12.4	8.5	7.9
Provincial Inequality	0.1	0.0	-0.6	-0.5	0.3
Agricultural Employment Share	0.0	0.1	-0.2	-0.1	-0.1
All Capital Market Changes					
Aggregate Real GDP Growth	-1.3	-1.4	12.0	9.0	8.1
Provincial Inequality	1.4	5.7	1.2	8.4	13.3
Agricultural Employment Share	0.1	0.1	-0.2	-0.0	0.1

Note: Displays the effect of changing the capital wedges and the aggregate cost of capital in each of the three five-year periods ending 2005, 2010, and 2015. The cumulative effect is reported in the final column. The change in regional inequality is reported as the change in the variance of log real GDP per worker across provinces. The change in agriculture's share of national employment is reported as the percentage point change.

would have increased aggregate real GDP by 1.6% but increased the variance of log provincial real GDP per worker by 11.8%. Similarly, if we start in 2005 and eliminate all capital wedges by 2010, we find aggregate real GDP gains of 1.8% but at the cost of a 10.8% increase in regional inequality. And for the five years ending 2015, aggregate gains would be 1.5% with 5.3% higher variance. Distorted capital markets, while misallocating capital (especially in later years in our sample), dampens regional income inequality.

4.4 Effect of Lower Trade Costs

Changes in the allocation of factors (labour and capital) have meaningful effects on growth, structural change, and inequality. So too do changes in the product market. Trade costs distort the pattern of production across space by shifting expenditures towards relatively less productive local producers. Since 2000, there has been a sharp decline in the costs of trading between China and the world and between China's own provinces internally. The period 2000 to 2005 was previously explored by Tombe and Zhu (2019), and here we extend this another five years to 2010.[4] As our contribution is not methodological, we omit a full discussion of the method used to estimate trade costs to the appendix. Briefly, we adopt the Head and Ries (2001) method of trade costs and adjust

[4]The trade data is derived from input-output data for 2002, 2007, and 2012. We treat these respectively as corresponding to 2000, 2005, and 2010 data for other variable in our analysis.

for trade cost asymmetries estimated based on Waugh (2010).

The pattern of trade cost changes differs significantly between the five year period ending 2005 and the period ending 2010. Initially, trade costs fell significantly both within China and internationally. But between 2007 and 2012, trade costs changed little – increasing for some and decreasing for others. Importantly, these bilateral trade costs are *relative* to within-region trade costs (which are necessarily normalized to $\tau^j_{nn} = 1$) and therefore higher relative trade costs does not imply higher trade costs in an absolute sense. In the appendix, we demonstrate that this pattern of trade costs changes for China is found in other datasets internationally. Specifically, we show that using the World Input Output Database one could conclude no additional improvements in international trade costs for China following the financial crisis.

To quantify the effect of such trade cost changes in growth and structural change, we simulate a counterfactual equilibrium where $\hat{\tau}^j_{ni}$ are set to their estimated changes and hold all other parameters constant. We report the results in Table 9. As in Tombe and Zhu (2019), internal trade cost reductions contribute significantly to growth initially. But for the following five-year period there is only modest changes due to the relatively small changes in relative trade costs over that period. Overall, for the first ten years of our analysis, we find lower trade costs increased aggregate real GDP by over 16%, but at the cost of 15.5% higher regional income inequality.[5] Structural change effects are modest, with internal trade cost reductions contributing to 1.2% of employment shifting to nonagricultural activities. Given our limited data on internal trade flows beyond 2012, we cannot simulate the third and final five-year period as we can with other components of our analysis.

4.5 Decomposing China's Growth and Structural Change, 2000 to 2015

To quantify the aggregate effect of the various changes in trade and migration costs, capital wedges, aggregate capital supply, and so on, we measure the contribution of each to China's observed real GDP growth from 2000 to 2015. As each the various changes interact with one another, we compute the average marginal contribution of each over all possible permutations of counterfactuals. We report the results of this in Table 10 along with the observed economic growth over the periods.

There are important differences across component and time. Overall, migration accounts for a large fraction of observed growth over the period. Between 2000 and 2015, lower migration costs contributed 17% to aggregate economic growth, and roughly 7% for the 2005-2015 period. Productivity, though overall the most important source of growth, declines sharply in importance between 2010 and 2015. Changes in the capital market also contributed significantly to China's growth, but only in the last five years of the sample. As we saw earlier, modest increases in capital misallocation subtracted -0.9% from aggregate growth between 2000 and 2005, -0.2% between 2005 and 2010, and -0.8% between 2010 and 2015. More than offseting this negative effect, though, was the rising capital/output nationally. That is, the aggregate cost of capital fell between 2010 and 2015, which increased the level of capital accumulation and therefore real GDP per worker. In the

[5] This is distinct from Fan (2019), although our focus is at the province level rather than cities and we do not separate skilled versus unskilled workers.

