Trade-Induced Urbanization and the Making of Modern Agriculture

Yuan Tian, Junjie Xia, and Rudai Yang*

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Abstract

Can structural transformation originate from growth in manufacturing? We study this question in the context of China's manufacturing trade growth after its entry into the World Trade Organization. We construct exposure to manufacturing trade shocks for rural villages by using initial internal migration networks and trade shocks experienced by destination prefectures in the manufacturing sector. We find that increases in manufacturing trade exposure led to an outflow of labor from the agricultural sector, more active land rental markets, and faster modernization of agricultural production through mechanization. Agricultural productivity improved through migrant selection and reductions in land misallocation.

JEL codes: F16, J24, O14, O4, Q12, Q15.

Keywords: Structural Transformation, Trade Liberalization, Internal Migration, Land Misallocation, Capital Adoption, Agriculture Modernization

*Tian: University of Nottingham, School of Economics (email: yuan.tian1@nottingham.ac.uk); Xia: Central University of Finance and Economics, School of Economics; Peking University, Institute of New Structural Economics (email: junjiexia@nsd.pku.edu.cn); Yang: Peking University, School of Economics (email: rdyang@pku.edu.cn).
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1 Introduction

No country has achieved a high level of income without a sharp reduction in agricultural employment and a concomitant modernization of agricultural production.[1] As economies develop, agricultural workers migrate to cities to find employment in industry and services (Clark 1940; Kuznets 1957). Historically in the first set of industrialized countries, technological innovations in agriculture favored this structural transformation process by releasing labor, increasing demand, and generating savings to finance industry and services. However, many developing countries have yet to experience significant industrialization. Understanding the underlying reasons is crucial to direct development policy efforts.

The economic literature on structural transformation hypothesizes two broad explanations for the drivers of this process: i) push forces, i.e., technological innovation in the agricultural sector, and ii) pull forces, i.e., increased attractiveness of urban areas and the manufacturing sector.[2] Despite rich theoretical discussions of these two channels, empirical studies of structural transformation are scarce. Prominently, recent empirical evidence using household-level and firm-level datasets has shown the effect of push forces, including Foster and Rosenzweig (2004; 2007) on green revolution in India, Bustos et al. (2016; 2020) on the adoption of genetically modified crops in Brazil, Asher et al. (2022) on the development of irrigation canals in India, and Imbert et al. (2022) on agricultural price shocks in China.[3] On the effect of pull forces, to the best of our knowledge, the only available empirical evidence is McCaig and Pavcnik (2018), where they document the export-induced reallocation of labor towards the formal industrial sector in Vietnam.[4]

In this paper, we provide a novel piece of micro-level empirical evidence on how structural transformation can be initiated by manufacturing growth and reinforced by the development process in agriculture along a range of dimensions. The pull forces driving the out-migration from rural areas came from the reduction in tariffs faced by manufacturing exporters after China entered the WTO. This resulted in an increase in labor demand in urban areas, and regions vary in their exposure to the shocks based on their initial industrial composition. Next, we establish a connection between an origin village and its corresponding migrant destination prefectures using the initial prefecture-to-prefecture migration network. A village was more exposed to manufacturing trade if its destination

[1] See Lewis (1954); Schultz et al. (1964); Taylor and Martin (2001); Lucas (2004); and Akram et al. (2017), among others.

[2] See Baumol (1967); Murphy et al. (1989); Kongsamut et al. (2001); Gollin et al. (2002); Ngai and Pissarides (2007); and Yang and Zhu (2013), among others. Other explanations include the decline in the relative cost of obtaining non-agricultural skills, as shown in Caselli and Coleman (2001).

[3] Other empirical studies on the channel of technological innovations in the agricultural sector include Nunn and Qian (2011); Michaels et al. (2012); and Hornbeck and Keskin (2015).

[4] There are other papers on this topic using more aggregated data, including Gollin et al. (2021) on Green Revolution using country-level and crop-level data, and Erten and Leight (2021) on trade liberalization using county-level aggregate statistics in China.

prefectures on average experienced larger declines in tariffs in export markets.

We show that increased labor demand in the urban manufacturing sector led origin villages to shift employment from agriculture to non-agriculture. Rural land markets became thicker, and rental activity increased. Land allocation efficiency also improved where more productive households operated larger farms. We also find that the villages facing larger trade shocks had faster modernization of production through the adoption of agricultural machinery. Overall, village-level agricultural productivity increased through migrant selection and reduction in land misallocation.

Our main data set is a nationally representative sample of rural households and villages from the National Fixed Point (NFP) Survey, with information on agricultural production and rural household living arrangements. The survey collects information on a panel of around 20,000 Chinese rural households in 300 villages. We use 2001–2010 data for the main analysis and 1995–2001 data to rule out confounding pre-trends.[5] We observe household-level occupation choices, land-in-operation, the amount of land rented from other households, and land transactions during the year. We calculate household-level and village-level total factor productivity (TFP) in crop farming using detailed information on output values, labor, capital, land, and intermediate inputs.[6]

We leverage cross-sectional variation in the reduction of manufacturing tariffs to create shocks to the pull factors that influence out-migration. Identifying the causal effect of out-migration on agricultural production is generally difficult. First, increases in agricultural productivity can lead to more out-migration if the technological change is labor-saving (Bustos et al. 2016). Second, expansion of rural transportation networks can incentivize out-migration *and* improve agricultural productivity through improved input quality. Third, economy-wide productivity shocks can generate correlated productivity growth in the manufacturing sector and the agricultural sector, and labor can flow out of agriculture if the manufacturing productivity growth dominates. We overcome these identification challenges by using the strong forces incentivizing internal migration generated by China's WTO accession in 2001 (Facchini et al. 2019; Tian forthcoming; Zi 2022). We employ a shift-share measure to construct a village's exposure to destination prefectures' trade shocks.

[5]This is the best available dataset on agriculture production and rural households in China. Kinnan et al. (2018), Chari et al. (2020), and Adamopoulos et al. (2022), among others, have used different segments of the dataset. To our knowledge, we are the first to use the full sample of households for a time period that spans before and after China's international trade liberalization.

[6]Our main productivity measure is a Solow residual estimated using a Cobb-Douglas production function. An alternative measure of agriculture productivity can focus on labor productivity (Lagakos and Waugh 2013). Our results on productivity are robust to using labor productivity. We measure household-level productivity instead of plot-level productivity since we can only follow households over time, not plots. An alternative story could be that the plots are heterogeneous in land productivity and TFP is higher in the most efficient plots. When the outside option of non-agriculture increases, the workers abandon the village and go to manufacturing, and wages in rural areas go up, so the less productive land plots shut down and are reallocated to more productive plots. This story involves no inefficiency and features Melitz-style reallocation among efficient producers. Our empirical evidence is not consistent with this story since when farmers move out of the villages, the land transactions and rents increase instead of decrease.

Following the standard method in the literature on the local labor market effect of trade liberalization (Topalova 2010; Kovak 2013; McCaig and Pavcnik 2018; Bombardini and Li 2020; and Tian forthcoming), a destination prefecture's exposure to manufacturing trade is measured as a weighted average of industry-level output tariffs faced by exporters, with each industry's employment share as weights. A reduction in the average tariff faced by a prefecture acted as a positive demand shock for the goods produced in the prefecture, and it resulted in an increase in labor demand in the manufacturing sector. An origin village's exposure to manufacturing growth is measured as the interaction of its initial migration network and the destination prefectures' trade exposures. The prefecture-to-prefecture migration network is constructed using a sample of one million individuals from the 2000 population census, where an individual's residence prefecture in 1995 and the current residence prefecture are observed.

These output tariffs were *imposed by importing countries on Chinese exports*, and we show the industry-level post-WTO tariff reductions were uncorrelated with pre-WTO export growth.[7] We find no evidence of pre-trends in the agricultural sector outcomes—the change in the trade exposure of an origin village from 2001 to 2010 was uncorrelated with changes in the out-migration rate, the share of land leased, the value of agricultural machinery, and TFP in the 1995–2001 period.

Further, we follow recent literature on the shift-share design (Adao et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2022) to discuss identification assumptions and conduct robustness checks. Notably, our paper is very closely related to a recent work, Imbert et al. (2022). While our paper is studying how trade shocks in the manufacturing sector drive agricultural modernization, Imbert et al. (2022) studies how shocks in agricultural prices affect labor intensity and innovation in the manufacturing sector. Although the focuses of these two papers are complementary, we employ a very similar research design where we both use internal migrant networks to connect origin and destination regions and to construct the exposure shares, and the variation in the shifts comes from the regional composition within the sector (regional employment shares in the 2-digit manufacturing industry in our paper, and regional crop patterns in Imbert et al. 2022). Thus, we follow Imbert et al. (2022) closely when we discuss sources of variation and identification issues.

We first show the impact of an origin village's trade exposure on rural workers' occupation choice. A one-standard-deviation larger decline in destination prefectures' output tariffs resulted in a three-percentage-point (or a 0.21-standard-deviation) larger increase in the share of non-agricultural labor in the origin village. The result is robust to (1) including agricultural trade shocks that could potentially be correlated with manufacturing trade shocks and affect agricultural production directly, (2) using alternative measures of out-migration collected at the village level, (3) controlling

[7] Similar industry-level evidence is provided in Tian (forthcoming) for the 2001-2007 period. Additionally, Tian (forthcoming) shows that a prefecture's tariff reduction was uncorrelated with its pre-WTO wage and GDP growth.

for the initial crop patterns and contemporaneous crop patterns, and (4) controlling for the share of migrants who moved to the top 10 migrant destinations.

