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The effect of migration policy on growth, structural change, and regional inequality in China[☆]

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ABSTRACT

Between 2000 and 2015, China's aggregate income quadrupled, its provincial income inequality fell by a third, and its share of employment in agriculture fell by a half. Internal migration is central to this transformation, with the number of internal migrant workers reaching 300 million by 2015. Combining rich data on migration with a spatial general equilibrium model of China's economy, we quantify the size and the impact of internal migration cost reductions in China between 2000 and 2015. During the 15-year period, China's internal migration costs fell by forty-five percent. In addition to contributing substantially 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 changes, including changes in trade costs, capital market distortions, average cost of capital, and productivity. While each contributes meaningfully to growth, migration policy changes are central to China's structural change and regional income convergence. We also find that the recent slow-down in aggregate economic growth between 2010 and 2015 is associated with smaller reduction in inter-provincial migration costs and a larger role of capital accumulation.

1. Introduction

China's economic growth since 2000 has been impressive. And although less well known, its rapid structural change and large regional income convergence are no less remarkable. Between 2000 and 2015, while the country's aggregate GDP per worker quadrupled, 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 300 million in 2015, mostly due to changes in

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policies that made migration easier. In this paper, we quantify the impact of migration policy changes on China's growth, structural change, and regional income convergence.

To accomplish this, we compile uniquely detailed data on production, capital, employment, trade, and migration in China. These data reveal four key facts concerning China's structural change and regional convergence. First, there was significant regional convergence in real GDP per worker between 2000 and 2015. The variance of the cross-province (log) GDP per worker declined by a third, from 0.24 in 2000 to 0.15 in 2015. Second, over the same period, there were little convergence in GDP per worker within the agricultural and non-agricultural sectors. Third, structural change was an important contributor to growth and convergence. The fraction of employment in agriculture fell from 53% in 2000 to 28% in 2015. The largest changes occurred in provinces with lower initial levels of income, higher initial shares of agricultural employment, and larger gaps in labor productivity between the agricultural and non-agricultural sectors. Therefore reallocation of labor from agriculture to the non-agricultural sector resulted in larger increases in aggregate GDP per worker in poor provinces than in richer provinces and contributed significantly to the convergence in aggregate income across provinces. Fourth, the structural change is closely related to inter-provincial migration. 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 spatial equilibrium 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. We find that between 2000 and 2015 migration costs fell by forty-five percent, with the cost of moving from agricultural rural areas to non-agricultural 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 income inequality. We compare the effect of migration policy changes with other important economic factors, including changes in trade costs, capital market distortions, average cost of capital, and productivity. While each contributes meaningfully to growth, migration policy changes are central to China's structural change and regional convergence. Finally, we find that the slow-down in growth between 2010 and 2015 is associated with a smaller reduction in inter-provincial migration costs and a larger role of capital accumulation during this five-year period.

Our model builds on recent developments in international trade. In particular, we extend the Eaton and Kortum, (2002) model to multi-sector as in Caliendo and Parro (2015) and incorporate both imperfect spatial and sector labor mobility as in Tombe and Zhu (2019). In addition, we allow for capital as an input in production and frictions in capital allocation across space and sectors. To better identify inter-sector migration costs, we also consider household preferences that are non-homothetic to control for the impact of income growth on rural-urban migration.

Our work contributes to the 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 labor 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 labor mobility restrictions. 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 of migration policy changes on growth, structural change, and regional inequality at the same time in a unified model with endogenous and frictional labor, capital, and production allocations.

Our work also builds on a large and growing literature quantifying the effects of internal migration (Caliendo et al., 2017; Heise and Porzio, 2019; Imbert and Papp, 2019; Schmutz and Sidibe, 2018). Most recently, Bryan and Morten (2019) show that internal labor migration in Indonesia has 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 trade and migration or structural change. Of particular relevance for China, Fan (2019) demonstrates that trade may exacerbate inequality, and Erten and Leight (2017) analyze the effect of China's accession to WTO in 2001 on structural change at the local level.

By linking reallocation of labor across sectors to migration, we contribute to the large literature on structural change (Herrendorf et al., 2014) and the agricultural productivity gaps (Gollin et al., 2014). Given such gaps in labor productivity between sectors, shifting labor from agriculture to non-agriculture can significantly boost aggregate productivity. Our emphasis on the role of structural change in regional income convergence is also directly related to Caselli and Coleman (2001), who study structural change and income convergence in the US. We document that a central factor behind China's structural transformation is migration, both within and between provinces. Eckert and Peters (2018) also examine the interaction between migration and structural change. But, unlike for China, they find regional migration contributed little to the decline in the agriculture's share of employment in the United States. Finally, we build on the recent work of Alder et al. (2019), Comin et al. (2015), and Boppart (2014), by allowing for income effect (through non-homothetic preferences) to be a driver of structural change. We find income effect magnifies the impact of reductions in migration costs on structural change and growth. We also show that ignoring income effect may lead one to overestimate both the initial levels of and reductions in migration costs.

Finally, our paper is closely related to and build on the work by Tombe and Zhu (2019). We extend their work theoretically by incorporating into the model physical capital as an input in production and income effect through non-homothetic preferences. We also extend their work empirically by extending their analysis of the impact of trade and migration on China's growth between 2000 and 2005 to a much longer and more recent period, from 2000 to 2015. Most important, we go beyond their analysis on aggregated GDP growth by studying the impact of migration cost changes and other changes on both structural change and regional income inequality in China.

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

2. Migration, structural change, and regional income convergence

In this section, we document large income disparity across provinces and between the agricultural and non-agricultural sectors in China in 2000, and the significant regional income convergence and structural change between 2000 and 2015. We also provide evidence suggesting that the structural change and regional income convergence are intimately related. We then discuss the migration policy changes and the resulting increases in internal migration as an important driver for both the structural change and regional income convergence. First, however, we discuss briefly the data we use for the paper.

2.1. Data

For our analysis, we combine three sources of data on internal migration, internal and international trade, and provincial economic accounts in China. We briefly list the important variables here, and provide a more thorough description in the appendix.

Migration. Our migration data are from China's population census. In addition to the 2000 and 2005 census data used by Tombe and Zhu (2019), we also use the confidential micro data of the 2010 and 2015 population census of China.[1] These census data provide detailed information about rural-urban and cross-province migration from 2000 to 2015.

Trade. We construct inter-provincial trade flows based on the inter-provincial input-output table for 2002, 2007, and 2012 from Li (2010), Liu et al. (2012), and Liu et al. (2018), respectively.

Provincial GDP and Employment. We construct provincial GDP, capital stock, and employment for agriculture and non-agriculture based mainly on the data published in the China Statistical Yearbook (CSY) by China's National Bureau of Statistics (NBS). The construction methods for GDP and employment are the same as in Tombe and Zhu (2019). However, after 2010, the NBS no longer publishes provincial level employment by sector. For 2015, we therefore estimate provincial employment based on the data published in the provincial yearbooks. We describe the full estimation procedure in the appendix.

Provincial Capital Stock. The CSY reports nominal Gross Fixed Capital Formation (GFCF) by province but not by sector. However, it does report the fixed-asset investment by province and sector. We approximate each sector's share of capital formation by using the sector's share of total fixed-asset investment. The real investment is nominal GFCF deflated using the province-specific investment price index reported in the CSY. We then construct capital stock using a perpetual inventory method assuming a depreciation rate of 7%. The average investment growth rates of the first ten years of a province are used to generate initial capital stock values for 1978. Our estimates of annual real investment, less depreciation, are then used to calculate capital stock in subsequent years.

2.2. Factor return dispersion across provinces and sectors

Tombe and Zhu (2019) document large differences in real labor income across provinces and between the agricultural and non-agricultural sectors in China in 2000, and they argue that an important reason for these differences is the *hukou* system that imposes severe restrictions on worker mobility within China. Here we show the evolution of the distribution of real returns to labor across provinces and sectors over the 15-year period after 2000.

Using data on real GDP, employment, and factor shares, the real marginal return to labor is

$$w_n^j = \alpha \tilde{\beta}^{j,l} \frac{Y_n^j}{L_n^j}, \tag{1}$$

where Y_n^j is real GDP of sector j in province n, L_n^j is employment, $\tilde{\beta}^{j,l}$ is labor's share of value-added, and α is the share of non-housing goods and services in GDP. We display the distribution of real marginal returns to labor for 2000, 2005, 2010, and 2015 in Fig. 1a, which reveals persistent within-sector dispersion of labor returns across provinces and large gaps

[1] These data are from NBS micro survey databases: 2010 China Population Census Mirco-database and 2015 1% Sample China Population Census Mirco-database.