Table 7: Change in Internal and External Trade Costs in China, 2002-2012

Importer	Exporter								
	North-East	Beijing-Tianjin	North Coast	Central Coast	South Coast	Central Region	North-West	South-West	Abroad
Relative Change in Trade Costs, 2002 to 2007									
Northeast	1.00	0.90	0.93	0.95	1.12	1.01	0.90	1.19	0.85
Beijing/Tianjin	0.90	1.00	0.95	0.87	1.01	0.92	0.82	1.03	0.80
North Coast	0.93	0.95	1.00	0.91	1.06	0.98	0.87	1.06	0.82
Central Coast	0.94	0.87	0.90	1.00	0.90	0.88	0.79	0.99	0.83
South Coast	1.12	1.01	1.06	0.91	1.00	0.85	0.82	0.80	0.90
Central Region	1.00	0.92	0.97	0.88	0.84	1.00	0.86	0.98	0.75
Northwest	0.89	0.81	0.86	0.79	0.82	0.87	1.00	0.96	0.72
Southwest	1.19	1.03	1.06	1.00	0.79	0.99	0.97	1.00	0.73
World	0.83	0.79	0.80	0.82	0.88	0.73	0.71	0.72	1.00
Relative Change in Trade Costs, 2007 to 2012									
Northeast	1.00	1.17	1.28	1.01	0.89	0.99	1.04	0.83	1.02
Beijing/Tianjin	1.18	1.00	1.13	1.13	1.07	1.04	1.18	1.13	0.99
North coast	1.29	1.13	1.00	1.13	1.04	1.11	1.12	1.03	0.99
Central coast	1.02	1.14	1.14	1.00	1.19	1.05	1.03	0.96	1.00
South coast	0.90	1.07	1.04	1.19	1.00	1.15	1.03	1.30	1.00
Central region	0.99	1.04	1.12	1.05	1.15	1.00	1.05	1.03	1.07
Northwest	1.05	1.19	1.13	1.03	1.03	1.05	1.00	1.04	1.11
Southwest	0.84	1.13	1.03	0.96	1.30	1.03	1.03	1.00	0.96
World	1.06	1.03	1.03	1.03	1.04	1.11	1.14	0.99	1.00

Note: Displays the relative change in trade cost levels from 2002 to 2007 and from 2007 to 2012. All trade cost levels are normalized to the within-region trade cost, which implicitly are such that $\tau^j_{nn} = 1$. Values above one therefore imply trade costs between regions grew relative to within-region trade costs, which does not necessarily imply they grew larger in an absolute sense. See text for detail.

Table 8: Internal and External Trade Shares of China, 2002-2012

Importer	Exporter									Total
	North-East	Beijing-Tianjin	North Coast	Central Coast	South Coast	Central Region	North-West	South-West	Abroad	Inter-Prov.
Trade Share in 2002 (%)										
Northeast	86.7	0.3	2.4	0.2	0.8	5.3	1.6	1.8	0.9	12.4
Beijing/Tianjin	3.3	70.7	5.4	0.7	1.0	6.8	3.0	3.4	5.7	23.6
North Coast	1.0	0.2	93.0	0.1	0.4	2.6	0.9	1.0	0.9	6.1
Central Coast	1.9	0.2	2.2	81.1	0.8	6.8	1.4	1.8	3.7	15.1
South Coast	1.0	0.1	1.3	0.2	86.8	3.0	0.9	1.3	5.5	7.7
Central Region	1.3	0.2	1.8	0.2	0.6	93.1	1.1	1.5	0.2	6.7
Northwest	0.5	0.1	0.8	0.4	0.4	1.2	95.1	0.8	0.5	4.4
Southwest	0.7	0.1	1.0	0.3	0.5	1.8	0.8	94.5	0.2	5.2
Trade Share in 2007 (%)										
Northeast	86.0	0.4	3.4	0.9	0.1	3.1	2.0	0.9	3.2	10.8
Beijing/Tianjin	8.6	30.0	11.4	3.2	3.0	12.5	8.6	11.1	11.6	58.4
North Coast	6.0	0.4	79.4	1.0	0.3	4.4	3.6	2.5	2.5	18.2
Central Coast	5.7	0.3	5.2	62.5	1.0	8.1	4.2	3.4	9.6	27.9
South Coast	0.3	0.1	1.5	0.5	71.5	8.4	1.2	6.3	10.1	18.3
Central Region	2.2	0.2	2.1	0.6	0.5	87.5	2.7	2.4	1.8	10.7
Northwest	1.0	0.1	1.5	0.7	0.9	4.7	84.9	3.1	2.9	12.1
Southwest	0.5	0.0	0.7	0.3	0.8	5.2	1.1	89.4	2.1	8.6
Trade Share in 2012 (%)										
Northeast	87.3	0.2	1.1	0.5	1.6	3.1	2.0	2.0	2.3	10.5
Beijing/Tianjin	5.0	36.4	6.0	1.9	5.5	12.2	7.5	6.9	18.5	45.0
North Coast	2.3	0.4	77.7	1.0	2.6	6.3	3.5	3.3	2.8	19.4
Central Coast	2.3	0.3	2.0	68.6	2.7	6.9	3.5	3.3	10.4	21.0
South Coast	2.2	0.2	1.6	0.7	72.5	5.3	3.1	3.2	11.2	16.4
Central Region	1.0	0.1	1.0	0.5	1.2	92.6	1.6	1.4	0.7	6.7
Northwest	1.4	0.2	1.4	0.5	1.6	3.5	88.2	2.0	1.2	10.6
Southwest	0.9	0.1	0.6	0.3	1.0	2.0	1.2	92.7	1.2	6.1

Note: Displays the share of each importing region's total spending allocated to each source region. The "Total Inter-Prov." reports spending shares on other provinces in China.