The results also imply larger effects for places that were less far along in the process of urbanization and agriculture modernization. We find that the effect was larger for villages with less land per agricultural worker in 2001. The initial land-to-labor ratio in agriculture was positively correlated with village characteristics that were pro-reallocation, such as the land market fluidity and the non-agricultural labor share, and was negatively correlated with factors that impeded land consolidation, such as ruggedness. Villages with a smaller land-to-labor ratio also had a larger correlation of the output value and TFP across households, which is a direct measure of allocation efficiency. Hence, regions with a smaller land-to-labor ratio had larger factor misallocation at the beginning of the period, and they reacted more strongly to out-migration shocks. This finding is consistent with the observed irreversibility of urbanization; as pointed out in Lucas (2004), "this transition is an irreversible process that every industrializing society undergoes once and only once."

We then investigate the effect of trade exposure on land and capital at the village level. We find that in the face of the trade shock, the land rental market became more active, and more agricultural machinery was adopted. There are several explanations for the increase in agricultural machinery. First, farmers may substitute labor with capital when labor costs increase (Manuelli and Seshadri 2014). Second, if there are scale-dependent returns to mechanization due to larger contiguous land areas, farmers may adopt machinery only when the land size is sufficiently large (Foster and Rosenzweig 2011; 2022). Third, the reduction in land misallocation can also lead to increased capital adoption, since productive agricultural households are able to lease more land and use more capital. Fourth, migrant remittances can ease the household credit constraint and facilitate capital adoption. We find evidence supporting the first three explanations, but not the last one.[8]

We additionally show that trade shocks increased the output-weighted village-level TFP, and we provide individual and household-level evidence to investigate channels of this productivity effect. First, we document negative selection in terms of agricultural productivity. Unproductive farming households were more likely to leave agriculture facing the trade shocks. Second, we find increased land allocation efficiency, with trade shocks facilitating the reallocation of land towards more productive households within a village.[9]

We focus on the output tariff shocks since they generate shocks to pull factors of out-migration for

[8]Overall, the finding on capital adoption is consistent with Hornbeck and Naidu (2014) and Clemens et al. (2018) with out-migration shocks resulting from natural disasters and labor market policies, respectively. Capital adoption reinforces the urbanization process: once machines are in place, the production is not likely to revert back to the labor-intensive mode. Similar transitional paths can be found in the manufacturing sector. See, for example, Acemoglu and Restrepo (2020).

[9]We do not find important roles for switching to high-value cash crops or husbandry.

origin villages; we do not intend to characterize the full impact of the WTO accession on the Chinese economy. The WTO accession affected manufacturing trade in China through multiple channels, including the reduction in output tariffs (Bombardini and Li 2020 and Tian forthcoming), reduction in input tariffs (Zi 2022 and Brandt et al. 2017), and the reduction in trade uncertainty induced by the establishment of the U.S.–China permanent normal trade relationship (PNTR)(Pierce and Schott 2016; Handley and Limão 2017; Facchini et al. 2019; and Erten and Leight, 2021, among others). We focus on the reduction in output tariffs since the output tariff reduction generates intuitive demand shocks to the manufacturing sector. Yet, when we empirically evaluate the effects of the PNTR shock, we find effects of similar magnitudes on the land market, capital, and TFP, and insignificant effects on the occupation choice. The PNTR shock is approximately orthogonal to the output tariff shocks, in the sense that controlling for the PNTR shock does not affect the coefficient estimates of output tariff shocks (also see Handley and Limão 2017 and Tian forthcoming).

The paper contributes to several strands of literature. First is the literature on structural transformation. As mentioned above, our paper is among the first to provide empirical evidence on the pull forces driving structural transformation. Compared to McCaig and Pavcnik (2018) where trade liberalization in the manufacturing sector drives the reallocation of labor into the formal manufacturing sector, our paper demonstrates direct evidence of how international trade in *manufacturing* accelerates the development process in the *agricultural* sector that are not directly exporters. Second, there is an extensive literature on how land misallocation affects agricultural productivity. The ambiguity of land rights in developing countries limits land reallocation and creates misallocation (Adamopoulos et al. 2022, among others), and land reforms that clarify land rights can improve land allocation efficiency and increase agricultural productivity (de Janvry et al. 2015; Chari et al. 2020). We complement this literature by showing that in addition to the institutional barriers, the lack of land leasing activity is partially due to the fact that farmers usually do not have good outside options in non-agricultural sectors. The opportunity to work in the manufacturing sector can create a more fluid land market, potentially reducing misallocation. Third, the existing literature on out-migration of rural residents focuses on its effect on self-insurance (Kinnan et al. 2018), participation in local risk-sharing networks (Morten 2019), individual migrant outcomes (Johnson and Taylor 2019), and rural labor markets (Akram et al. 2017; Dinkelman et al. 2017). We demonstrate that when out-migration is not motivated by income smoothing when facing temporary shocks, but as a part of the structural transformation, factor markets adjust, leading to productivity changes. Fourth, the paper contributes to the literature on the impact of international trade liberalization on the Chinese economy. Most literature discusses the impact of trade liberalization on manufacturing productivity and exports (Khandelwal et al. 2013; Brandt et al. 2017; Handley and Limão 2017, among others), migration (Facchini et al. 2019; Zi 2022), sectoral employment shifts (Erten and Leight, 2021), and reforms in labor institutions (Tian forthcoming).

We show that manufacturing trade affects *the development process of the agricultural sector* through land reallocation, capital investment, and worker selection. Our paper is also broadly related to the literature using natural experiments to study reductions in misallocation during liberalization periods in developing countries (Khandelwal et al. 2013 and Bau and Matray 2023).

The rest of the paper is organized as follows. Section 2 provides background information on the land market and the WTO-induced trade shocks in China. Section 3 presents the new data for outcomes in the agricultural sector, and Section 4 shows the measurement of trade shocks. Section 5 presents the main empirical specification and findings at the village level. Section 6 discusses additional individual and household-level evidence. The last section concludes.

2 Background

2.1 The Rural Land Market in China

Land market conditions are an important aspect of the agricultural sector since land is an essential input in agricultural production, and developing countries usually suffer from weak land rights protection.[10] Since the establishment of the Household Contract Responsible System (HCRS) in the early 1980s, Chinese agricultural land has been collectively owned by the village and contracted to households within the village commune. The initial land distribution was set mainly based on household sizes at the time of HCRS's establishment. The initial contracts, lasting about 15 years, were extended for another 30 years around 1998. Households are entitled to use the contracted land for agricultural production, and since 1988, they have had the legal right to lease their land to other households within the same village commune.[11]

However, the rural land market remained notably inactive before the 2000s. Despite the existence of *de jure* tenure security, within-village land reallocation happened, and village leaders had discretion in the reallocation (Rozelle et al. 2002). In addition, institutions that supported dispute resolution were absent.[12] This insecurity surrounding land rights diminished the appeal of renting land. Households were concerned that if they didn't work on their land themselves, they might forfeit their rights to it in the next land allocation cycle(Benjamin and Brandt 2002; Rozelle et al. 2002; and Adamopoulos et al. 2022). If rural households did not have stable means of living other than agricultural production, they might be hesitant to lease their land to other households even if other households were more productive, due to the perceived "use it or lose it" rule. Given the

[10]See Adamopoulos and Restuccia (2014); de Janvry et al. (2015); Chen (2017); Adamopoulos et al. (2022); and Chen et al. (2023), among others.

[11]See the full description of the timing of the reforms in Appendix A.1.

[12]The *Law of the People's Republic of China on the Mediation and Arbitration of Rural Land Contract Disputes* was enacted in 2010. Before that, several regulations issued by the central government tried to address the issues of contract disputes starting from 1992.

initial egalitarian distribution rule, this missing rural land market created a misallocation of land across households.

The land leasing market became more active alongside urbanization since the opportunity cost of remaining in crop farming became higher. According to decennial population censuses, the share of the population living in urban areas increased from 26% in 1990 to 36% in 2000, and then to 50% in 2010. Meanwhile, the share of households with land lease income increased from about 4% in the 1990s to 12% in 2010.[13]

2.2 Internal Migration and the WTO Shock

Urbanization came alongside large flows of internal migration. The Chinese household registration system, i.e., the Hukou system, assigns all residents with a prefecture-sector-specific registration status, where a sector is either agriculture or non-agriculture. A person is an internal migrant when living and working in a prefecture sector different from their registration. According to the decennial censuses, in 2000, 11% of the population were migrants, and the number increased to 20% in 2010. Migration is closely tied with sectoral employment shifts: 93% of migrants work in the non-agricultural sector.

China's accession to the WTO was an important driver of the fast growth in the manufacturing sector and increased internal migration (Brandt et al. 2017, Facchini et al. 2019, Tian forthcoming, and Zi 2022). We use applied tariffs from the World Bank TRAINS dataset on the 2-digit SIC level in the manufacturing sector to measure the tariff on exports faced by Chinese exporters. The tariff on exports is the weighted average of tariffs on Chinese exports imposed by importing countries, with their 2001 import values as weights.

The WTO accession reduced international trade barriers, with the average tariff on Chinese exports declining from 3.7% in 2001 to 2.4% in 2010 (Figure 1, the line with solid dots). The average tariff is the weighted average across industries, using industry export values as weights. Manufacturing exports from China increased from less than 400 trillion dollars in 2001 to 1,750 trillion in 2010 (Figure 1, the line with hollow diamonds). This substantially increased demand for labor in the manufacturing sector, and resulted in increased internal migration (Tian forthcoming).[14]

Regions varied in the extent of the export demand shock based on their initial industrial composition, since the size of tariff reductions was different by industry. Figure 2 uses the 2001–2010 change as an example to show the variation in tariff reductions and export growth by industry.

[13] The share of households is calculated using the NFP Survey, which will be introduced in Section 3. Additionally, in Appendix B.1.5, we document substantial changes in the agriculture sector in terms of labor, land, capital, and productivity from 1995 to 2010. There is also a trend break in 2001, suggesting the role of trade liberalization, as shown in the next section.