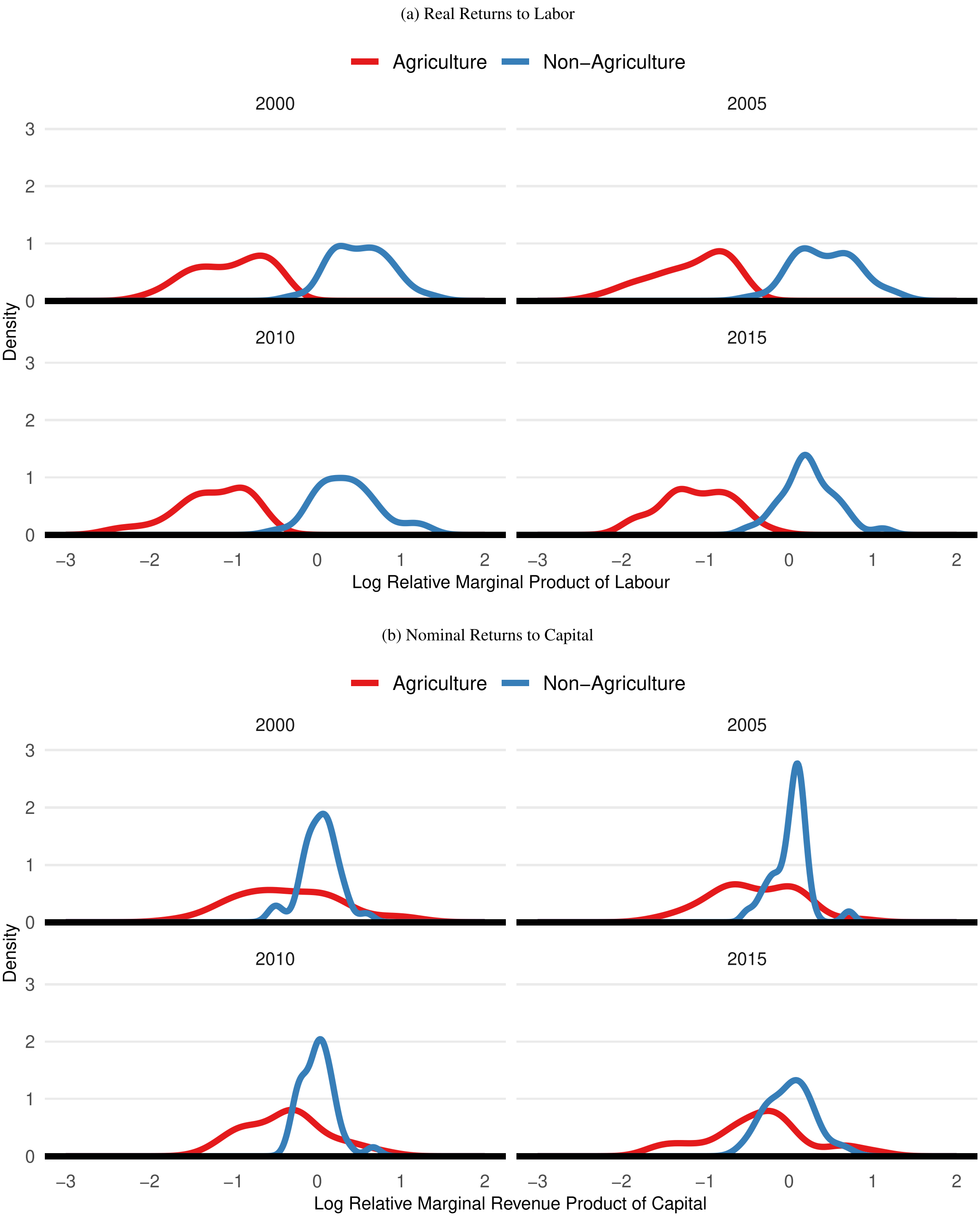

Fig. 1. Dispersion in Returns to Labor and Capital in China. Panel (a) displays the dispersion of returns to labor across provinces, by sector, from 2000 to 2015. Panel (b) displays the dispersion in capital wedges over the same period.

between agriculture and the non-agriculture. Only in the last five years, between 2010 and 2015, did the within-sector dispersion in returns and the between sector gaps in returns decline slightly.

For comparison, we also report the distribution of returns to capital across provinces and sectors in Fig. 1b. Specifically, the returns to capital in province n and sector j is

$$r_n^{j,k} = \alpha \tilde{\beta}^{j,k} \frac{P_n^j Y_n^j}{K_n^j}, \tag{2}$$

where $\tilde{\beta}^{j,k}$ denotes capital's (k) share of value-added and $P_n^j Y_n^j$ the nominal GDP of sector j in province n. Note that we examine nominal rather than real returns to capital because capital owners can invest across locations and sectors without having to consume at the investment destinations. Therefore they care about nominal return differences only and the differences in the cost of living across locations and sectors do not directly affect their investment decisions. If there are no capital market frictions, then investors' arbitrage would imply that the nominal returns $r_n^{j,k}$ equalize across all sectors and provinces. So, the dispersion in the nominal returns to capital reflects frictions that result in capital misallocation. As illustrated in Fig. 1b, the dispersion of capital returns across provinces was persistently large in agriculture, but significantly smaller in the non-agricultural sector. There was a decline in the dispersion of capital returns in the non-agricultural sector between 2000 and 2005, but the dispersion then increased between 2010 and 2015. The Chinese government's massive infrastructure and stimulus spending after the global financial crisis may have contributed to the worsening capital allocations during that period, as pointed out by Bai et al. (2016).

2.3. Regional income convergence and structural change

While the within-sector dispersion in labor income did not show a significant decline between 2000 and 2015, there was a dramatic reduction in the inequality of the aggregate provincial labor income over the same period. The cross-province variance of log real GDP per worker was 0.24 in 2000. But by 2015, this variance declined to 0.15 – a one-third reduction in regional income inequality. Behind this significant decline was the faster labor income growth experienced by initially lower-income regions. In panel (a) of Fig. 2, we display the growth rates of real GDP per worker between 2000 and 2015 of all the provinces against their initial real GDP per worker levels in 2000. There is a significant negative relationship between the initial level of income and subsequent income growth, implying strong income convergence over this 15-year period. Regressing the average growth on initial real GDP per worker reveals a precisely estimated $\beta-$convergence coefficient of approximately 2%. That is, a 10% higher initial income level is associated with a 0.2% lower average annual growth rate.

What's behind this reduction in regional inequality? In panel (b) of Fig. 2, we plot the growth rates of real GDP per worker within each sector. The negative relationship between the growth rate and initial income is 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 agriculture and the non-agricultural sectors were 0.20 and 0.12, respectively, in 2000, and 0.18 and 0.11 in 2015. In other words, there were only slight declines in within-sector income inequality. These facts suggest that changes in the sectoral composition of labor income or structural change must be an important reason for the convergence of aggregate GDP per worker across China's provinces.

Structural change has been significant in China over this 15-year period, during which the share of employment in agriculture fell nearly in half from 53% to 28%. Since labor productivity in agriculture is significantly lower than in non-agriculture, reallocation of labor towards the latter can increase a province's overall labor productivity. Therefore, structural change can contribute to convergence in regional incomes if the pace of structural change was faster in poor provinces than in rich provinces. And this is indeed the case. In panel (a) of Fig. 3, we display the change in the non-agricultural employment shares by province between 2000 and 2015. Provinces with a relatively small non-agricultural sector in 2000 (and therefore lower average income) saw significantly larger employment shifts into this sector by 2015. Among those provinces with the smallest initial non-agricultural employment share (at or below 40%), nearly one-third of total provincial employment moved out of agriculture. Among those with the largest initial non-agricultural employment share (at or above 80%), only 10% of workers switched. In addition, there is a relationship between structural change and a province's agricultural productivity gap (the gap between the agricultural and non-agricultural real GDP per worker). In panel (b) of Fig. 3, we plot the initial agricultural productivity gap in 2000 by province against each province's change in the non-agricultural sector's share of provincial employment between 2000 and 2015. With the exception of the six provinces with particularly low levels of structural change (three municipalities, and three peripheral regions), there is a positive relationship between the initial agricultural productivity gap and the pace of structural change.