Table 9: Effect of Lower Trade Costs, 2000-2015

Counterfactual	Five-Year Growth (%) for Year Ending 2005	2010	2015	Cumulative Effect	Homothetic Preference
Aggregate Real GDP Growth	16.3	-0.9	–	15.28	26.0
Provincial Inequality	13.5	3.5	–	17.4	15.2
Agricultural Employment Share	-0.3	-0.1	–	-0.4	-1.7
Changes in Internal Trade Costs Only					
Aggregate Real GDP Growth	10.4	-0.8	–	9.5	20.2
Provincial Inequality	10.4	0.4	–	10.8	8.3
Agricultural Employment Share	-0.2	-0.2	–	-0.4	-1.8
Changes in External Trade Costs Only					
Aggregate Real GDP Growth	5.7	-0.1	–	5.6	5.4
Provincial Inequality	3.7	3.2	–	7.1	6.9
Agricultural Employment Share	-0.1	-0.0	–	-0.1	-0.1

Note: Displays the effect of changing trade costs in each of the three five-year periods ending 2005 and 2010. Data for 2015 is not yet available. The cumulative effect is reported in the final column. The change in regional inequality is reported as the change in the variance of log real GDP per worker across provinces. The change in agriculture's share of national employment is reported as the percentage point change.

ten years from 2000 to 2010, a modestly higher cost of capital subtracted roughly 3.5% from growth. But for the five-years ending 2015, we estimate that a notable reduction in the cost of capital, and consequent capital accumulation, added over 11.6% to national growth – nearly one-third of all observed growth.

Trade cost reductions also added to growth, but only in the first five-year period. Despite the large increase in infrastructure construction in China, we estimate only modest decreases in internal trade costs between the years 2007 and 2012 for which we have data. And although we do not have more up to date data, the average international trade costs implied by international trade flows suggests no further reduction in international trade costs after 2007. In the appendix, we document this more fully. To the extent that trade costs are indeed changing, though, our measure of productivity changes will be soaking up the effect. Any potential interaction with migration cost, capital wedges, or aggregate capital/output changes should therefore be negligible.

Finally, China's structural change – the movement of workers out of agriculture and into nonagriculture – is accounted entirely accounted for by decreases in migration costs. In the bottom panel of Table 10, we show the average change in agriculture's share of employment due to each component. As with our growth decomposition, we average across all permutations of changes. Of the 15% reduction in agriculture's employment share, migration costs cause a slightly larger reduction. Productivity changes, between 2005 and 2010 in particular, offset some of this reallocation. And the large increase in internal and international trade over the ten years for which we have data contributes roughly 0.8 percentage points towards China's structural change over

Table 10: Decomposing China's Growth and Structural Change

	Five-Year Change			Share of Five-Year Change (%)		
Counterfactual	2005	2010	2015	2005	2010	2015
Aggregate Real GDP Growth (%)						
Data	55.0	65.2	37.0			
Overall	56.0	60.6	30.7	100.0	100.0	100.0
Productivity Changes	37.2	59.3	15.8	66.2	98.0	51.6
Internal Trade Costs	9.4	-1.3	–	16.8	-2.2	–
External Trade Costs	4.8	-0.1	–	8.5	-0.1	–
Migration Costs	8.0	4.4	4.1	14.2	7.2	13.4
Capital Wedges	-1.2	-0.3	-1.0	-2.1	-0.4	-3.2
Aggregate Capital/Output	-2.1	-1.5	11.7	-3.7	-2.4	38.1
Change in Agriculture Share of Employment (percentage points)						
Data	-7.6	-11.0	-3.9			
Overall	-6.3	-6.3	-5.0	100.0	100.0	100.0
Productivity Changes	-1.3	0.1	-0.2	19.9	-1.5	4.7
Internal Trade Costs	-0.1	-0.1	–	1.5	0.8	–
External Trade Costs	-0.3	0.0	–	4.5	0.2	–
Migration Costs	-4.8	-6.4	-4.6	75.6	101.3	91.9
Capital Wedges	0.0	0.0	0.0	-0.5	-0.3	0.3
Aggregate Capital/Output	0.0	0.0	-0.2	-0.8	-0.5	3.1
Change in Provincial Real GDP/Worker Inequality (%)						
Data	3.5	-11.6	-25.0			
Overall	11.7	-11.7	-26.1	100.0	100.0	100.0
Productivity Changes	33.4	-11.6	-11.6	284.9	99.0	44.4
Internal Trade Costs	6.5	-2.4	–	55.7	20.3	–
External Trade Costs	3.2	3.0	–	26.9	-25.7	–
Migration Costs	-26.5	-4.4	-12.6	-225.6	37.6	48.1
Capital Wedges	-5.0	3.6	-1.5	-42.7	-30.4	5.6
Aggregate Capital/Output	0.1	0.1	-0.5	0.8	-0.7	1.9

Note: Displays the growth in China's aggregate real GDP and the change in agriculture's share of employment over the three five-year periods ending 2005, 2010, and 2015. Each row displays the marginal contribution to growth of each counterfactual change in internal trade costs, external trade costs, migration costs, capital wedges, and aggregate capital/output across all permutations of those changes. Changes in employment shares are the percentage point change in agriculture's share of total employment. Changes in provincial inequality reflect the percent change in the variance of log real GDP per worker.

this period.