[14] In addition, Tian (forthcoming) shows that regions with more favorable export shocks started to provide more amenities for migrant workers, and these changes further increased the incentive to migrate.

Similar to Tian (forthcoming), we use the reduction in output tariffs on Chinese exports to measure the WTO shock. The reduction in tariffs was due to China's eligibility for the Most-Favored-Nation status, and a reduction in the output tariff effectively increased the output price. As shown in Appendix Table B7 Column (1), the export elasticity with respect to tariffs can be estimated using a panel regression of log exports on tariffs on the industry-year level, with industry fixed effects and year fixed effect. The elasticity estimate is 7.8 using 26 two-SIC code industries and 2001–2010 data. It indicates that a one-percentage-point decline in the tariff on exports is correlated with a 7.8% increase in exports. In addition, the post-2001 export growth cannot be predicted by pre-2001 export growth (Column 2), and the post-2001 tariff declines are uncorrelated with the pre-2001 export growth (Column 3).

Additionally, one might be concerned that the agricultural sector faced tariff changes on its output that were correlated with manufacturing sector tariff changes. Overall, the WTO's direct impact on the agricultural goods market is less clear. China's import tariff on soybeans declined from over 100 percentage points to zero, and soybean imports increased from less than 5 trillion dollars in 2001 to 25 trillion in 2010. For other crops, however, imports and exports fluctuated over time, and there were no clear patterns of tariff changes.[15]

3 New Data for Outcomes in the Agricultural Sector

3.1 Labor, Land, and Capital

Our outcome measures in the agricultural sector come from the NFP Survey, a longitudinal survey conducted by the Research Center for the Rural Economy under the Ministry of Agriculture in China. The survey began in 1986 and continues to the present. Multi-stage sampling is used to get a nationally representative sample of around 300 villages and 20,000 households per year. Households and villages are followed with little attrition and are added over time for representativeness.[16] The core module of the household questionnaire consistently includes information on household-level demographics, agricultural production, assets, income, and expenditure. We use the 2001–2010 data for the main analysis of the post-WTO period and the 1995–2001 data to check pre-trends.[17] Our main analysis is based on the household-level information and village-level measures aggregated from

[15]Oil crop, flax, vegetable, and fruit experienced large increases in the value of import, although the scale was much smaller than soybean. See trade and tariff trends of major crops in Appendix B.2.3. In Appendix C.4.1, we show that our main results are robust to controlling for agricultural trade shocks.

[16]We provide evidence on the absence of selective attrition with respect to trade shocks in Appendix B.1.1.

[17]The data is not available in 1992 and 1994. After 2003, demographic information is collected at the individual level, and production information is more detailed, with inputs and outputs information by crop.

household data, and we supplement it with the village questionnaire and individual questionnaire.[18] An administrative village or subdistrict represents the lowest level of government administration in China, followed by county, prefecture, and province as successively more aggregate levels of government. A prefecture is composed of rural villages and village-equivalent urban units (towns and districts), and we will use prefecture-to-prefecture migrant flows from the census data to construct internal migrant networks.[19]

One key element of our analysis is the definition of a rural resident's occupation. There are broadly three categories: laborer, entrepreneur, and public-sector employee.[20] We focus on laborers who are wage earners: they are employed outside their own households and work for wages. Thus, a wage earner can be (1) working in his own village and employed by other households, (2) employed by firms in his own village, (3) working outside the village, but within the same prefecture, or (4) working in a different prefecture.

We use information in the NFP data to investigate the empirical importance of each possibility. We find that Case (1) is not prevalent in rural China: hired labor days are on average only 2% of total labor days in any family operations during the 2001–2010 period. The share of Case (2) workers is also likely to be small. According to the individual-level data between 2003 and 2010, a wage earner spends 212 days working *outside the village* on average. Thus, the majority of the wage earners are working outside the village, either in the urban areas of their own prefectures (Case 3) or in other prefectures (Case 4). In addition, we find that 97% of the wage earners work in the non-agriculture sector (Appendix B.1.2). Thus, they are likely to be employed in the manufacturing or service sector and are subject to shocks in these sectors.

Our main measure for the occupation choice is the non-agricultural labor share of a village, and it is the ratio of the total number of wage earners to the total number of laborers in a village, where both numbers are aggregated from the information in the household questionnaire (Table 1). The village questionnaire has information on the number of laborers outside the village and decomposes the number into within-county, between-county, and between-provinces; we use this information in the robustness checks.[21]

In terms of land market outcomes, we observe the total amount of land used in agricultural production, the amount of land that is used in agricultural production and leased from other households (i.e., the stock of leased land), the amount of land leased from other households in this

[18] The survey intends to get an accurate and consistent picture of agricultural production and rural household life for the support of policy making. Also, see Benjamin et al. (2005) and Banerjee et al. (2020) for other descriptives of the data.

[19] Appendix A.2 provides descriptions of levels of administrative units in China.

[20] Entrepreneurs are managers of firms and businesses. Public-sector employees include teachers, medical workers, and civil servants.

[21] The village questionnaire is filled by village heads, and we think the village-level aggregates from household questionnaires are of higher quality, which is what we use in the main analysis.

specific year (i.e., the flow of land leased), and the income from land leasing. On capital, we observe the amount of agricultural machinery used in production, which may include both household-owned and rented capital.

3.2 Total Factor of Productivity (TFP) Estimation

Household TFP In order to track migrant selection and land allocation patterns, we construct household-level quantity TFP. Crop outputs are available in all years in quantities (kilos), but the input data varies by year. There are four types of inputs in crop farming: land (in hectares), labor (in labor days in agriculture), capital (in initial book value), and intermediate inputs (in value, including seed and seedlings, fertilizers, agricultural films, and pesticides). In our main analysis, we aggregate across crops to generate household-level outputs and inputs to estimate the household-level TFP.

The output value is constructed using a common vector of year-specific national crop prices and household-level crop outputs. We include 11 types of crops that are consistently measured in the data: wheat, rice, corn, soybean, cotton, oil crops, sugar crops, flax, tobacco, fruits, and vegetables.[22] For each crop, we calculate the sales price in yuan per kilo for all households with positive sales. The price of a crop in a particular year is calculated as the national average of all households. Then the household-level output is the sum of the physical outputs of crops evaluated at the common national prices. We deflate the household-level output using the national output price indices to make output values comparable across years, using 1995 as the baseline year.[23,24]

We also make adjustments on the input side. The intermediate input value is the total value of inputs in all crops, deflated by province-level agricultural input price indices, using 1995 as the baseline year. The capital stock is recorded in initial book value. To take into account differential prices across years, depreciation of capital stock, and missing values of capital in some observations, we use the perpetual inventory method to reconstruct the capital stock at the household level.[25]

Assuming that agriculture production in crop farming follows a Cobb-Douglas form, we estimate the production function using the following equation:

$$\log(y_{h(v)t}) = \alpha \log(d_{h(v)t}) + \beta \log(k_{h(v)t}) + \gamma \log(l_{h(v)t}) + \delta \log(m_{h(v)t}) + \phi_{h(v)t}, \tag{1}$$

[22]Crop area of these 11 crops comprises 90% of total areas in our data, both as the sample mean for households and as the aggregate share. Crops that do not show up in all years include potato, mulberry, tea, and herbal medicine.

[23]The national output price deflator is the price index of crop farming from the National Statistics Yearbook of Agriculture. We use the national price deflator instead of province-level price deflators since the latter is only available after 2003.

[24]We use common prices to eliminate the price variation across households. In addition, we want to evaluate a household's output value even in the absence of crop sales, since the household may consume the output for food or livestock feed.

[25]See the details of the method in Appendix B.1.3.

where $y_{h(v)t}$ is the output value in crop farming in household h, village v, and year t. Labor days in agriculture, capital, land, and intermediate inputs are $d_{h(v)t}$, $k_{h(v)t}$, $l_{h(v)t}$, and $m_{h(v)t}$, respectively. Cobb-Douglas parameters α, β, γ, and δ represent output elasticities with respect to each input and are assumed to be constant over time and across households. We further decompose the log of TFP as follows:

$$\phi_{h(v)t} = \phi_{vt} + \phi_h + e_{h(v)t}.$$

Here, a household's productivity in a given year is comprised of factors common to its village in the year (e.g., weather and other aggregate shocks), ϕ_{vt}, its intrinsic ability to farm and other time-invariant household-level factors, ϕ_h, and idiosyncratic shocks, $e_{h(v)t}$.