To quantify in a simple way the degree to which structural change is driving regional convergence consider the following simple decomposition of a province's aggregate real GDP per worker,

$$y_{n,t} = y_{n,t}^{ag} + l_{n,t}^{na} \cdot \left(y_{n,t}^{na} - y_{n,t}^{ag}\right), \tag{3}$$

where $l_{n,t}^{ag}$ is province n's non-agricultural employment share in year t and $y_{n,t}^{j}$ is the real GDP per worker of sector j in province n and year t. Holding each sector's real GDP per worker fixed at their 2000 levels, we calculate the counterfactual real GDP in province n as

$$\bar{y}_{n,t} = y_{n,2000}^{ag} + l_{n,t}^{na} \cdot \left(y_{n,2000}^{na} - y_{n,2000}^{ag}\right). \tag{4}$$

We find the variance of $ln(\bar{y}_n)$ falls by one-quarter when only $l_{n,t}^{na}$ is changing over time as in the data. Our simple back-of-the-envelope calculation therefore suggests that structural change accounts for two-thirds of the observed convergence between China's provinces.

Of course, this simple calculation ignores potential endogenous relationships between the labor reallocation and the labor productivity in the two sectors, which we will take into account in our quantitative analysis of a full general equilibrium model later. The simple calculation also does not tell us what drives the structural change. Next, we present evidence that

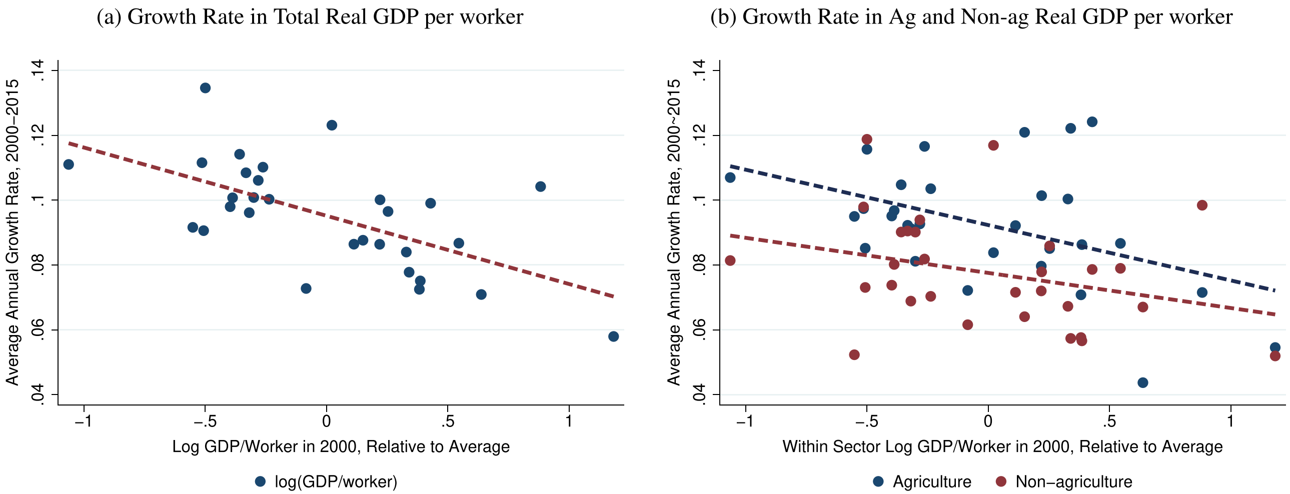

Fig. 2. Convergence in Provincial Real GDP per Worker, 2000–2015. Displays the average annual growth rate in real GDP per worker in total, agriculture and non-agriculture from 2000 to 2015 against each province's initial real GDP per worker in 2000. The negative relationship implies systematic convergence across provinces, while convergences are much smaller within either of the two sectors.

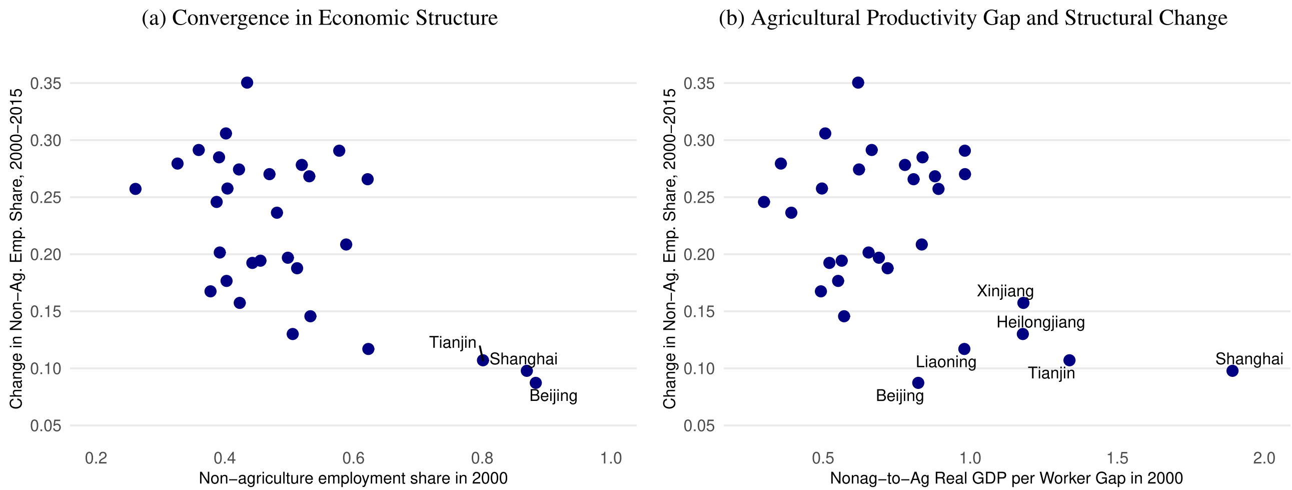

Fig. 3. Structural Change across Provinces in China, 2000–2015. Panel (a) and (b) displays the change in the non-agricultural sector's share of provincial employment between 2000 and 2015 against the initial share in 2000 and the agricultural productivity gap in 2000, respectively.

Table 1
Worker Migration in China, 2000–2015.

	Intra-Provincial				Inter-Provincial			
	2000	2005	2010	2015	2000	2005	2010	2015
Total Migrant Stock	101.5	132.6	176.2	215.7	29.7	47.0	79.2	90.2
Share of Employment (%)								
Total Migrants	14.1	17.8	22.9	28.0	4.1	6.5	10.3	11.7
Ag-to-Nonag Migrants	13.0	16.5	21.6	25.5	3.3	5.2	8.6	7.0
Non-migrant Ag Workers	63.0	55.5	46.3	31.6	63.0	55.5	46.3	31.6

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

worker migration from agriculture to non-agriculture, both within- and between-provinces, can be an important driver of the structural change in China.

2.4. Internal migration in China

Before turning to the data on migration and structural change, we first provide a summary of China's internal migration policy and recent changes to it. 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. In addition, 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/non-agricultural 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 tightened 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.

Based on population census data, we report in Table 1 both inter-provincial and intra-provincial migration in China for the years of 2000, 2005, 2010, and 2015.[2] As a reference, we also report the share of workers who are non-migrant agricultural workers. A worker is defined as an inter-provincial migrant if they worked outside their province of *hukou* registration. And they are defined as an intra-provincial migrant if they worked within their province of registration but outside their sector of *hukou* registration. Our definition of intra-provincial migration is broader than usual. Some workers with agricultural *hukou* may work in non-agriculural jobs locally (within the village or township of their *hukou* registration) and they are classified as intra-provincial migrant workers. We choose this definition because we find from the 2005 mini-census data that the average income of these local "migrant workers" is more than 2.5 times as high as that of the local farmers. This suggests that there are significant frictions for rural workers switching sectors locally. In our robustness analysis later, we will consider a stricter definition of migrant workers.