5 Conclusion

Using uniquely detailed data on production, employment, capital, trade, and migration, we decompose the various contributing factors behind China's growth, structural change, and income convergence between 2000 and 2015. In particular, by combining rich individual-level data on worker location and occupation decisions from 2000 to 2015 with a spatial general equilibrium model of China's economy, we quantify the size and consequences of policy-driven reductions in internal migration costs. We find that between 2000 and 2015 migration costs fall in half, with the cost of moving from agricultural rural areas to nonagricultural urban ones falling even more. Through a variety of counterfactual exercises, we demonstrate these migration cost changes account for the majority of the drop in regional inequality and the reallocation of workers out of agriculture. We compare the effect of migration policy changes with other important economic developments in China, including change in trade costs, capital market distortions, aggregate capital cost reductions, and productivity. While each contributes meaningfully to growth, migration policy is central to China's structural change and regional convergence. Finally, we find the slowdown in growth between 2010 and 2015 is associated with smaller reduction in inter-provincial migration costs and a larger role of capital accumulation during this five-year period.

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Data Appendix

GDP and GDP Deflator

Official statistics published in the annual China Statistical Yearbook (CSY) and statistic books report nominal GDP for each province and by agriculture, industry, and services in each of China's provinces, which we aggregate to agriculture and non-agriculture. The Yearbooks cover provincial and three-sector nominal GDP and real GDP growth rate from 1990 to 2015. There are a major revisions following the 2004 Economic Census, which revise up both nominal and real output in the tertiary sector (Holz, 2006). The revised 1993-2004 provincial and sectoral data from *GDP 1952-2004* are employed following the suggestion of Holz (2006). Provincial-sectoral nominal GDP is then proportionally rescaled such that the sum across provinces equals the national total reported in the 2016 CSY.

The CSY also reports both the rural and urban Consumer Price Index (CPI) for each province. Brandt and Holz (2006) constructed rural and urban price levels in 1990 for each province. We combine these 1990 price levels and the published CPI indices to calculate the price levels in other years, and then calculate real incomes by deflating agricultural GDP and non-agricultural GDP with rural and urban price levels, respectively.

Employment

The CSY reports employment data at the province level by primary, secondary and tertiary sectors. The major problem is that CSY underestimates the rate of decline in primary sector employment (Rawski and Mead, 1998). An alternative estimate of agricultural employment is constructed from the Rural-Urban employment table:

$$\begin{aligned}\text{Agriculture Employment} = {} & \text{Rural Employment - Township and} \\ & \text{Village Enterprise Employment - Rural Private} \\ & \text{Employment - Rural Self-Employed}\end{aligned}$$

The residual employment is nonagriculture employment. This estimate is close to Brandt and Zhu (2010).

Provincial agriculture and nonagriculture employment is calculated the same way but only up to 2010 because the NBS stops reporting provincial rural-urban employment table after 2010 in almost all published resources. The 2015 provincial employment can only be estimated from yearbooks published by each province.

We take 2010 and 2015 sectoral employment data from each of the provincial yearbooks to calculate primary and non-primary sector employment growth between 2010 and 2015. We use primary sector employment growth to approximate farmer growth and non-primary sector growth for non-farmer growth.

Then, 2015 provincial employment for farmer (non-farmer) is 2010 farmer (non-farmer) level times the estimated 2010-2015 provincial farmer (non-farmer) growth rate.

Additionally, NBS slightly revised down national employment levels for 2001-2010 following the 2010 Census. To adjust for this revision, provincial employment is deflated such that provincial summation equals to the revised national level reported in 2016 CSY.

Capital Stock

We construct capital stock for agricultural and nonagricultural sector at the provincial level. First, we construct nominal Gross Fixed Capital Formation (GFCF) by province by sector and investment price index by province. Second, we calculate real capital stock for each province.

Before 1996, the statistical book *GDP 1952-95* reports nominal GFCF and GFCF real growth rate by province and the three main sectors. However, CSY no longer report these series by sectors. To solve for this problem, we construct agricultural GFCF for each province with provincial fixed investment data. The available data series are:

- Nominal GFCF and GFCF real growth rate by province by sectors 1978-95, from *GDP 1952-95*
- Nominal GFCF and GFCF real growth rate by province (not by sector) 1996-2015, from CSY
- National fixed investment by three main sectors (not by province) 1996-2015, from CSY
- Provincial fixed investment by detailed sectors 1996-2015: 1997-99, 2003-04 *Fixed Asset Yearbook*, 2005-2015 CSY. Supplement provincial total fixed investment 1999 and 2000 from *Statistics on Investment in Fixed Assets of China 1950-2000*.