We estimate Equation (1) controlling for village-year (ϕ_{vt}) fixed effects and household (ϕ_h) fixed effects.[26] The log of household TFP is measured as the following residual term,

$$\hat{\phi}_{h(v)t} \equiv \log(y_{h(v)t}) - \hat{\alpha}\log(d_{h(v)t}) - \hat{\beta}\log(k_{h(v)t}) - \hat{\gamma}\log(l_{h(v)t}) - \hat{\delta}\log(m_{h(v)t}). \tag{2}$$

Village TFP We are interested in measuring the village-level TFP since it is informative about the overall productivity of the village and reflects the efficiency of local land allocation, an important aspect of agricultural modernization. The village-level productivity (Φ_{vt}) is constructed as the weighted average of log household TFPs, using the output value ($y_{h(v)t}$) as weights,

$$\Phi_{vt} \equiv \sum_h w_{h(v)t}\hat{\phi}_{h(v)t} = \sum_h \frac{y_{h(v)t}}{\sum_{h'} y_{h'(v)t}}\hat{\phi}_{h(v)t}. \tag{3}$$

In addition, similar as in Chari et al. (2020), we decompose the village-level TFP in the following way,

$$\Phi_{vt} = \overline{\phi}_{vt} + \sum_h (w_{h(v)t} - \overline{w}_{vt})(\hat{\phi}_{h(v)t} - \overline{\phi}_{vt}) \equiv \overline{\phi}_{vt} + E_{vt}, \tag{4}$$

where $\overline{\phi}_{vt} \equiv \frac{1}{N_h}\sum_h \hat{\phi}_{h(v)t}$ and $\bar{w}_{vt} \equiv \frac{1}{N_h}\sum_h w_{h(v)t} = \frac{1}{N_h}$ represent unweighted means, with N_h as the number of households in the village-year. The second term E_{vt} is the sample covariance between

[26] See the details of the TFP estimation in Appendix B.1.4. The estimates for the output elasticity of inputs are similar as in Chow (1993), Cao and Birchenall (2013), and Chari et al. (2020). An alternative method is to use the log value-added as the outcome variable (the output value minus the intermediate input value), and the estimated TFP is denoted as $\hat{\phi}^V_{hvt}$. To alleviate the concern that the input choices are correlated with unobserved idiosyncratic productivity shocks, we use two methods: (1) using the lagged inputs as instruments for the inputs in the current period, and (2) using the choice of intermediate inputs to proxy for productivity shocks as suggested in Levinsohn and Petrin (2003). The TFP estimates generated from these two methods are very similar to the OLS estimates, so we use the OLS estimates directly. The estimates are also similar when we use a balanced panel of households. In the empirical analysis, we check the robustness of our results when we use labor productivity instead of quantity TFP and value-added TFP instead of quantity TFP.

the household-level output weights and productivity multiplied by $N_h - 1$. A larger E_{vt} indicates that the productive household generates more output and has a larger weight in the calculation of the village-level TFP. Thus, we use it as our measure of allocation efficiency.

4 Measuring Trade Shocks

4.1 Migration Network

In order to measure pre-existing migration connections between prefectures, we use the 0.095% individual sample of the 2000 census to construct the prefecture-to-prefecture migration network. The census has information on the residence prefecture in 2000 and the residence prefecture in 1995 (Table 1). Thus, we can determine the number of people who lived in prefecture i in 1995 and moved to prefecture j before 2000 (m_{ij}).[27]

We also use the census to construct the share of cross-prefecture migrants out of all migrants. The share of cross-prefecture migrants is relevant for our analysis since an origin village's exposure to other prefectures' trade shocks is larger if initially, a larger share of the village residents were working in those prefectures. The total number of cross-prefecture migrants from prefecture i is $m_i^{between} \equiv \sum_{j \neq i} m_{ij}$. The within-prefecture migrants are identified using the question on the registration place of Hukou. A person is defined as a within-prefecture migrant if his Hukou registration is in the same prefecture, but in different counties. Denoting the number of within-prefecture migrants as m_i^{within}, we calculate the share of cross-prefecture migrants as

$$s_i = \frac{m_i^{between}}{m_i^{between} + m_i^{within}}.$$

Given that the prefecture is the finest geographical unit we can get for the migration information, we make the assumption that all villages (v) in a prefecture (i) share the same migration network that connects other prefectures. If this assumption is violated, it will drive the empirical results toward zero. We also assume that the propensity of cross-prefecture migration is the same for all villages within a prefecture. Thus, $s_{v(i)} = s_i$ for all villages (v) in a prefecture (i).[28]

4.2 Regional Trade Exposure

We first construct the prefecture-year level trade exposure in the manufacturing sector. Following Kovak (2013), the regional output tariff in prefecture i and in year t is

[27] See Appendix B.3 for descriptives of the migration network.

[28] If this assumption is violated, we have measurement errors in the village-to-prefecture migration network. If the measurement error is classic, the exposure to trade shock will be measured with error, and the effect of trade exposure on the outcomes will be biased toward zero.

$$\tau_{it} = \sum_k \beta_{ik} \tau_{kt},$$

$$\text{where} \qquad \beta_{ik} = \frac{\lambda_{ik} \frac{1}{\theta_{ik}}}{\sum_{k'} \lambda_{ik'} \frac{1}{\theta_{ik'}}}, \tag{5}$$

$\lambda_{ik} = \frac{L_{ik}}{\sum_{k'} L_{ik'}}$ is the fraction of regional labor allocated to industry k, and $1 - \theta_{ik}$ is the cost share of labor in industry k. λ_{ik} and θ_{ik} are calculated using the 2000 Industrial Enterprises Survey data, and only manufacturing industries are included.[29] τ_{kt} is the industry-year-specific tariff. A village v's (in prefecture i) exposure to its own prefecture's output tariff is

$$\tau_{v(i)t}^{own} = \tau_{it}. \tag{6}$$

Accordingly, its exposure to tariffs in other prefectures through the migrant network is

$$\tau_{v(i)t}^{network} \equiv \sum_{j \neq i} \frac{m_{ij}}{\sum_{j' \neq i} m_{ij'}} \tau_{jt}, \tag{7}$$

where m_{ij} is the number of people who are in prefecture i in 1995 and reside in prefecture j in 2000.

Figure 3 shows the geographic distribution of own prefecture's output tariff reduction and exposure to tariff reductions through migrant networks, using the 2001–2010 change as an example. Panel (a) shows the distribution of the own prefecture's output tariff reduction, defined as $\tau_{2010}^{own} - \tau_{2001}^{own}$, and Panel (b) shows the distribution of exposure to output tariff reduction through migrant networks, $\tau_{2010}^{network} - \tau_{2001}^{network}$. Darker colors represent larger reductions. We can see that the distributions are different for the two types of tariff reductions. The declines in own prefecture's output tariff ranged from –3.96 to –0.14 and were distributed unevenly across the country. The exposure to tariff declines through migrant networks ranged from –1.69 to –0.54 and was larger in northern China.

In Appendix B.4, we present alternative measures of trade exposures. We show that our main measure τ_{it} is highly correlated with alternative measures when omitting θs in Equation (5) and when using a finer definition of the manufacturing industry (4-digit instead of 2-digit). We also show that our main measure is negatively correlated with trade exposure measures as in Autor et al. (2013), where we replace tariffs (τ_{kt}) with actual export values and omit θs in Equation (5). This is a reassurance of negative trade elasticities shown at the industry level in Section 2.2.

[29] The 2-digit industry codes in the survey are different from the SIC code, and we provide concordance in Appendix B.2.1.

4.3 Tariff Reductions Led to Increases in Internal Migration

We argue that the outflow of labor from agriculture was closely related to the fast growth of manufacturing exports after 2001. In Appendix B.4, we show that tariff reductions in destination regions led to increases in wages, generating pull forces of out-migration for the origin place. This is consistent with evidence documented in Tian (forthcoming). In Figure 4, we present direct evidence of migrant inflows to the destination regions. The horizontal axis is the change in output tariffs from 2000 to 2010 ($\tau^{own}_{2010} - \tau^{own}_{2000}$), and the vertical axis is the change in the share of migrants in a prefecture, calculated using the 2000 and 2010 censuses. The slope is –0.016 and statistically significant at the 5% level, indicating that a one-percentage point larger decline in output tariffs in export markets resulted in a 1.6-percentage point larger increase in the share of migrants in a destination prefecture.[30]

5 The Effect of Trade Shocks on Village-Level Agricultural Outcomes

5.1 Specification, Identification, and Inference

Our empirical analysis intends to show the impact of trade shocks on various outcomes in the agricultural sector. The baseline estimation equation is as follows:

$$y_{vt} = \beta_0 + \beta^{network}\tau^{network}_{v(i)t} + \beta^{own}\tau^{own}_{v(i)t} + X_{vt}\Gamma + I_{pt} + I_v + \epsilon_{vt}, \tag{8}$$

where y_{vt} is the outcome variable, including the share of non-agricultural laborers, various measures of the land and the capital market, and the village-level TFP in village v and year t. $\tau^{own}_{v(i)t}$ and $\tau^{network}_{v(i)t}$ are village v's exposure to its own prefecture i's tariff and its tariff exposure through migrant networks, respectively. We include a matrix of controls X_{vt}, including the log total number of laborers, the log total number of households, and the log government transfers plus one to take into account the role of the size of the village and agricultural subsidy from the government. Province-year fixed effects I_{pt} are controlled to take into account unobserved province-year specific weather conditions and various government policies that potentially affect sectoral employment choices and land allocation rules.[31] Village fixed effects I_v control for all time-invariant village characteristics such as overall land quality, climate, other agro-geographical characteristics, and social norms regarding migration and land allocation. Standard errors are clustered at the province

[30] We show the robustness of this relationship in Appendix C.2.1 by using bin scatter plots and by dropping outliers.

[31] For example, Chari et al. (2020) shows that provinces implemented the 2003 national land contract law at different times.

level and at the year level to take into account correlated shocks within provinces and within years.

$\beta^{network}$ and β^{own} are the reduced-form parameters of the impact of exposure to manufacturing tariffs on agricultural production. A reduction of output tariffs in the manufacturing sector effectively increases the price of goods received by exporters. Thus, wages in the manufacturing sector increase, acting as a pull factor for labor to move out of the agricultural sector. Both the trade shocks in one's own prefecture and other prefectures through migrant networks can impact sectoral employment choices. $\beta^{network}$ and β^{own} being negative means that lower output tariffs on manufacturing goods in export markets increase y_{vt}.