As documented by Tombe and Zhu (2019), the relaxation of *hukou* restrictions on migration between 2000 and 2005 resulted in significant increases in both intra- and inter-provincial migration.[3] The general trend seems to have continued between 2005 and 2015, with the intra- and inter-provincial migrant workers' shares of total employment increased from 17.8% and 6.5%, respectively, in 2005, to 28% and 11.7% in 2015. Between 2010 and 2015, however, the increase in inter-provincial migration slowed significantly, and the cross-provincial rural-urban migrant workers' share of total employment in 2015 is actually lower than that in 2010. In contrast, within-province rural-urban migration continued to increase significantly through 2015. These patterns are consistent with the policy changes adopted by the Chinese government after 2010 that have made moving to top tier cities, the destinations of much of the inter-provincial migration, much harder for people with rural *hukou* and, at the same time, encouraged local urbanization in poor inland and western provinces.

[2] The migration stocks are calculated from the data on migrant shares from the census data and the total employment data in the China Statistics Yearbooks. See appendix for details.

[3] Our estimated migration stocks are slightly different from those reported by Tombe and Zhu (2019) because we now use more detailed sample weights provided by the NBS.

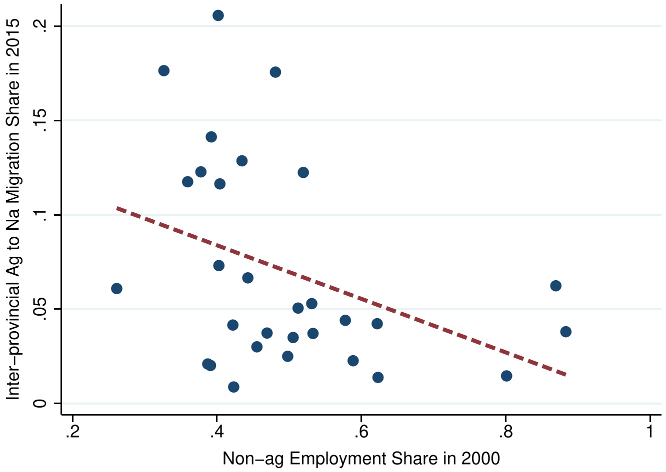

Fig. 4. Migration and Structural Change. The figure displays the fraction of initially agricultural workers that now work in non-agricultural sectors, overall and out of province. This captures the relationship between migration and structural change.

To see the impact of migration on structural change, in Fig. 4, we plot for all the provinces their initial share of employment in agriculture in 2000 against their share of all the workers with agricultural *hukou* in that province who work in the non-agricultural sector in another province in 2015. We can see that provinces with higher shares of initial agricultural employment tend to have a larger proportion of workers move out of agriculture and into the non-agricultural sector outside their *hukou* registration provinces in 2015. Simply put, reductions in the share of employment in agriculture in poor provinces are associated with inter-provincial out-migration of farmers.

In summary, the facts we document in this section suggest that migration policy changes and the associated increases in migration have important effects on structural change and regional income convergence in China between 2000 and 2015. We now turn to our main analysis that precisely quantifies these effects using a spatial general equilibrium model of trade and migration.

3. A spatial model of trade and migration

The focus of our model is on quantifying the impact of migration cost changes on growth, structural change, and regional income convergence in China between 2000 and 2015. During this period, however, there were changes in trade costs, capital costs, and province-sector specific TFPs that could also affect growth, structural change, and regional income convergence in China. To identify the impact of migration cost changes, we use a tractable quantitative model of trade and migration based on the one used in Tombe and Zhu (2019), but extended to allow for capital in production and capital market frictions. In addition, since the recent literature on structural change have emphasized the importance of income effect, we further extend the model with non-homothetic preferences to allow for income effect on structural change. The details of the model follow.

3.1. Individual agents

There are $N+1$ regions: 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 region and sector as L_n^j. For the N provinces in China, we also denote the number of individuals registered in each province and sector as $\bar{L}_n^j$. As workers are mobile within China, the number of workers in a province need not equal the number of individuals holding a *hukou* registration there. The number of *hukou* registrants in a province and sector is fixed.

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

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

for individuals of type-q (either migrants or non-migrant locals) with earnings $e_n^j(q)$. The parameter γ governs the sensitivity of expenditure shares to changes in relative prices, ϵ governs the sensitivity of expenditure shares to changes in income, and $B \geq 0$ governs the importance of relative prices. This specification is useful for aggregating individuals with differing levels of income within each region in a tractable manner.[4] And although a closed form representation of the direct utility function does not exist, it includes the standard Cobb-Douglas preferences as a special case when $B = 0$ and $\epsilon = 1$. The implied aggregate shares of spending allocated to goods and housing are provided in the following proposition.

Proposition 1. *The fraction of aggregate expenditures allocated to the agricultural good, non-agricultural good, and housing in region n and sector j are*

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

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

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

where $\bar{e}_n^j = \left[\sum_q e_n^j(q)^{-\epsilon}\omega_n^j(q)\right]^{-1/\epsilon}$ *is the weighted harmonic 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 the agricultural good converges to $\alpha\phi$ from above. Similarly, the share allocated to the non-agricultural good converges to $\alpha(1-\phi)$ from below. And the share allocated to housing is fixed. In the rest of the paper, we will consider the case when $B = 1$.

In certain situations, it is convenient to represent utility as a function of real incomes and expenditure shares. Using Eq. (6) to substitute for relative prices in Eq. (5), one can write the utility of an individual with real income $\upsilon_n^j(q)$ allocating a share $\psi_n^{j,ag}(q)$ of their income to agriculture goods as

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

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 labor, 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 that the marginal cost of production is inversely 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

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

[4] An alternative choice is the nonhomothetic CES preferences (Comin et al., 2015). However, in this case, we cannot aggregate consumption demand of the migrants and non-migrants into the demand of a representative agent. It is primarily for this reason that we opt for the PIGL specification.

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 Fréchet, with CDF given by $F_n^j(z) = e^{-T_n^j z^{-\theta}}$, 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

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

In both Eqs. (14) and (15), the constant of proportionality is common across regions and sectors.

Trade shares from Eq. (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. Incomes from employment, land, and capital

Workers earn income from work and, for non-migrant workers, from their claims to land and capital returns. Broadly consistent with China's institutional setting, we presume only local non-migrant individuals receive income from land and capital in their province and sector. 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 ratio of total income including rebate of land and capital income to labor income. We show how to determine the equilibrium value of δ_n^j below.

Total rebates in each province and sector 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 $\beta^{j,k} R_n^j = r_n^{j,k} K_n^j$. 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

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

where $\lambda^j = \alpha\beta^{j,l}/(\beta^{j,l} + \beta^{j,h} + \beta^{j,k}) < 1$. 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 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*

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

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 $n = i$ and $j = s$ and equal 1 otherwise.

3.4. Capital market clearing condition

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 province 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 average cost of capital common to all sectors and the capital wedge facing that particular sector and province. Specifically, given capital wedges t_n^j such that $\beta^{j,k} R_n^j / K_n^j = r_n^{j,k} \equiv \bar{r}/(1-t_n^j)$, we have

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

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 average 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.

3.5. Worker mobility across provinces

Workers in China choose where to live (and work) to maximize welfare. Workers are heterogenous in their taste for different provinces and sectors, and face costs when living outside their province of *hukou* registration. Labor 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 j compares the potential utility level in all destinations V_{ni}^{js}, the migration costs between (n, j) and (i, s), and the potential loss of land and capital income reflected in δ_{ni}^{js}. From Eq. (9), V_{ni}^{js} is as follows

$$V_{ni}^{js} = \begin{cases} \left(\frac{\delta_i^{s\epsilon}}{\epsilon} - \frac{\psi_i^{s,ag} - \alpha\phi}{\gamma} \right) v_i^{s\epsilon} & if \quad n = i, j = s \\ \left(\frac{1}{\epsilon} - \frac{\psi_i^{s,ag} - \alpha\phi}{\gamma} \right) v_i^{s\epsilon} & if \quad n \neq i, j \neq s \end{cases} \tag{23}$$

where $\psi_i^{s,ag}$ and v_i^s are the spending share on agriculture goods and real income per worker for migrating workers living in province n and sector j. In addition, let worker preferences over locations be captured by z_i^s, which is distributed identically and independently across workers and follows a Fréchet 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. We provide the equilibrium migration shares in the follow proposition:

Proposition 3. *Given indirect utilities V_{ni}^{js}, migration costs μ_{ni}^{js}, and a Fréchet 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*

$$m_{ni}^{js} = \frac{\left(V_{ni}^{js} / \mu_{ni}^{js} \right)^{\kappa}}{\sum_{s' \in \{ag,na\}} \sum_{i'=1}^{N} \left(V_{ni'}^{js'} / \mu_{ni'}^{js'} \right)^{\kappa}} \tag{24}$$

where V_{ni}^{js} is indirect marginal utility from Eq. (23).