Fixed investment includes GFCF as well as land expenditure. Fixed investment and GFCF are indistinguishable throughout much of the period. The fixed investment starts to increase after 2002 because of the growing importance of expenditure on land. Following (Brandt and Zhu, 2010), we scale provincial sectoral fixed investment to be consistent with the GFCF for post-1996 data.

Firstly, we use agricultural sector share of national fixed investment and national total GFCF to estimate the national GFCF of agricultural sector. Then, we assume the provincial share of agricultural fixed investment are the same as provincial share of agricultural GFCF. To estimate provincial agricultural GFCF, we rescale provincial agricultural fixed investment such that the provincial sum of agricultural fixed investment equals national agricultural sector GFCF. The provincial total (all-sector) GFCF is the directly from the CSY.

Secondly, for a full period GFCF, we simply append provincial 1996-2015 total and agricultural GFCF to the pre-1995 sectoral GFCF from *GDP 1952-95*. Due to the data limitation, we are still short of 2001 provincial total GFCF and 1999-2001 provincial agricultural GFCF. We use linear estimation (STATA command "ipolate") to bridge the gap. The nonagricultural GFCF is the difference between total GFCF and agricultural GFCF.

The CSY report provincial investment index from 1991 to 2015. The implicit investment index derived from nominal GFCF and GFCF real growth rate reported by *GDP 1952-95* was criticised of being too low compare to later years (Brandt and Zhu, 2010). The pre-1991 investment index can to be estimated from a regression of provincial GFCF index on the implicit provincial index and national GFCF index from 1978 to 2015. To capture price level difference across provinces in our base year 1990 (same base year as real GDP), the 1990 investment price index is set to each provinces' CPI relative to the national average. The real investment is nominal GFCF deflated using the province-specific investment price index.

We construct capital stock with a perpetual inventory method. Let I_{it}^{j} and K_{nt}^{j} denote real investment and capital stock of province n sector j in period t. Assuming depreciation rate is $\delta = 7\%$, for each province n sector j, we calculate initial capital $K_{n0}^{j} = I_{n0}^{j}/(\delta + g_{n}^{j})$, where g_{n}^{j} is investment growth rate between 1978-1988[6]. Perpetual inventory method gives us provincial capital stock in the rest of the period $K_{nt}^{j} = K_{nt-1}^{j}(1-\delta) + I_{nt}^{j}$.

Migration Share

We construct migration matrix for 2000, 2005, 2010 and 2015 from China's Population Census. We define the registered province as the workers Hukou location, and registered sector as their Hukou type. Particularly, 2015 China's 1% Population stopped to report individuals' Hukou type. We use the indicator whether individuals have ownership of farmland as the proxy of registered sector. Workers owning farmland are defined as agricultural registrants. In addition, we define the workers current address location and employed industry as their destination province and sector. In this way, we can aggregate the microdata to get the fraction m_{ni}^{js} for workers registered in n province and j sector and currently working in i province and s sector.

Trade Share

We use provincial input-output table to construct equilibrium trade share for 2002, 2007 and 2012. The data is disaggregeted by 42(30) sectors in 2002 and 2012 (2007). We define "Animal, husbandry, and fishery products and services" as agriculture sector, and aggregate other sectors to non-agriculture sector. For any sector (agriculture or non-agriculture), the goods flow from province n to province j is calculated by the summation of intermediate use, final consumption and capital formation expect inventory changes of province n on the goods produced in province i. Trade share π_{ni}^{j} is just the value of goods flow from province i to province n divided by the total absorption in province n.

[6] Since Chongqing was separated from Sichuan province in 1997, we use 1997-2007 average investment rate to calculate 1997 capital stock as the initial capital stock of these two provinces.

Proofs of Propositions

Proof for proposition 1

Proof. Roy's identity implies the consumption on sector s is

$$c_n^{j,s}(q) = -\frac{\partial V_n^j(q)/\partial P_n^s}{\partial V_n^j(q)/\partial e_n^j(q)} \tag{26}$$

The expenditure share is

$$\phi_n^{j,s}(q) = \frac{c_n^{j,s}(q) P_n^s}{e_n^j(q)} \tag{27}$$

Therefore, the fraction of expenditure allocated to agriculture, non-agriculture and housing for agent q in province n and region j are

$$\begin{aligned}
\phi_n^{j,ag}(q) &= \alpha\phi + \left(\frac{P_n^{ag}}{P_n^{na}}\right)^{\gamma} \left[\frac{e_n^j(q)}{\left(P_n^{ag\,\phi} P_n^{na\,1-\phi}\right)^{\alpha} r_n^{j,h\,1-\alpha}}\right]^{-\epsilon}, && (28)\\
\phi_n^{j,na}(q) &= \alpha(1-\phi) - \left(\frac{P_n^{ag}}{P_n^{na}}\right)^{\gamma} \left[\frac{e_n^j(q)}{\left(P_n^{ag\,\phi} P_n^{na\,1-\phi}\right)^{\alpha} r_n^{j,h\,1-\alpha}}\right]^{-\epsilon}, && (29)\\
\phi_n^{j,h}(q) &= 1-\alpha && (30)
\end{aligned}$$