Our main parameter of interest is $\beta^{network}$. If both the own prefecture's output tariff and tariff exposure through the migrant networks affect agricultural production only due to the labor demand effect in the urban manufacturing sector, we expect declines in either one leading to increased outflow of labor from agriculture. However, manufacturing trade can also affect agricultural production through other channels. For example, the positive shocks to manufacturing trade increase the income of urban residents, and the increase in income leads to higher demand for agricultural goods with larger income elasticities. Then agricultural production is affected by the manufacturing growth through the agricultural goods market and the income effect. If we assume that the agricultural goods market is relatively local, then we expect such income effects to be captured in β^{own} rather than in $\beta^{network}$. In other words, we posit that $\beta^{network}$ is more likely to capture the pure labor demand effect.[32]

The key identification assumption is that the counterfactual changes in the outcome variables are the same across villages in the absence of trade shocks. We provide some evidence regarding pre-trends and discuss identification issues in light of the recent shift-share literature.

1. Pre-trends Since the counterfactual is not observed, we use pre-trends to provide suggestive evidence on the exogeneity of trade shocks. The hypothesis is that there were no village-level trends in the share of non-agriculture labor, land rental, agricultural capital, and TFP before 2001 that could predict post-2001 changes in $\tau^{own}_{v(i)t}$ and $\tau^{network}_{v(i)t}$. We present our main evidence on the absence of pre-trends in the non-agriculture labor share in Section 5.2 and additional evidence in Appendix C.3.

2. Shift-share identification and inference Recent research on shift-share designs suggests several exercises to better understand the source of variation, conduct tests in support of the identification assumptions, and do inference (see Adao et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2022). Similar to the setting of Imbert et al. (2022), in our case, since the pre-

[32]In general, prefecture-to-prefecture goods trade and migration can still be correlated due to common costs, such as transportation.

existing migrant connections are likely to reflect bilateral migration costs and origin and destination characteristics before the WTO shock, they are likely to be endogenous to the agricultural sector performances. Thus, the validity of our shift-share design will require that the shifts, i.e., the output tariff faced by the destination regions, be exogenous to agricultural outcomes. Borusyak et al. (2022) shows that a consistent estimator using a shift-share design would require (i) shifts being as-good-as-randomly assigned as if arising from a natural experiment, and (ii) that there are many sufficiently independent shifts, each with sufficiently small average exposure to the shocks.

In our context, condition (i) is likely to hold since the output tariff exposure in migrant destination regions is unlikely to be correlated with unobservables that affect agricultural sector outcomes. Regarding (ii), we want to understand the dispersion of the migration network since they determine the exposure to the shocks for the origin villages. In the 2000 population census, there are 338 prefectures with at least one migrant, resulting in 338 shares in our analysis. Denote the share of migrants from origin prefecture i to destination prefecture j in the baseline year 2000 as $\mu_{ij} \equiv \frac{m_{ij}}{\sum_{j'=i} m_{ij'}}$, and the number of origin prefectures as N ($N = 215$). We find that the Herfindahl index of destination contributions, $\sum_j (\frac{\sum_i \mu_{ij}}{N})^2$, is 0.014. This is a relatively small number, indicating that the shares are dispersed and that the effect is not driven by a few destinations. Additionally, given the fact that there are a few big metropolitans such as Beijing, Shanghai, and Guangzhou that attract a lot of migrants from all across China, we will conduct a robustness check where we directly control for the share of migrants moving to the ten most popular destination prefectures.

Additionally, we would like to check that there is variation in the migrant network from an origin prefecture's point of view; otherwise, if the migration patterns are the same across origin prefectures, the exposure to shocks from the destination prefectures will also be the same across origins. To do this, we calculate the Herfindahl index of the shares for each origin prefecture ($\sum_j \mu_{ij}^2$). Then we calculate the mean and the standard deviation of these Herfindahl indices across origins. While the mean is 0.118, the standard deviation is 0.08, indicating that different origin prefectures do have differences in where they send migrants.

Finally, following Borusyak et al. (2022), we conduct the equivalence exercise where exposure-weighted regressions are done with both the outcome variables and the explanatory variables inverted to the shift level, which is the destination-prefecture level in our case. In this specification, we are also able to cluster the standard errors at the destination-province level for robustness, to allow for spatial correlation in errors at the shock level. We will introduce these tests and corresponding results at the end of Section 5.

Our second main specification takes into account that regions differ in their share of cross-prefecture migrants $s_{v(i)}$ out of all migrants. The impact of pull factors of cross-prefecture migration is larger if, at the beginning of the period (2000), a larger share of people moved across prefectures rather than within prefectures. In other words, $s_{v(i)}$ intensifies the impact of tariff exposure through migrant networks on the origin village's tendency to leave agriculture. Thus, our second main specification adds an interaction term of tariff exposure through migrant networks $\tau_{v(i)t}^{network}$ and the share of cross-prefecture migrants $s_{v(i)}$,

$$y_{vt} = \beta_0 + \beta^{network}\tau_{v(i)t}^{network} + \beta^{inter}\tau_{v(i)t}^{network} \times s_{v(i)} + \beta^{own}\tau_{v(i)t}^{own} + \Gamma X_{vt} + I_{pt} + I_v + \epsilon_{vt}, \tag{9}$$

and we expect the coefficient β^{inter} to be negative.

5.2 Village-Level Results

Occupation Choice We first investigate the impact of output tariffs on the occupational choice for rural residents in Table 2. Panel A Column (1) regresses the share of non-agricultural labor on tariff exposure through migrant networks, controlling for province-year fixed effects and village fixed effects. The coefficient for tariff exposure through migrant networks is –0.08 and significant at the 1% level, indicating that a one-standard-deviation larger decline in tariff exposure through migrant networks resulted in a 3.5-percentage-point (or a 0.25-standard-deviation) larger increase in the share of non-agricultural labor. Column (2) adds its own prefecture's output tariff, and the coefficient of tariff exposure through migrant networks becomes smaller and statistically significant at the 1% level. Column (3) follows the specification in Equation (8), adding the village-year specific controls (i.e., the log total number of laborers, the log total number of households, and the log government transfers plus one). The coefficient for tariff exposure through migrant networks remains stable. Column (4) follows the specification in Equation (9), adding an interaction of tariff exposure through migrant networks with the share of cross-prefecture migrants. As anticipated, the coefficient for the interaction is negative, indicating that villages with a larger share of cross-prefecture migrants experienced a more substantial impact from tariff exposure through migrant networks. Overall, we find that trade shocks in other regions pulled labor out of agriculture; more so for villages with higher shares of cross-prefecture migrants.

We also find heterogeneous effects of tariff exposure through migrant networks with respect to the initial land-to-agriculture-labor ratio. Column (5) interacts tariff exposure through migrant networks with the log agricultural land-to-labor ratio in 2001. The coefficient for tariff exposure through migrant networks is –0.16, and the interaction term is 0.05. The positive interaction means that for villages with a larger land-to-labor ratio in agriculture, the effect of a decline in tariff exposure through migrant networks was smaller. This message is clearer in Column (6), where we interact tariff exposure through migrant networks with quintile indicators of a village's land per agricultural worker in 2001. For villages with the smallest land per agricultural worker in 2001 (i.e., in the first quintile), a one-standard-deviation larger decline in tariff exposure through migrant networks led to an 8-percentage-point larger increase in the share of non-agricultural labor. For villages in the fifth quintile, the effect was 3 percentage points.[33]

We interpret the heterogeneous effect of tariff exposure through migrant networks with respect to the land-to-labor ratio as capturing the role of the extent of factor misallocation at the beginning of the period. In villages with more active land markets, the land is likely to be allocated more efficiently across households according to their productivity, which allows workers with comparative advantage in non-agriculture to move out of agriculture. This is also related to the process of urbanization in general. In regions where urbanization already took place and people moved out of agriculture, additional shocks to out-migration had smaller impacts.

This interpretation is supported by the descriptive evidence in Table 3. We regress different measures of baseline village characteristics in 2001 on the log land per agriculture worker, controlling for province fixed effects. Columns (1)–(3) use direct measures of land market fluidity as the outcome variables, and the size of land leased is positively correlated with the log land per agricultural worker. There are two measures for the land leased. The stock measure comes from the decomposition of the total land at the end of the year, and the flow is a separate measure of how much land a household leased during the year. Column (4) shows that a village's ruggedness is negatively correlated with the land-labor ratio. An explanation is that land consolidation is harder for villages with a more rugged surface, thus land reallocation is limited.[34] Column (5) indicates that the share of non-agriculture labor is positively correlated with the land-labor ratio. Column (6) provides the most direct evidence: the allocation efficiency (E_{v2001}, which is the covariance between output and productivity) is positively correlated with the land-labor ratio.

The coefficient estimate for the own prefecture's output tariff is positive in all columns in Table 2, indicating that a reduction in the own prefecture's output tariff led to smaller labor outflows from agriculture. The positive estimates of the own prefecture's output tariff impact suggest that there could be alternative channels through which trade shocks affected the non-agricultural labor share. One potential channel is the local demand for agricultural goods. A reduction in manufacturing output tariffs in prefecture i increased the wage, and the income effect could lead to higher demand for agricultural goods, especially food such as dairy products, vegetables, and fruits. Thus, it could be more profitable for farmers to stay in agriculture. We find evidence in Appendix C.8 on how an increase in own prefecture's trade exposure led to an increase in the revenue share of cash crops, although the effect is not statistically significant.

[33]Note that the sample sizes are different in Columns (1)–(4) and Columns (5)(6) since not all villages in the 2001–2010 sample show up in the 2001 sample. When we restrict the sample to the village-year observations whose villages are included in the 2001 sample and run the baseline regression as in Column (1), the coefficient for tariff exposure through migrant networks is –0.09, which is between -0.16 for the first-quintile villages and –0.06 for the fifth-quintile villages.

[34]The ruggedness data is from Nunn and Puga (2012) with cells on a 30 arc-seconds grid. The cell-level data is aggregated at the county level, and our assumption is that villages within a county have the same ruggedness level.