Proof. See the appendix. □

This expression for migration shares conveniently summarizes the pattern of inter-provincial and inter-sectoral moves by workers. Note that the parameter κ measures the elasticity of migration with respect to utility. From Eq. (9), we can see that the elasticity of migration with respect to real income is $\epsilon\kappa$, which can be directly estimated from the data. So, for any given value of ϵ, we can use the estimated income elasticity of migration to infer the utility elasticity κ.

Finally, given the migration shares and *hukou* registrations, total employment in each province and sector is

$$L_n^j = \sum_{i=1}^{N} \sum_{s \in \{ag,na\}} m_{in}^{sj} \bar{L}_i^s, \tag{25}$$

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

4. Quantitative analysis

We now bring the full model to data. We first calibrate the values of the time-invariant model parameters. Given these parameter values and for each of the four years (2000, 2005, 2010, and 2015), we calibrate the migration costs, trade costs, capital wedges, the average cost of capital, and the province-sector specific TFPs so that the model matches trade, migration, capital stocks, and real GDP in the data. This provides estimates of trade and migration costs, capital market distortions, and average cost of capital over time. To quantify their effect on overall economic activity and regional income inequality in China, we simulate the model under various counterfactual experiments detailed below.

Table 2
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.

4.1. Calibration of time-Invariant parameters

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}, migration shares m_{ni}^{js}, and numbers of registered workers $\bar{L}_n^j$. In particular, we use the migration share matrix from the 2000 census and the employment by province and sector from the 2000 CSY to back out the initial numbers of registered workers by province and sector,[5] and keep them constant for all the quantitative analysis.[6]

We describe the calibration of each time-invariant model parameter in detail below, and report the relevant values in Table 2. Production function parameters are calculated to match the share of sector 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 CSY 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.

Some model parameters correspond to empirical elasticities and other moments in the data. We set their values to correspond to common values from the literature, and explore the sensitivity of our results to alternative values in the appendix. In particular, the elasticity 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 and non-agricultural 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). There are other researchers who choose lower values for ϵ. For example, Boppart (2014) sets it to 0.22 and Eckert and Peters (2018) set it to 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. The value of γ is set to 0.3, close to Boppart (2014)'s estimate of 0.41 and Eckert and Peters (2018)'s of 0.32. We show that our results are robust to alternative values for ϵ and γ in the appendix. Finally, the long-run share of spending allocated to agriculture ϕ is set to 0, which simplifies Eq. (23) with very little quantitative effect on our results, as we demonstrate in the appendix.

4.2. Size and impact of migration cost reductions

We first estimate the size of migration cost changes before quantifying its effect on growth, structural change, and regional convergence. In addition, we compare our main results to a model with homothetic preferences and to estimates based on an alternative definition of migration.

[5] We use this approach to eliminate the gaps in employment between the census and CSY. The Chinese population census and the NBS labor survey, the source of the employment data in CSY, use different survey methods in enumerating agricultural and non-agricultural employment. The census provides more accurate information about migration, but less accurate information on employment. We discuss this in more detail in the data appendix.

[6] For robustness, we also report the results with registered worker changing for each five year period in the appendix, and our main results do not change much.

Table 3
Average migration costs in China.

Year	Average cost 2000	2005	2010	2015	Relative to 2000 2005	2010	2015
Overall, Including δ_n^j	3.96	3.59	2.90	2.17	0.91	0.73	0.55
Direct migration costs μ_{ni}^{js}	1.75	1.63	1.31	0.96	0.93	0.75	0.55
Agriculture to Nonagriculture μ_{ni}^{js}							
Overall	2.68	2.23	1.57	1.04	0.83	0.58	0.39
Within Provinces	2.25	1.87	1.32	0.87	0.83	0.59	0.39
Between Provinces	11.38	9.55	5.95	4.88	0.84	0.52	0.43
Between Province μ_{ni}^{js}							
Overall	9.14	8.00	5.54	3.68	0.88	0.61	0.40
Within Agriculture	11.61	13.48	10.62	14.99	1.16	0.91	1.29
Within Nonagriculture	5.67	5.06	4.14	1.92	0.89	0.73	0.34

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.

4.2.1. Estimating migration cost changes

With the calibrated parameters and 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 the direct migration costs μ_{ni}^{js} such that Eq. (24) holds, and from Eq. (23), we can calculate the migration cost as follows:

$$\mu_{ni}^{js} = \frac{V_{ni}^{js}}{V_{nn}^{jj}} \left(\frac{m_{ni}^{js}}{m_{nn}^{jj}} \right)^{-1/\kappa} = \underbrace{\frac{1/\epsilon - (\psi_i^{s,ag} - \alpha\phi)/\gamma}{\delta_n^{j\epsilon}/\epsilon - (\psi_n^{j,ag} - \alpha\phi)/\gamma}}_{\substack{\text{Nonhomotheticity} \\ \text{and rebates}}} \underbrace{\left(\frac{v_i^s}{v_n^j} \right)^{\epsilon} \left(\frac{m_{ni}^{js}}{m_{nn}^{jj}} \right)^{-1/\kappa}}_{\substack{\text{Overall} \\ \text{Cost}}} \tag{26}$$

We use data on real GDP by province and sector to estimate real wages and land and capital rebates, using Eq. (20), and data on consumption shares by province and rural or urban area to estimate agricultural spending shares. With these estimates in hand, we report the resulting migration-weighted average migration costs in Table 3.

The average of the direct migration costs μ_{ni}^{js} is reported in the second row of the table. It was substantial in 2000, but fell by 45% over the next 15 years. The first row of the second panel in the table show that the average of rural-to-urban or agriculture-to-nonagriculture migration costs was even higher in 2000 and also fell more, by 61% between 2000 and 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. The first row of the table shows the average overall cost of moving that includes the foregone returns to land and capital.[7]. It was roughly equivalent to around 60% of annual income in 2000. By 2015, the overall average cost declined by 45% and was roughly equivalent to 40% of annual income. Over the three 5-year periods, the magnitude of the migration cost reductions generally increased over time, but the between-province rural-to-urban migration cost reduction between 2010 and 2015 is lower than the reduction between 2005 and 2010. This is most likely due to the strict population control policy implemented after 2010 in all the first-tier and some second-tier cities in China.

4.2.2. Quantifying the effect of migration cost changes

To quantify the effect of these migration cost changes, we start from the 2000 initial equilibrium and solve for relative changes in the model where change in μ_{ni}^{js} are set to their estimated values and all other model parameters are held constant. Though we report only the average changes in migration costs in Table 3, we simulate the effect of changes in migration costs across all bilateral province-sector pairs. Table 4 reports the resulting changes in aggregate real GDP, provincial income inequality, and agriculture's employment share.

Changes in internal migration costs have significant effects on aggregate economic activity, regional income inequality, and structural change. The top three rows of Table 4 show the effect of all estimated migration cost changes. First, as a result of these changes, the aggregate real GDP increases by 4.4%, 5.9%, and 6.9%, respectively, over the three 5-year periods ending in 2005, 2010, and 2015. The cumulative effect over the 15-year period is an 18% increase in the aggregate real GDP. The second and third panel of Table 4 show separately the impact of the reductions in within- and between-province agriculture to non-agriculture migration costs. They increase the aggregate GDP by about similar amount, 9.4% and 8.1%, respectively. To put the magnitude of the aggregate GDP increase (or aggregate labor productivity increase since we have normalized the total employment to one) in perspective, we compare our results to two recent studies on the gains from reducing spatial misallocation in some other economies. Fajgelbaum et al. (2019) estimate that a *hypothetical* complete elimination of state

[7] The last two terms of Eq. (26)

Table 4
Effect of lower migration costs, 2000–2015.