The aggregate expenditure share of sector s is

$$\Psi_n^{j,s} = \frac{X_n^{j,s}}{R_n^j} = \sum_q \phi_n^{j,s}(q) \frac{e_n^j(q)}{R_n^j} = \sum_q \phi_n^{j,s}(q) \omega_n^j(q) \tag{31}$$

which implies the results. □

Proof for proposition 2

Proof. Total employment income of workers in province n and sector j is $w_n^j L_n^j$. Total income of non-migrant workers in this same province and sector is $\delta_n^j w_n^j L_{nn}^{jj}$, by definition of δ_n^j. Total income from all sources is therefore

$$\begin{aligned}
\bar{e}_n^j L_n^j &= w_n^j L_n^j + (\delta_n^j - 1) L_{nn}^{jj}, && (32)\\
&= w_n^j L_n^j \left(1 + (\delta_n^j - 1)\frac{L_{nn}^{jj}}{L_n^j}\right). && (33)
\end{aligned}$$

Sources of income are employment, land returns, and capital returns. Combined, these are

$$\begin{aligned}
w_n^j L_n^j + r_n^{j,h} \bar{H}_n^j + r_n^{j,k} K_n^j &= w_n^j L_n^j + \beta^{j,h} R_n^j + (1-\alpha)\bar{e}_n^j L_n^j + \beta^{j,k} R_n^j, \\
&= w_n^j L_n^j + \beta^{j,h} w_n^j L_n^j / \beta^{j,l} + (1-\alpha)(1-\alpha)\bar{e}_n^j L_n^j + \beta^{j,k} w_n^j L_n^j / \beta^{j,l}, \\
&= w_n^j L_n^j \left(1 + \beta^{j,h}/\beta^{j,l} + (1-\alpha)\frac{\bar{e}_n^j L_n^j}{w_n^j L_n^j} + \beta^{j,k}/\beta^{j,l}\right). \qquad (34)
\end{aligned}$$

Income received by workers must equal income generated by these three sources. Thus, from equations 33 and 34,

$$\begin{aligned}
\frac{\bar{e}_n^j L_n^j}{w_n^j L_n^j} &= 1 + \beta^{j,h}/\beta^{j,l} + (1-\alpha)\frac{\bar{e}_n^j L_n^j}{w_n^j L_n^j} + \beta^{j,k}/\beta^{j,l}, \\
\Rightarrow \alpha\left(1 + (\delta_n^j - 1)\frac{L_{nn}^{jj}}{L_n^j}\right) &= 1 + \beta^{j,h}/\beta^{j,l} + \beta^{j,k}/\beta^{j,l}, \\
\Rightarrow \lambda &= \left(1 + (\delta_n^j - 1)\frac{L_{nn}^{jj}}{L_n^j}\right)^{-1}, \qquad (35)
\end{aligned}$$

where $\lambda = \frac{\alpha\beta^{j,l}}{\beta^{j,l}+\beta^{j,h}+\beta^{j,k}}$, and therefore

$$\delta_n^j = 1 + \frac{1-\lambda}{\lambda}\frac{L_n^j}{L_{nn}^{jj}}. \qquad (36)$$

which is our result.

□

Proof for proposition 3

Proof. The share of workers from (n, j) that move to (i, s) is determined by the share whose preferences for that destination z_i^s are such that

$$m_{ni}^{js} \equiv Pr\left(\xi_{ni}^{js} v_i^{s\epsilon} z_i^s / \mu_{ni}^{js} \geq \max_{i',s'}\left\{\xi_{ni'}^{js'} v_{i'}^{s'\epsilon} z_{i'}^{s'} / \mu_{ni'}^{js'}\right\}\right). \qquad (37)$$

The distribution of idiosyncratic tastes is Frechet and therefore so too is the distribution of $\xi_{ni}^{js} v_i^{s\epsilon} z_i^s / \mu_{ni}^{js}$. Specifically,

$$\begin{aligned}
Pr\left(\xi_{ni}^{js} v_i^{s\epsilon} z_i^s / \mu_{ni}^{js} \leq x\right) &= Pr\left(z_i^s \leq x\mu_{ni}^{js} / \xi_{ni}^{js} v_i^{s\epsilon}\right), \\
&= exp\left\{-\left(x/\phi_{ni}^{js}\right)^{-\kappa}\right\}, \qquad (38) \\
& \qquad (39)
\end{aligned}$$

which is Frechet with parameter $\phi_{ni}^{js} = \xi_{ni}^{js} v_i^{s\epsilon} / \mu_{ni}^{js}$. One can similarly show that

$$Pr\left(\max_{i' \neq i, s' \neq s} \left\{\xi_{ni'}^{js'} v_{i'}^{s'\epsilon} z_{i'}^{s'} / \mu_{ni'}^{js'}\right\}\right) = exp\left\{-\left(x/\Phi_{ni}^{js}\right)^{-\kappa}\right\},$$

is Frechet with parameter $\Phi_{ni}^{js} = \left(\sum_{s' \neq s} \sum_{i' \neq i} \left(\xi_{ni'}^{js'} v_{i'}^{s'\epsilon} / \mu_{ni'}^{js'}\right)^{\kappa}\right)^{1/\kappa}$. Finally, since the probability that one Frechet random variable x_1 distributed $F(x_1) = e^{-ax^{-\kappa}}$ is larger than another x_2 distributed $F(x_2) = e^{-bx^{-\kappa}}$ is $Pr(x_1 > x_2) = a/(a+b)$ we have