In Panel B, we conduct tests for pre-trends. We regress the pre-2001 share of non-agricultural laborers (1995–2001) on the post-2001 tariff exposures through migrant networks (2004–2010) and corresponding post-2001 controls. We find no statistically significant effects of the post-2001 tariff exposure on pre-existing non-agricultural migrant shares, indicating that there are no pre-trends in the outcome variable that are systematically correlated with the trade shocks.[35]

We provide robustness checks in Appendix C.4.1, by (1) including agricultural trade shocks, (2) controlling for the reduction in trade uncertainty induced by the establishment of the U.S.-China permanent normal trade relationship (PNTR), (3) using the migration-related information in the village questionnaire in Appendix C.4.2, and (4) controlling for the initial crop patterns and contemporaneous crop patterns in Appendix C.4.3. We find that agricultural import and export tariffs and agricultural goods market access did not have significant effects on the occupation choice; this is consistent with the fact that China's most salient growth in trade was in the manufacturing sector instead of the agricultural sector. Including the PNTR shocks does not affect the estimates of our actual tariff effects ($\beta^{network}$ and β^{own}). The village questionnaire includes village-level measures of the number of households exclusively in agriculture, the number of laborers working outside the village, and excess labor. The occupation choice and migration results are consistent with the findings in Table 2. The effects on excess labor are insignificant. The crop patterns did not affect the relationship between tariff exposures through the migrant network and out-migration patterns.

Overall, we find that villages with migrant connections to prefectures facing larger tariff declines in export markets had larger flows of labor from agriculture to non-agriculture. The effect was stronger for villages with larger shares of cross-prefecture migration, and also for villages that were in earlier stages of urbanization and had worse land allocation at the beginning of the period.

Land Market When more people moved out of agriculture, the rental market of agricultural land became more active. Table 4 shows how tariff exposure through migrant networks affected the origin village's land market fluidity. For each outcome variable that measures land market fluidity, we use the two main specifications as in Table 2 Columns (3) and (4). A one-standard-deviation larger decline in tariff exposure through migrant networks led to a 26% (or a 0.16-standard-deviation) larger increase in the stock of land leased, and the effect is significant at the 1% level (Column 1). The effect was larger for villages whose prefecture had higher between-prefecture migrant rates (Column 2). We find similar patterns when we use the log flow of land leased (Columns 3 and 4) and the log income from land leasing (Columns 5 and 6) as the measure for the activeness of the land market.

How did the trade shocks affect the land distribution? Columns (7) and (8) show the impact

[35] This test uses a panel structure as in the main specification. Alternatively, we can test the pre-trends year by year. The results using the year-by-year specification are shown in Appendix C.3, where we also show the absence of pre-trends in other key outcomes (i.e., land, capital, and productivity).

on the number of households with land larger than one-third hectare. The median land size of households in the 2001–2010 period was 0.32 hectare. Thus, we consider households with more than 1/3 hectare of land, i.e., the ones with relatively large land. The decline in tariff exposure through migrant networks led to an increase in the number of households with relatively large land in villages where the share of cross-prefecture migrants was larger than 58%.[36]

In sum, we find several aspects of the agricultural land distribution being affected by tariffs facing exporters in migrant-connected prefectures. First, the land rental market became more fluid, measured by the size of rental transactions within a year and the stock of rented land. Second, there is some evidence of land consolidation: the decline in tariff exposure through migrant networks led to an increase in the number of households with relatively large land, especially in villages with high cross-prefecture migration rates.

Another important aspect of the land market is the potential reduction in land misallocation. In Section 6, we provide supplementary household-level analysis where we show that through trade shocks, the initially productive households obtained larger farms, indicating reductions in land misallocation.

Adoption of Agricultural Machinery We proceed to investigate the changes in the capital market. With labor leaving agriculture, capital adoption is likely to increase through several channels. The first channel is the increased size of farms (Foster and Rosenzweig 2011; 2022). Considering the fixed costs associated with acquiring agricultural machinery, it becomes economically viable for farmers to invest in such equipment only when their farm size is sufficiently large. The second is due to the substitution between labor and capital (Manuelli and Seshadri 2014). When the local labor costs increase due to the outflow of labor from agriculture, farmers tend to substitute labor with capital. Third, capital adoption can increase when land misallocation decreases. When land is reallocated from unproductive farmers to productive farmers, since the increase of the marginal product of capital for productive households is higher than the decrease of the marginal product of capital for unproductive households, the overall amount of capital can increase. Finally, capital adoption can also increase through migrant remittance. Suppose that there is no well-functioning credit market in rural areas, and farmers are not able to buy machinery due to their credit constraints. Out-migration from agricultural households can bolster household income, alleviate credit constraints, and subsequently promote the adoption of capital.

Table 5 presents the impact of trade exposure on capital. Agricultural machinery increased more in villages that had larger declines in tariff exposure through migrant networks, and the effect was stronger where the share of cross-prefecture migrants was high (Columns 1 and 2). Evaluated at

[36]We have additional results showing insignificant effects on the overall land size at the village level, indicating that people were not leaving their land idle when they move to work in the urban manufacturing sector.

the mean of cross-prefecture migrant share (0.46), a one-standard-deviation larger decline in tariff exposure through migrant networks led to an 8% (or a 0.05-standard-deviation) larger increase in the value of agricultural machinery.

We find evidence supporting the first channel of increased capital adoption, i.e., through increased land size. We find that the number of households with positive agricultural machinery and relatively large land increased in response to tariff declines (Columns 3 and 4), even when we control for the number of households with positive agricultural machinery and relatively small land (Columns 5 and 6). By controlling for the number of households with positive agricultural machinery and relatively small land, we address the potential concern that maybe in villages with larger trade shocks, *all* households increased capital adoption. We find that compared to the households with relatively small land, the households with relatively large land still had more intensive capital adoption.[37]

Regarding the second channel, the capital-labor substitution, we provide evidence of the increased labor cost in Columns (7) and (8). An important fact about rural China is that hired labor was not prevalent. In the NFP sample, the share of hired labor days is 2% on average during the 2001–2010 period. This includes hired labor *by rural households within the village* in both agricultural and non-agricultural production. Thus, the measurement errors can be big for wages and hired labor days: although the implicit labor cost increased with labor outflows, the wages and hired labor days could be noisily measured. Some villages even had no hired labor, so the number of observations in these two columns is smaller than that in Columns (1) and (2). Overall, we find that tariff declines in migrant-connected prefectures led to an increase in wages of locally hired labor, for villages with a large share of cross-prefecture migrants. However, the effects are statistically insignificant.

There is also evidence supporting the land misallocation channel. In Section 6, we will show that the reallocation of land was towards the relatively productive farmers within a village.

In the specific context of our study, we don't find evidence supporting the remittance channel, aligning with findings from De Brauw and Rozelle (2008).[38] As shown in Appendix C.5, the expenditure on productive fixed assets was negatively correlated with wage income but was positively correlated with income from farming and government subsidies. This suggests that households were not investing in agricultural capital using their income from urban wages but only using their farm profits and farm subsidies. This finding is consistent with the overall trend of urbanization since people were not trying to fund their agricultural production through migration remittances, but rather leaving agriculture in the long run. Only the workers who decided to remain in agriculture

[37]However, we do not have plot-level information to know if the newly-rented plot was contiguous with the original plot or not.

[38]Similarly, Dinkelman et al. 2017 find that migrant remittance increased capital formation in non-agricultural sectors.

re-invest in their production.

Overall, we find positive impacts of tariff exposure through migrant networks on capital adoption. We provide suggestive evidence showing that the capital adoption was likely to be caused by land consolidation, increased local labor costs, and improved land allocation across households, rather than larger migrant remittance. Capital adoption in agriculture can further make the urbanization process irreversible. Once the agricultural sector modernizes, it is not likely to go back to labor-intensive production. This process is similar to the modernization of the manufacturing sector when robots and machines replace workers.

Productivity and Allocation Finally, the adjustments in the factor markets may also lead to changes in the overall productivity of the villages. We find a positive impact of exposure to manufacturing trade on agricultural productivity: a one-standard-deviation larger decline in tariff exposure through migrant networks led to a 30% (or a 0.33-standard-deviation) larger increase in the output-weighted village-level TFP (Columns 1 and 2 in Table 6). At the same time, there was no significant effect on the unweighted TFP (Columns 3 and 4). This allocation effect is directly demonstrated in Columns (5) and (6), where the allocation efficiency (i.e., the difference between the output weighted and unweighted TFP) increased more in villages that had larger declines in tariff exposure through migrant networks.[39]

How to understand these village-level productivity effects? The first is through migrant selection. If unproductive farmers leave and productive farmers remain, agricultural productivity will increase. The second is through land reallocation. When the land was more allocated toward the productive farmers and such farmers adopted more capital for production, they would be able to produce more output and have higher weights in the village-level TFP. We will present evidence supporting both hypotheses using individual and household-level analysis in the next section.

An alternative hypothesis on the TFP effect is that villages with more out-migration switch from cereal crops to cash crops, and this switch increases the TFP estimated using the output value since the cash crops have higher prices. We investigate this hypothesis in Appendix C.8. Overall, we don't find that big-shock regions had differential rates of switching from cereal crops to cash crops. The decline in tariff exposure through migrant networks had insignificant effects on the revenue share of cash crops and led to a decline in the number of households in cash crop production. This finding is consistent with two facts. First, the share of households in cash crop production had a similar declining trend as the households with cereal crops from 2001 to 2010. Thus, households were moving out of all types of crop farming. Second, cash crops can be more labor-intensive than

[39]The results in Table 6 use the TFP calculated using the output method. Appendix C.6 shows that the results are similar to the TFP calculated using the value-added method. Alternatively, agricultural productivity can be calculated as the log output per labor day in agriculture, i.e., in terms of labor productivity. The results using labor productivity are similar, also shown in Appendix C.6.

cereal crops. Take the most common cash crop, vegetables, as an example. As estimated in Chari et al. (2020), the output elasticity of labor of vegetables is among the highest in all crops. Also, it is intuitive that with the harvest cycle of vegetables, more labor input is needed to attend to the production process. We indeed find households moving out of vegetable production in the face of positive out-migration shocks.