	Five-year growth (%) for year ending			Cumulative	Homothetic
Changes in All Migration Costs	2005	2010	2015	effect	preferences
Aggregate Real GDP Growth	4.3	5.9	6.9	18.0	12.6
Provincial Income Inequality	−10.6	−14.4	−19.2	−38.2	−35.2
Agriculture's Employment Share	−3.2	−5.5	−7.7	−16.3	−13.8
Changes in Ag to Non-ag, Within-Province Migration Costs					
Aggregate Real GDP Growth	2.5	2.9	3.8	9.4	5.6
Provincial Income Inequality	−1.9	−3.4	−7.2	−12.1	−5.7
Agriculture's Employment Share	−2.3	−3.6	−6.1	−12.0	−10.0
Changes in Ag to Non-ag, Between-Province Migration Costs					
Aggregate Real GDP Growth	1.9	3.5	2.5	8.1	6.8
Provincial Income Inequality	−6.9	−11.3	−13.0	−28.2	−30.3
Agriculture's Employment Share	−1.0	−2.4	−2.0	−5.4	−5.0

Note: Displays the effect of changing migration costs in each of the three five-year periods ending in 2005, 2010, and 2015. The cumulative effects with benchmark model and homothetic-preference model are reported in the last two column. Changing ag-to-nonag migration costs affects move between agriculture and non-agriculture only. This is further decomposed into its within-province and between-province components. The change in provincial income 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.

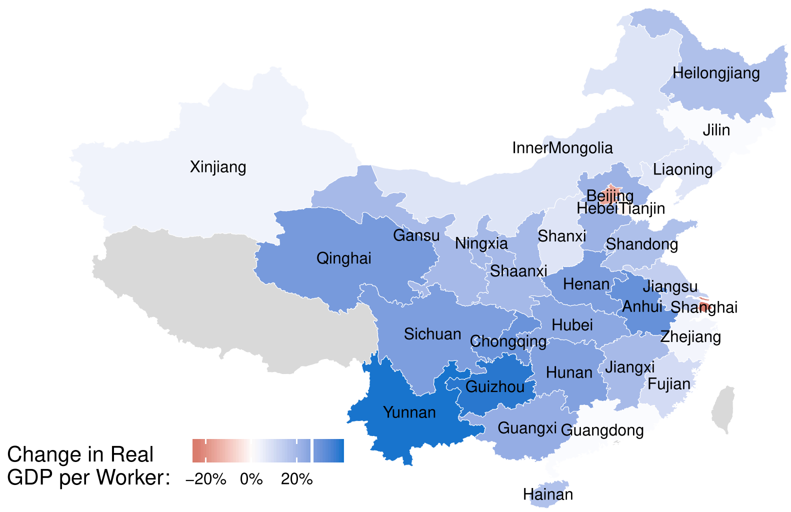

Fig. 5. Real GDP/Worker Gains from Lower Migration Costs, 2000 to 2015. Displays the gains in provincial real GDP per worker, across all sectors, in response to changes in migration costs between 2000 and 2015. Blue illustrates increases while red illustrates decreases. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

business tax wedges in the US would result in 0.6% increase in welfare for the US, and Bryan and Morten (2019) estimate that a *hypothetical* reduction of the migration costs in Indonesia to the US levels would result in 7% increase in the aggregate labor productivity in that economy. In contrast, the 18% increase in the aggregate GDP in China is a result of the estimated *actual* reductions in migration costs in China. There was significant spatial misallocation in China due to its *hukou* system that imposed severe restrictions on China's internal labor mobility and therefore the gain from relaxing those restrictions is large. Despite the reduction in migration costs, however, the labor mobility in China is still much lower than that in the US. Table 1 shows that the inter-provincial migrant workers as a percentage of total employment was only 11.7% in 2015, much lower than the share of workers in the US who work out of their state of birth, which has been around one third.

The second row of Table 4 shows that the migration cost reductions also significantly reduce regional inequality. Overall, the variance of log real GDP per worker across provinces falls by over one-third. We plot the income gains across each of China's provinces as a choropleth in Fig. 5 to illustrate that the lower income interior regions gain notably more from the migration cost reductions than the coastal ones and therefore the decline in regional income inequality. The second and the third panel of the table show that, not surprisingly, the between-province migration cost reductions contribute much

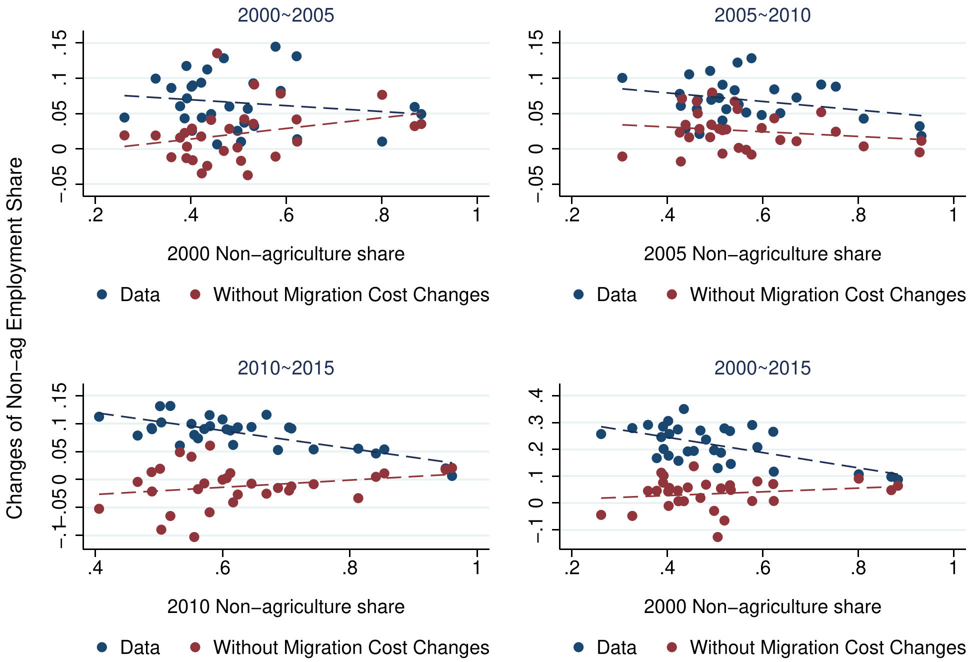

Fig. 6. Structural Change without Migration Cost Reductions. Displays the structural change in data and counterfactual results without migration cost reductions.

more to the decrease in provincial income inequality than the within province migration cost reductions, about two-third vs. one-third.

The third row of Table 4 shows that about 16% of total employment shifts from agriculture to non-agricultural activities as a result of the change in migration costs. And the second and the third panel of the table show that the within-province migration cost reductions are more important than the between-province migration cost reductions in generating the decline in the agriculture's share of employment. To further illustrate the important role of migration cost reductions in structural change, in Fig. 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, but with actual changes in trade costs, capital costs, and province-sector specific TFPs. Without 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 across provinces in China.

4.2.3. Comparison with homothetic preferences model

Finally, to examine the role of income effect on structural change, we report a simulation analysis using the homothetic Cobb-Douglas preferences as in Tombe and Zhu (2019). The results are reported in the last column of Table 4. For ease of comparison, we keep the migration cost changes the same as those estimated from our benchmark model, but feed them into the homothetic model in simulating the equilibrium changes. Without income effect, the reduction in the migration costs would induce less migration and less structural change. As a result, the impact on aggregate GDP growth is smaller.

This exercise also suggests that applying the migration cost reductions estimated from the benchmark model to the homothetic preferences model under-predicts the increases in migration. To match the actual increases in migration, then, the homothetic preferences model requires larger reductions in migration costs. In other words, without taking into account the income effect on structural change and migration, matching the homothetic preferences model to data would overestimate the reductions in migration costs. Table 5 presents the implied migration costs from the homothetic preferences model. Indeed, the estimated migration cost changes are much larger than those from the benchmark model. We also present the impact of these migration cost changes predicted by the homothetic preferences model in Table 6. Even with the larger reductions in migration costs, their effects on growth, regional inequality, and structural change are still smaller than those in our benchmark model with income effect.

4.2.4. Alternative definition of within-province migration

As we discussed in Section 2.4, our definition of intra-provincial migration is quite broad: anyone who switch sector within a province is classified as an intra-provincial migrant. We use this broad definition because we find in the 2005 census data large differences in labor income between agricultural and non-agricultural workers who are in the same village

Table 5
Average migration costs in China (Homothetic preferences).