$$\begin{aligned} m_{ni}^{js} &= \frac{\phi_{ni}^{js\,\kappa}}{\phi_{ni}^{js\,\kappa} + \Phi_{ni}^{js\,\kappa}}, \\ &= \frac{\left(\xi_{ni}^{js} v_i^{s\epsilon} / \mu_{ni}^{js}\right)^{\kappa}}{\sum_{s'} \sum_{i'=1}^{N} \left(\xi_{ni'}^{js'} v_{i'}^{s'\epsilon} / \mu_{ni'}^{js'}\right)^{\kappa}}, \end{aligned} \tag{40}$$

which is our result. □

Supplementary Analysis

Homothetic Preferences

Our estimate of migration costs depends on worker preferences. Migration decisions, after all, depend on the marginal utility of income. Here we re-estimate both the level and changes in migration costs when preferences are homothetic.

Table 11: Average Migration Costs in China (Homothetic Preferences)

	Average Cost				Relative to 2000		
Year	2000	2005	2010	2015	2005	2010	2015
Overall	1.93	1.49	0.94	0.67	0.77	0.49	0.35
Between Sectors							
Overall	1.76	1.37	0.86	0.62	0.78	0.49	0.35
Within Provinces	1.47	1.15	0.72	0.52	0.78	0.49	0.35
Between Provinces	22.89	13.19	7.33	6.56	0.58	0.32	0.29
Between Provinces, Within-Sectors							
Overall	15.95	8.79	9.87	3.53	0.55	0.62	0.22
Within Agriculture	46.03	42.69	36.78	49.81	0.93	0.80	1.08
Within Nonagriculture	14.30	7.71	8.74	3.03	0.54	0.61	0.21
Agriculture to Nonagriculture							
Overall	2.68	1.76	0.84	0.59	0.65	0.31	0.22
Within Provinces	2.16	1.42	0.67	0.47	0.66	0.31	0.22
Between Provinces	22.63	13.04	7.13	6.39	0.58	0.31	0.28
Nonagriculture to Agriculture							
Overall	0.75	0.73	0.97	0.78	0.98	1.30	1.04
Within Provinces	0.73	0.71	0.95	0.76	0.98	1.30	1.04
Between Provinces	36.26	20.81	119.23	49.34	0.57	3.29	1.36

Note: Displays the weighted-average migration cost for various years and various types of migration moves. The last three columns display the migration costs in each year relative to 2000.

Table 12: Decomposing China's Growth (Homothetic Preferences)

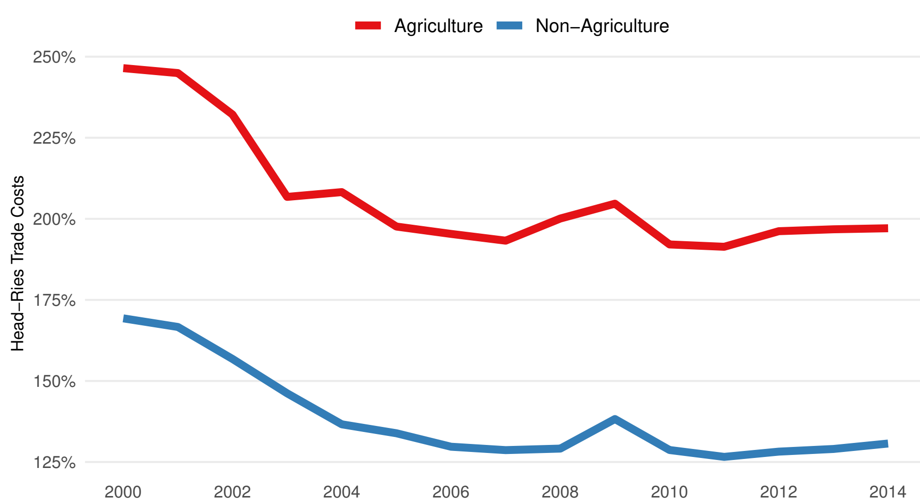
Changes	Five-Year GDP Growth (%)			Share of Five-Year Growth		
	2005	2010	2015	2005	2010	2015
Overall	53.70	59.29	30.35	100.00	100.00	100.00
Productivity	36.77	56.80	16.84	68.47	95.80	55.48
Internal Trade Costs	9.43	0.40	0.00	17.55	0.68	0.00
External Trade Costs	4.93	-0.01	0.00	9.17	-0.02	0.00
Migration Costs	4.80	3.60	3.22	8.94	6.07	10.61
Capital Wedges	-0.28	-0.13	-0.67	-0.51	-0.23	-2.22
Aggregate Capital/Output	-1.95	-1.37	10.97	-3.63	-2.30	36.13

Note: Displays the growth in China's aggregate real GDP over the three five-year periods ending 2005, 2010, and 2015. Each row displays the marginal contribution to growth of each counterfactual change in internal trade costs, external trade costs, migration costs, capital wedges, and aggregate capital/output across all permutations of those changes.