Shift-Share Equivalence Result and a Summary As discussed in previous sections of the paper, in Appendix C.7.1, we verify the equivalence results following the method in Borusyak et al. (2022). In addition, when the regression is at the destination-prefecture level, we can cluster the standard errors at the destination-province level to take into account spatially correlated error terms coming from common shocks at the destination-province level. Our main results remain similar across specifications.

Additionally, in Appendix C.7.2, we show that our results are robust when we control for the initial share of migrants who moved to the top 10 migrant destinations. This is reassuring since it confirms that our results are not driven by a few big destination prefectures.

In sum, we show that the increase in trade exposures in destination prefectures attracted farmers to exit agriculture and enter manufacturing and service, and all sub-sectors in agriculture experienced a negative labor supply shock. This labor supply shock triggered a battery of changes in the agricultural sector. The land market became more fluid, capital adoption increased, and village-level TFP improved. The trade-induced manufacturing growth led to an agricultural sector with better factor allocation and modern production technologies.[40]

6 Individual and Household Level Evidence

The previous section focused on the village-level outcomes. In order to further understand productivity growth at the village level, we provide evidence at both the individual and the household levels.

First, we show the importance of migrant selection. Using individual characteristics, we find that the correlation between a person's agriculture and non-agriculture productivity is low. At the household level, we find that in the face of the trade shock, the households that were more relatively unproductive in the agriculture sector had more members moving out of the agriculture sector. Thus, overall, we find a negative selection in terms of agricultural productivity, contributing to the improved agricultural productivity at the village level when the trade shock occurred.

Second, we show that the land allocation efficiency improved. When the land rental market

[40] Although the focus of our paper is on crop farming, we also test the out-migration effect on husbandry. The effect is very similar to the one discussed above, on cash crops. We don't find any significant effect on husbandry.

became active, the relatively productive households obtained more land, and this contributed to the village-level productivity growth both directly and indirectly through capital adoption.

6.1 Migrant Selection

In this section, we investigate the role of migrant selection in driving the productivity results documented in the previous section. Importantly, we need to understand whether productive farmers are also productive manufacturing workers, in order to know who leaves the agricultural sector.

When rural areas face a negative labor supply shock, the amount of land on the rental market increases, and the rental price of land should decrease. Lower rental prices of land increase the appeal of remaining in agriculture. Specifically, high-productivity farmers have a higher marginal product of land, thus they may obtain more land than low-productivity farmers. This effect alone can improve land allocation efficiency.

Additionally, if agricultural productivity and non-agricultural productivity are uncorrelated, farmers of different productivity levels will earn similar wages in the urban manufacturing sector. In this case, unproductive farmers would be more likely to leave agriculture in response to the positive labor demand shock in non-agriculture, since their opportunity costs of leaving agriculture are smaller. This negative selection out of the agricultural sector will improve the village-level TFP. If the two productivities are highly positively correlated, the selection pattern will be unclear. If they are negatively correlated, the selection effect will be even stronger.

6.1.1 Skill Heterogeneity and Occupation Choice

Who were the productive farmers and productive non-agricultural workers? We investigate the characteristics of individuals that were correlated with productivity in Table 7, using individual-level information from 2003 to 2008.[41] The baseline specification is as follows,

$$y_{dt} = \delta_0 + \delta_1 \text{edu}_{dt} + \delta_2 \text{train}_{dt}^{non-agr} + \delta_3 \text{train}_{dt}^{agr} + \delta_4 \text{age}_{dt} + \delta_5 \log(\text{labor})_{d(h)t} + I_t + \xi_{it},$$

where the outcome variable is either the log of TFP in agriculture for an individual d in household h and year t, or the log income from working outside the village for individual d in year t. The individual characteristics include years of education, a dummy variable indicating whether the person had non-agricultural occupational training, a dummy variable for agricultural training, age, and the size of the household. We also control for year fixed effects to take into account year-specific shocks to productivity and wages.

[41] The 2009 and 2010 questionnaires have different definitions of occupational and agricultural training, so we only use the 2003–2008 data for consistency.

Table 7 Columns (1) and (4) show the results on agricultural productivity and on wages, respectively. One additional year of education (or a 0.44-standard-deviation larger education) was correlated with a 3.5-percentage-point larger TFP (or a 0.05-standard-deviation increase in the log TFP). Individuals with agricultural training had 16-percentage-points larger TFP, and the individuals with non-agricultural training had 8-percentage-point lower TFP. For individuals with positive income from working outside the village, 75% report their industry as non-agriculture. We find a larger correlation of education with income from outside the village: a one-year larger education level was correlated with a 5.6-percentage-point larger income. Having occupation training was correlated with a 30-percentage-point larger income, and having agricultural training was correlated with a 4-percentage-point smaller income. We find small age effects on both outcomes.

Columns (1) and (4) suggest that educated individuals were likely to be in more productive agricultural households and had higher earnings in non-agriculture. In addition, having sector-specific training was correlated with higher sector-specific productivity. Table B3 shows that only 2% of individuals had both agricultural training and non-agricultural training, while 6% only had non-agricultural training, and 5% only had agricultural training. Thus, there is evidence of sector-specific human capital investments.

However, we find that the education and training effects were more significant and robust for the non-agricultural income than for agricultural productivity. When including village fixed effects in Columns (2) and (5), the education and training effects on agricultural productivity become very small, while the effects on non-agricultural income remain. In addition, the R^2 value undergoes a substantial change from Column (1) to Column (2), and the change from Column (4) to Column (5) is smaller. The results suggest that observable characteristics of individuals explain only a small share (3%) of the variation in agricultural productivity, while village-specific time-invariant characteristics explain about 53% of the variation. In contrast, education levels and training explain a sizable share (11%) of the variation in the non-agricultural income, and the village fixed effects explain an additional 20%.

We also find that initial agricultural productivity is more informative about agricultural productivity than about non-agricultural productivity in later years. Column (3) shows the persistence of agricultural productivity. When regressing the log TFP on the log TFP in 2001, the coefficient indicates that a household that is 10% more productive in 2001 is 18% more productive in the years 2003–2008. Thus, the initial agricultural productivity is a good indicator of the agricultural ability in later years. Column (6) regresses the non-agricultural income on the initial agricultural productivity, and the coefficient is insignificant.

Overall, we find no evidence of a strong positive correlation between agricultural and non-agricultural abilities. Individuals with higher non-agricultural productivity usually choose higher education, since education is often seen as a type of human capital investment that pays off in the non-agricultural sector. We do not find that education is highly correlated with non-agricultural productivity, once the village fixed effects are controlled; neither do we find significant effects of training on agricultural productivity. In addition, the agricultural productivity in 2001 is a good predictor for later years' agricultural productivity, but not a good predictor for non-agricultural income once the individual works in the non-agricultural sector.

6.1.2 Out-Migration Patterns

We then investigate whether the responsiveness to trade shocks was different across households with different initial productivity by using a split-sample regression. The baseline specification is as follows,

$$y_{h(v)t} = \delta_0 + \delta_1 \tau^{network}_{v(i)t} \times s_{v(i)} + \delta_2 \tau^{own}_{v(i)t} + \delta_3 \text{labor}_{h(v)t} + I_{pt} + I_h + \xi_{ht},$$

where $y_{h(v)t}$ represents the number of non-agricultural laborers of household h in village v and year t, and $\tau^{network}_{v(i)t} \times s_{v(i)}$ represents the tariff exposure through migrant network. We control the own prefecture's output tariff, the total number of labor in the household, province-year fixed effects, and household fixed effects.

Table 8 shows that unproductive farmers were more responsive to trade shocks. Column (1) uses the sample of households whose TFP in 2001 was below the median, i.e., the relatively unproductive farmers, and Column (2) uses the above median sample. We find that with a one-standard-deviation larger decline in the tariff exposure through migrant networks (0.59), the unproductive households had a 0.24 larger increase in the number of non-agricultural laborers (Column 1). In comparison, the productive households had a 0.17 larger increase. Columns (3) and (4) repeat the exercises by replacing the household fixed effects with the village fixed effects, and the results are similar.

In sum, we find evidence that unproductive agricultural households were more likely to move out of agriculture in response to trade shocks. Admittedly, our empirical evidence on negative selection is indirect since we do not have direct measures of a person's agriculture and non-agriculture productivity. An alternative way is to use a quantitative exercise to back out these two productivities. In Appendix D, we present such an exercise. We build a simple two-sector open-economy model with agricultural land market frictions. Using empirical moments combined with the model structure, we calibrate the correlation between agricultural and non-agricultural productivity. Consistent with our empirical evidence, we find a small positive correlation.[42]

[42]The quantitative exercise also serves another purpose. We build in an agricultural land market frictions to investigate the relative importance of the push factors driving out-migration (i.e., the reduction in land market frictions) versus the pull factors of out-migration (i.e., relative productivity growth in the two sectors). We do so since another strand of literature emphasizes the importance of land reform in facilitating agriculture modernization. In the context of China, Chari et al. (2020) shows that land reforms enacted after 2003 across different provinces led to an increase in agriculture productivity. In our empirical analysis, we take this into account by controlling for

6.2 Land Reallocation Between Households

The active land rental market could also affect the land distribution across households, potentially shifting land from unproductive households to productive households. This additional channel would affect village-level productivity through the reduction of land misallocation, both direct, and indirectly by affecting capital adoption.