	Average cost				Relative to 2000		
Year	2000	2005	2010	2015	2005	2010	2015
Overall, Including δ_n^j	5.86	5.00	3.73	2.47	0.85	0.64	0.42
Direct Migration costs μ_{ni}^{js}	3.02	2.51	1.76	1.09	0.83	0.58	0.36
Agriculture to Nonagriculture μ_{ni}^{js}							
Overall	3.93	3.12	1.89	1.05	0.79	0.48	0.27
Within Provinces	3.23	2.56	1.56	0.85	0.79	0.48	0.26
Between Provinces	27.47	23.05	12.18	9.27	0.84	0.44	0.34
Between Provinces μ_{ni}^{js}							
Overall	25.43	21.89	12.93	7.68	0.86	0.51	0.30
Within Agriculture	43.42	49.87	35.65	54.31	1.15	0.82	1.25
Within Nonagriculture	19.07	16.70	12.75	4.41	0.88	0.67	0.23

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.

Table 6
Effect of lower migration Costs, 2000–2015 (Homothetic preferences).

	Five-year growth (%) for year ending			Cumulative
Changes in all migration costs	2005	2010	2015	effect
Aggregate Real GDP Growth	2.8	4.9	6.1	14.4
Provincial Inequality	−4.2	−13.8	−18.9	−33.0
Agricultural Employment Share	−2.1	−4.7	−7.7	−14.6
Changes in Ag to Non-ag, Within-Province Migration Costs				
Aggregate Real GDP Growth	1.8	2.3	3.3	7.6
Provincial Inequality	0.4	−3.1	−6.8	−9.3
Agricultural Employment Share	−1.8	−3.1	−6.1	−11.0
Changes in Ag to Non-ag, Between-Province Migration Costs				
Aggregate Real GDP Growth	1.3	3.0	2.3	6.7
Provincial Inequality	−4.6	−10.9	−12.9	−25.9
Agricultural Employment Share	−0.8	−2.2	−2.0	−4.9

Note: Displays the effect of changing migration costs in each of the three five-year periods ending 2005, 2010, and 2015. The cumulative effects with benchmark model and homothetic-preference model are reported in the last two column. Changing ag to non-ag migration costs affects move between agriculture and non-agriculture only. This is further decomposed into its within-province and between-province components. 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.

Table 7
Intra-provincial worker migration in China, 2000–2015.

	Broad definition				Inter-county			
	2000	2005	2010	2015	2000	2005	2010	2015
Total Migrant Stock	101.5	132.6	176.2	215.7	12.8	15.4	27.3	33.5
Share of Employment (%)								
Total Migrants	14.1	17.8	22.9	28.0	1.78	2.06	3.55	4.31
Ag-to-Nonag Migrants	13.0	16.5	21.6	25.5	1.73	2.02	3.50	4.25

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.

or township, which suggest potentially large frictions to switching sectors locally. Our broad definition of migration captures the reduction in these frictions as changes in intra-provincial migration costs. Here we explore an alternative and stricter definition of intra-provincial migration. Any worker who switches sectors within a province will be classified as a migrant worker only if the worker is outside their county of *hukou* registration. For workers working within their *hukou* registration county, we assume there is no explicit nor implicit cost of switching sectors. That is, they can switch sectors without cost and are entitled to receive land and capital income rebates from the sector they work in.

In Table 7, we compare the migration stocks under the new definition with those under our original definition. The intra-provincial migration decreases by around 85 percent compared to the broad definition. However, like the original definition,

Table 8
Average migration costs in China (excluding within county migration).

	Average cost				Relative to 2000		
Year	2000	2005	2010	2015	2005	2010	2015
Overall, Including δ_n^j	18.28	16.24	11.94	8.93	0.89	0.65	0.49
Direct Migration costs μ_{ni}^{js}	7.98	7.57	5.62	4.18	0.95	0.70	0.52
Agriculture to Nonagriculture μ_{ni}^{js}							
Overall	9.22	8.46	5.78	4.90	0.92	0.63	0.53
Within Provinces	6.63	6.41	4.59	3.49	0.97	0.69	0.53
Between Provinces	11.41	10.05	6.63	6.13	0.88	0.58	0.54
Between Provinces μ_{ni}^{js}							
Overall	9.13	8.38	6.19	4.47	0.92	0.68	0.49
Within Agriculture	12.41	14.92	12.28	19.86	1.20	0.99	1.60
Within Nonagriculture	6.21	5.79	4.92	2.57	0.93	0.79	0.41

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.

Table 9
Effect of lower migration Costs, 2000–2015 (excluding within county migration).

	Five-year growth (%) for year ending			Cumulative
Changes in all migration costs	2005	2010	2015	effect
Aggregate Real GDP Growth	2.5	4.6	4.1	11.6
Provincial Inequality	−8.6	−12.0	−13.5	−30.4
Agricultural Employment Share	−1.3	−3.8	−3.1	−8.2
Changes in Ag to Non-ag, Within-Province Migration Costs				
Aggregate Real GDP Growth	0.3	1.0	1.3	2.6
Provincial Inequality	−0.2	−1.5	−3.0	−4.6
Agricultural Employment Share	−0.2	−1.2	−1.6	−3.0
Changes in Ag to Non-ag, Between-Province Migration Costs				
Aggregate Real GDP Growth	1.9	3.8	2.2	8.2
Provincial Inequality	−6.2	−10.0	−9.1	−23.2
Agricultural Employment Share	−1.2	−3.0	−1.8	−5.9

Note: Displays the effect of changing migration costs in each of the three five-year periods ending 2005, 2010, and 2015. The cumulative effects with benchmark model and homothetic-preference model are reported in the last two column. Changing ag to non-ag migration costs affects move between agriculture and non-agriculture only. This is further decomposed into its within-province and between-province components. 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.

the migration share still doubled from 2000 to 2015. According to the new migration matrices, we re-calculate the migration costs by province and sector from 2000 to 2015. Table 8 displays the average migration costs from 2000 to 2015. The overall migration cost changes are very similar to those we estimated from the benchmark case. For the agriculture to the non-agriculture migration costs, however, the new definition implies a little less than 40% reduction in the average migration costs, which is smaller than the 60% reduction in the benchmark case.

We report the counterfactual results under this alternative definition of migration in Table 9. Not surprisingly, the impact of the between-sector and within-province migration cost reductions is smaller, while the impact of inter-provincial migration cost reductions is very similar to the benchmark case. This result suggests that the changes in the costs of switching sectors within a county contributed non-trivially to aggregate growth, regional inequality declines, and structure change in China between 2000 and 2015.

4.3. Effect of lower trade costs

Changes in the labor market have important effects on growth, structural change, and regional 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

Table 10
Changes 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 11
Internal and external trade shares of China, 2002–2012.

Importer	Exporter North-East	Beijing-Tianjin	North Coast	Central Coast	South Coast	Central Region	North-West	South-West	Abroad	Total 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 12
Effect of lower trade costs, 2000–2015.

	Five-year growth (%) for year ending			Cumulative	Homothetic
Changes in All Trade Costs	2005	2010	2015	effect	preferences
Aggregate Real GDP Growth	15.5	0.2	–	15.8	20.7
Provincial Inequality	13.7	1.8	–	15.7	16.5
Agricultural Employment Share	−0.3	−0.7	–	−1.0	−1.1
Changes in Internal Trade Costs Only					
Aggregate Real GDP Growth	10.7	0.3	–	11.0	16.1
Provincial Inequality	10.4	−0.5	–	9.9	10.8
Agricultural Employment Share	−0.5	−0.7	–	−1.2	−1.3
Changes in External Trade Costs Only					
Aggregate Real GDP Growth	4.9	0.0	–	4.9	4.6
Provincial Inequality	3.9	2.5	–	6.5	6.3
Agricultural Employment Share	0.1	−0.1	–	0.0	0.0

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.

Tombe and Zhu (2019), and here we extend this another five years to 2010.[8] 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 for trade cost asymmetries estimated based on Waugh (2010).

The pattern of trade cost changes differs significantly between the five year period ending 2007 and the period ending 2012. 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.[9] In the appendix, we demonstrate that this pattern of trade costs changes for China is found in other datasets internationally. Specifically, we show using the World Input Output Database that there appears to have been no additional improvements in international trade costs for China following the financial crisis.

To quantify the effect of such trade cost changes on 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 12. 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 16% higher regional income inequality.[10] Structural change effects are modest, with internal trade cost reductions contributing to 1.2% of employment shifting to non-agricultural activities. Given our limited data on internal trade beyond 2012, we cannot simulate the third and final five-year period as we can with other components of our analysis.