International Trade Costs from WIOD

Although we do not have trade data within China for years up to 2015, we use standard international trade data to demonstrate that the Head-Ries measure of trade costs between China and the world stopped falling after 2007. Indeed, during the financial crisis there was a notable increase in trade costs. To show this, we calculate the simple symmetric trade cost measure $\tau_{ni}^{j} = \left(\frac{\pi_{nn}^{j}\pi_{ii}^{j}}{\pi_{ni}^{j}\pi_{in}^{j}}\right)^{-1/2\theta}$ and report the weighted average in Figure 7. We show that after significant declines in trade costs from 2000 to 2007, there is little gain afterward. This analysis suggests that while we have incomplete trade data within-China over the whole period of our analysis, trade costs were unlikely to change much – at least internationally. Large infrastructure construction in China may affect internal trade costs, but our main analysis between 2010 and 2015 implicitly soaks up that effect into provincial and sectoral productivity.

Figure 7: Average International Trade Costs, China vs World



Displays the symmetric Head-Ries Index of trade costs for China's trade flows with the rest of the world from 2000 to 2014. We average across pairs using trade volume weights. The agricultural are sectors A01-03 and nonagricultural ones are all other sectors. We use $\theta = 4$ for both sectors.

Sensitivity of Main Results to Alternative Estimates

We explore the sensitivity of our main results to alternative parameter values. In Table 13 we report the effect of changing migration costs between 2000 and 2015 if the consumer price effect were significantly higher (4 instead of 0.3), the elasticity of migration were higher (3 instead of 1.5), the elasticity of trade were higher (8 instead of 4), and if we used a small but non-zero long-run agriculture's share of consumer expenditures (0.02 instead of 0). No results are sensitive to these choice. We conclude our main results are not sensitive to alternative, but reasonable, values for these parameters.

Table 13: Robustness: Effect of Lower Migration Costs, 2000-2015

	Five-Year Growth (%) for Year Ending			Cumulative
Year	2005	2010	2015	Effect
Higher Price-Effect: $\gamma = 4$				
Aggregate Real GDP Growth	5.5	4.2	4.0	14.3
Provincial Inequality	-15.8	-4.8	-14.9	-31.7
Agricultural Employment Share	-3.4	-5.7	-3.2	-12.3
Higher Migration Elasticity: $\kappa = 3$				
Aggregate Real GDP Growth	5.7	5.3	4.3	16.1
Provincial Inequality	-20.1	-6.0	-15.5	-36.6
Agricultural Employment Share	-4.0	-7.4	-4.7	-16.1
Higher Trade Elasticity: $\theta = 8$				
Aggregate Real GDP Growth	6.6	4.8	4.4	16.6
Provincial Inequality	-18.5	-5.8	-13.4	-33.5
Agricultural Employment Share	-4.3	-7.3	-4.8	-16.4
Non-Zero Long-Run Agriculture Share: $\phi = 0.02$				
Aggregate Real GDP Growth	6.1	4.6	4.0	15.4
Provincial Inequality	-19.9	-4.3	-14.1	-34.1
Agricultural Employment Share	-4.2	-7.0	-4.7	-15.9

Note: Displays the effect of changing migration costs in each of the three five-year periods ending 2005, 2010, and 2015. The cumulative effect is reported in the final column. Changing between-sector migration costs affects μ_{ni}^{jk} only if $i \neq k$. Changing between-province, within-sector migration costs affects μ_{ni}^{jk} only if $i = k$ and $n \neq i$. The change in regional inequality is reported as the change in the variance of log real GDP per worker across provinces. The change in agriculture's share of national employment is reported as the percentage point change.

We also report alternative migration costs it $\kappa = 1.5$ below in Table 14.

Table 14: Average Migration Costs in China

Year	Average Cost 2000	2005	2010	2015	Relative to 2000 2005	2010	2015
Overall	2.05	1.66	1.05	0.77	0.81	0.51	0.37
Between Sectors							
Overall	1.87	1.52	0.96	0.70	0.81	0.51	0.38
Within Provinces	1.57	1.28	0.81	0.59	0.82	0.52	0.38
Between Provinces	19.81	11.27	6.72	6.35	0.57	0.34	0.32
Between Provinces, Within-Sectors							
Overall	17.11	9.56	11.51	4.40	0.56	0.67	0.26
Within Agriculture	46.39	44.63	38.05	54.63	0.96	0.82	1.18
Within Nonagriculture	15.39	8.39	10.25	3.79	0.55	0.67	0.25
Agriculture to Nonagriculture							
Overall	2.48	1.70	0.88	0.64	0.68	0.35	0.26
Within Provinces	2.00	1.38	0.71	0.52	0.69	0.36	0.26
Between Provinces	19.47	11.05	6.52	6.18	0.57	0.34	0.32
Nonagriculture to Agriculture							
Overall	0.94	1.08	1.43	1.12	1.14	1.52	1.18
Within Provinces	0.92	1.05	1.40	1.09	1.14	1.52	1.18
Between Provinces	45.48	32.67	173.86	69.38	0.72	3.82	1.53

Note: Displays the weighted-average migration cost for various years and various types of migration moves. The last three columns display the migration costs in each year relative to 2000.