4.4. Effect of capital wedges and average cost of capital

As documented in Section 2, China experienced some changes in the distribution of capital returns across space and sectors in recent years. The widening dispersion of returns between 2010 and 2015 suggests worsening misallocation of capital and lower aggregate productivity. In addition, we also calculate the average nominal cost of capital from Eq. (22) and deflate it using national CPI from (Brandt and Holz, 2006) to arrive at the real average cost of capital. The average real cost of capital increases from 15.9% in 2000 to 16.6% in 2010, but then decreases markedly to 13.3% by 2015. The rise in the dispersion of capital returns across space and the large decline in the average real cost of capital between 2010 and 2015 is related to the Chinese government's large fiscal stimulus and credit expansion policy launched after the global financial crisis.

To quantify the effect of the changes in both the distribution of capital returns and the average real cost of capital, we simulate the equilibrium changes when $\hat{t}^j_n$ and $\hat{\bar{r}}$ changes are set to their estimated levels while holding all other parameters constant. We report the results in Table 13. Overall, the changes in the capital wedges add modestly to growth between 2000 and 2010, but reduce the aggregate real GDP growth by 0.2% between 2010 and 2015. In general, the changes in capital wedges have small effect on aggregate GDP growth and structural change. This is consistent with the finding of Brandt et al. (2013) that most of the TFP loss associated with capital misallocation can be attributed to the within-province

[8] 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.

[9] Importantly, these bilateral trade costs are *relative* to within-region trade costs and therefore higher relative trade costs does not necessarily imply higher trade costs in an absolute sense.

[10] 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 13
Effect of capital market changes, 2000–2015.

	Five-year growth (%) for year ending			Cumulative	Homothetic
	2005	2010	2015	effect	preference
Changes in Capital Wedges					
Aggregate Real GDP Growth	1.3	0.2	-0.2	1.3	1.3
Provincial Inequality	1.8	8.0	2.5	12.6	14.0
Agricultural Employment Share	0.0	0.0	0.0	0.0	0.0
Changes in Average Real Cost of Capital					
Aggregate Real GDP Growth	−1.7	−0.4	11.6	9.3	8.9
Provincial Inequality	0.0	0.0	−0.2	−0.2	0.2
Agricultural Employment Share	0.0	0.0	−0.2	−0.1	−0.2
All Capital Market Changes					
Aggregate Real GDP Growth	−0.4	−0.2	11.4	10.7	10.2
Provincial Inequality	1.8	8.0	2.3	12.5	14.2
Agricultural Employment Share	0.0	0.0	−0.2	−0.1	−0.2

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.

misallocation of capital between the state and non-state firms. The changes in wedges, however, does increase regional inequality by nearly 13%, which is almost entirely accounted for by changes in non-agricultural capital wedges. This result is contrary to the policy discussions in China claiming that the government-led infrastructure investments as part of the stimulus plan can help to reduce regional income inequality.

The average cost of capital increased from 2000 to 2010, contributing negatively to aggregate GDP growth. This is consistent with the finding of Zhu (2012) that China's high growth performance prior to the global financial crisis is not driven by capital investment. Between 2010 and 2015, however, the reduction in the average cost of capital associated with the rapid credit expansion and increase in capital accumulation contributed nearly 12% to growth over that 5-year period. Investment-driven growth is therefore much more important in China in recent years.

4.5. Decomposing growth, regional income convergence, and structural change

So far we have examined the impact of the changes in migration costs, trade costs, and capital costs one at a time, while holding others at their 2000 initial values. We now put all these changes together. Furthermore, we also choose the changes in province-sector specific TFPs (T_n^j) so that the model implied changes in aggregate GDP per worker match those in the data exactly. We then measure the marginal contributions of migration cost changes, trade cost changes, capital cost changes, respectively, to growth, regional income convergence, and structural change over the period 2000 and 2015. As each of the various changes interact with one another, the marginal contribution of a particular change depends on the order the sequence of changes are introduced into the model. We therefore compute the average marginal contribution of each over all possible sequences of changes. The results are reported in Table 14. We discuss below separately the contributions of different components to growth, structural change, and regional income convergence.

Contributions to Growth: As noted by Tombe and Zhu (2019), province-sector specific TFP growth is the largest contributor to the aggregate GDP growth. The slow growth of the last 5-year period between 2010 and 2015 is associated with a significant slow-down in the TFP growth. It declined from 51.9% between 2005 and 2010 to only 18% between 2010 and 2015. In contrast, change in the average cost of capital and the associated capital accumulation played a small negative role before 2010, but became a major contributor to growth in the last five years, account for almost 11% of the GDP growth between 2010 and 2015. Trade costs changes, especially the internal trade cost reductions, played an important role in growth between 2000 and 2005, but their contribution were small and negative after 2005. The changes in capital wedges have negligible effect on growth. Finally, the migration cost reductions have consistently contributed to GDP growth, and their contribution have increased over time.

Contributions to Structural Change: Migration cost reductions contributed most to the decline in agriculture's share of employment over the entire fifteen-year period. In the first ten years, province-sector specific TFP growth also contributed to the decline in the agriculture's share of employment. In the last five years, however, its contribution to structural change became negative. The effects of changes in trade costs and capital costs on structural change are negligible.

Contributions to Regional Income Convergence: Migration cost reductions also contributed significantly to the decline in cross-province income inequality throughout the fifteen year period. During the first five-year period, around the time of China's accession to WTO, trade cost reductions and province-sector specific TFP growth both increased income dispersion across provinces in China, but a large chunk of the increase was offset by the reduction in the migration costs that reduced income differences across China's provinces. Without the migration cost reductions, China's regional inequality would have

Table 14
Decomposing China's growth, income convergence, and structural change.

	Five-year change			Share of five-year change (%)		
	2005	2010	2015	2005	2010	2015
Aggregate Real GDP Growth (%)						
Data	63.1	65.0	36.3			
Overall	54.3	55.0	34.9	100.0	100.0	100.0
Productivity Changes	38.4	51.9	18.0	69.5	95.8	47.3
Internal Trade Costs	8.3	−1.8	–	15.9	−4.7	–
External Trade Costs	4.7	−0.1	–	9.2	−0.4	–
Migration Costs	4.1	5.5	6.5	8.0	10.6	20.3
Capital Wedges	0.5	−0.1	−0.5	0.7	−0.1	−1.7
Average Real Capital Cost Changes	−1.7	−0.5	10.9	−3.3	−1.2	34.1
Change in Agriculture Share of Employment (percentage points)						
Data	−8.2	−8.1	−8.4			
Overall	−5.1	−8.4	−6.3	100.0	100.0	100.0
Productivity Changes	−1.6	−3.1	1.6	32.5	37.0	−24.6
Internal Trade Costs	0.1	0.2	–	−1.6	−2.5	–
External Trade Costs	−0.3	0.0	–	5.7	−0.6	–
Migration Costs	−3.2	−5.6	−7.7	63.3	66.4	121.1
Capital Wedges	0.0	0.0	0.0	0.9	−0.2	0.5
Average Real Capital Cost Changes	0.0	0.0	−0.2	−0.7	−0.1	3.1
Change in Provincial Real GDP/Worker Inequality (%)						
Data	4.3	−11.2	−31.8			
Overall	10.9	−12.0	−31.9	100.0	100.0	100.0
Productivity Changes	17.2	−2.1	−14.6	157.6	17.6	45.7
Internal Trade Costs	6.3	−4.0	–	57.5	33.6	–
External Trade Costs	2.8	2.1	–	26.0	-17.7	–
Migration Costs	−13.1	−14.2	−18.1	−119.4	118.8	56.6
Capital Wedges	−2.4	6.2	0.8	−21.9	−52.2	−2.6
Average Real Capital Cost Changes	0.0	0.0	−0.1	0.1	−0.1	0.3

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.

increased significantly after its accession to WTO. Since 2005, and especially after 2010, there had been convergence in TFP across provinces and sectors that also contributed to the decline in regional inequality.

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 fell by 45%, with the cost of moving from agricultural rural areas to non-agricultural urban ones falling even more. Through a variety of quantitative exercises, we demonstrate that 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 changes 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. We also find that a notably slower pace of between-sector and between-province migration after 2010 and increasing reliance on credit expansion and capital accumulation in generating growth in recent years. Given the importance of internal migration to China's economic development that we have quantified in this paper, we think future policy reforms that further reduce the inter-provincial rural-urban migration costs can have large benefits in terms of promoting growth, speeding up structural change, and reducing regional income inequality in China.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmoneco.2020.03.003

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