First, we show that the land allocation efficiency increased in villages with bigger trade shocks by presenting the correlation between land and TFP. Intuitively, in an efficient allocation, productive households should work on larger farms.[43] In Figure 5, we split the villages into two groups using the size of the trade shock they experienced from 2001 to 2010. The 2001 to 2010 trade shock is defined as the difference between a village's tariff exposure through migrant networks in 2001 and 2010, i.e., $(\tau_{2010}^{network} - \tau_{2001}^{network}) \times s$, where s is the share of cross-prefecture migrant share. The shocks larger than the median magnitude (in absolute values) are defined as large shocks, and the shocks smaller than the median are defined as small shocks. Panel (a) shows the correlation between the log land and log TFP for households in the villages with small shocks. In 2001, the slope was –0.10, indicating that households that had larger productivity worked on smaller land (the squares and the solid lines). The slope became 0.10 in 2010, which suggests an improvement in land allocation efficiency (the crosses and the dashed lines). However, the increase was bigger for villages that experienced an above-median trade shock: the slope was –0.24 in 2001 and increased to 0.19 in 2010 (Panel b).[44]

Formally, we further investigate the differential impacts of the tariff exposure through migrant networks on households with different agricultural productivity in 2001, using the following baseline specification,

$$\log(land)_{h(v)t} = \alpha_0 + \alpha_1 \log(TFP)_{h(v)2001} + \alpha_2 \tau_{v(i)t}^{network} + \alpha_3 \log(TFP)_{h(v)2001} \times \tau_{v(i)t}^{network} + \alpha_4 \tau_{v(i)t}^{own} + I_{pt} + I_v + \epsilon_{h(v)t},$$

where the log land for household h in village v and year t is regressed on the households' initial productivity, $\log(TFP)_{h(v)2001}$, tariff exposure through migrant network, $\tau_{v(i)t}^{network}$, and the interaction of the two. We control for a village's own tariff, province-year fixed effects, and village fixed effects. By controlling for the village fixed effects, we are essentially comparing households within a village and identifying the land allocation effect within villages rather than across villages. The

province-year fixed effects. Here, using the quantitative exercise, we find that the pull factors had a larger impact on structural transformation than the push factor. Note that although the model does not have trade liberalization directly, the trade shock used in the empirical regressions enters into the non-agriculture productivity growth, since the reduction in tariff faced by exporters can be understood as a productivity shock.

[43] We show the formal proof in Appendix D. This positive correlation is also shown in, e.g., Adamopoulos et al. (2022).

[44] Corresponding bin scatter plots are shown in Appendix Figure C4.

parameter of interest is α_3, with a negative value indicating that a household with a relatively large TFP in 2001 gained more land than a household with a relatively small TFP in the same village, and the gap in the land increase was larger in villages with larger declines in tariff exposure through migrant networks.

Table 9 shows the household-level land allocation effect. We find that the shift of land from unproductive farmers to productive farms was stronger in villages that experienced larger shocks. The coefficient estimate of α_3 is –0.061 and is statistically significant at the 1% level. To interpret the coefficient, let us compare two households (A and B) in the same village. Household B had a one-standard deviation larger log TFP in 2001 than household A. Holding the trade exposure constant, household B had 18% larger land during the 2001–2010 period than household A. In villages with a one-standard-deviation larger tariff decline in destination prefectures, household B had 21% larger land than household A. In other words, villages that experienced larger shocks of the non-agricultural sector allocated land more toward the initially productive households. Results are similar in Column (2) where we control for household fixed effects instead of village effects, and in Columns (3) and (4) where we use the measure for tariff exposure through migrant networks by taking into account the share of cross-prefecture migrants. Overall, villages with a one-standard-deviation larger tariff decline through migrant network had a 20% larger elasticity of land to TFP at the household level.[45]

7 Conclusion

In this paper, we study how manufacturing growth can generate structural transformation. Beginning its journey as a developing country with more than half of the population in agriculture, China experienced fast growth in the manufacturing sector and substantial urbanization after 2001. China's accession to the WTO provides a unique context to study the structural change stemming from manufacturing growth. Using destination prefectures' trade shocks in the manufacturing sector resulting from China's accession to the WTO and the origin village's initial migration network, we construct the exposure to manufacturing trade shocks through migrant connections for 295 villages from 2001 to 2010. Our findings indicate that villages with greater exposures experience increased out-migration, elevated land rental rates, and more significant growth in agricultural productivity. Productivity gains resulted from migrant selection and the allocation of land towards more productive farmers within a village. In addition, these villages modernized their production by adopting more agricultural machinery.

As China advanced up the global value chain, it reallocated numerous labor-intensive manufac-

[45] The 2001 household TFP is highly correlated with TFP in later years. Appendix C.9.2 uses the current TFP instead of the initial TFP, and the results are very similar.

turing jobs to other developing countries, such as Vietnam, the Philippines, and Indonesia, it is likely that the manufacturing growth in those countries can similarly accelerate the development process in the agriculture sector. In this light, international trade could generate welfare gains in the developing world by acting as a catalyst for economic modernization. Studies of these alternative contexts with similar forces are left to future research.

The shift of employment from rural to urban areas can provide additional engines for economic growth, if human capital accumulation is faster in the urban areas, as hypothesized in Lucas (2004). Through learning by doing in urban jobs and access to urban amenities, workers can acquire useful skills that can generate gains in lifetime earnings. Such skill acquisition contributes to a broader enhancement of labor productivity across the economy. This important issue presents numerous opportunities for in-depth exploration in future research endeavors.

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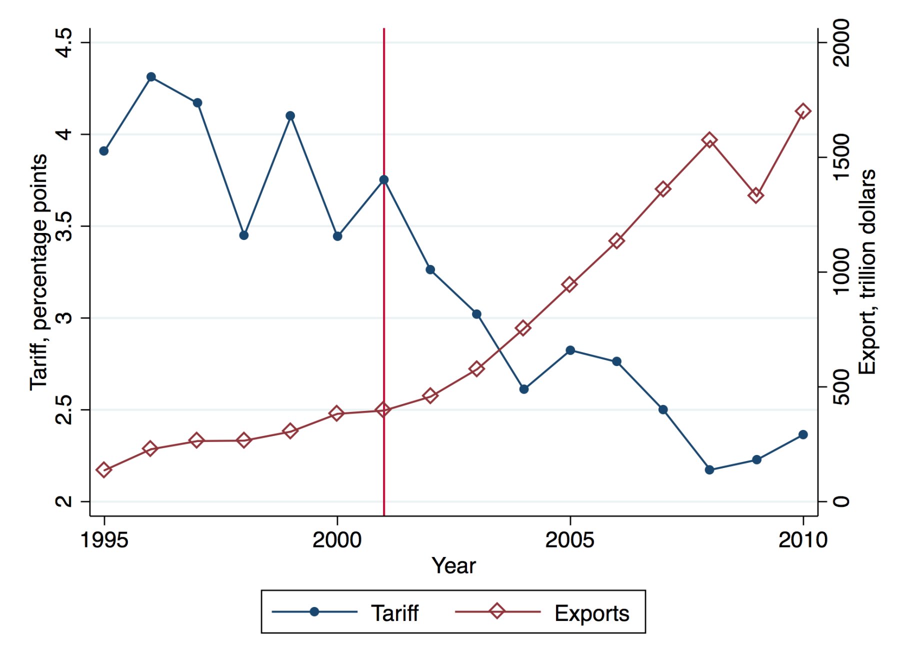
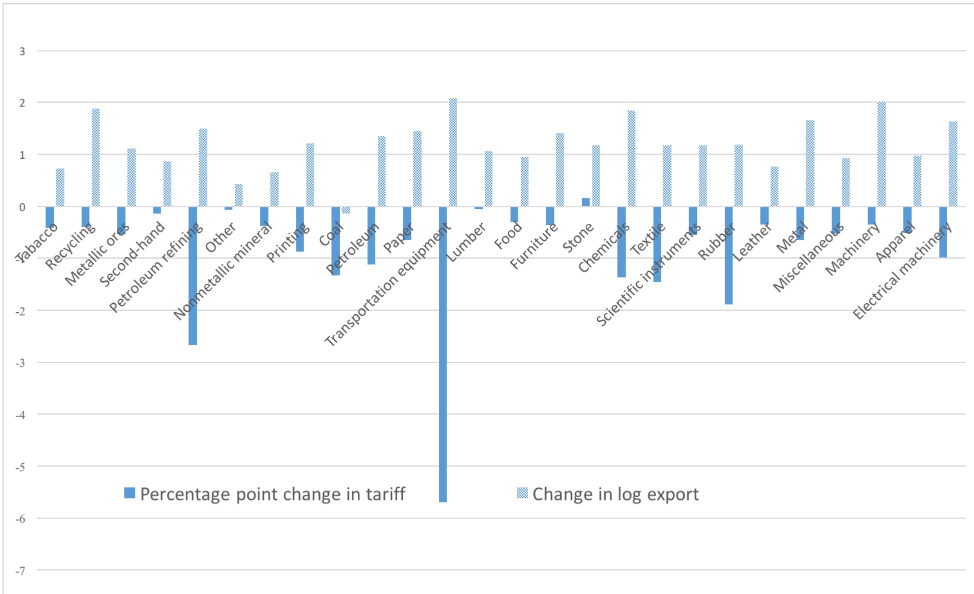
Figures and Tables

Figure 1: Trends in manufacturing trade, export value and tariffs on exports



Note: This graph shows the trends of Chinese exports and tariffs on Chinese exports in the manufacturing sector, using the data from the World Bank TRAINS dataset. The solid dots are the weighted average of industry-level tariffs on Chinese exports in a year, using export values as weights. The diamonds are the total value of Chinese exports in a year. Industry-level tariffs are calculated as the weighted average of tariffs on Chinese exports imposed by importing countries, using the 2001 import values as weights.

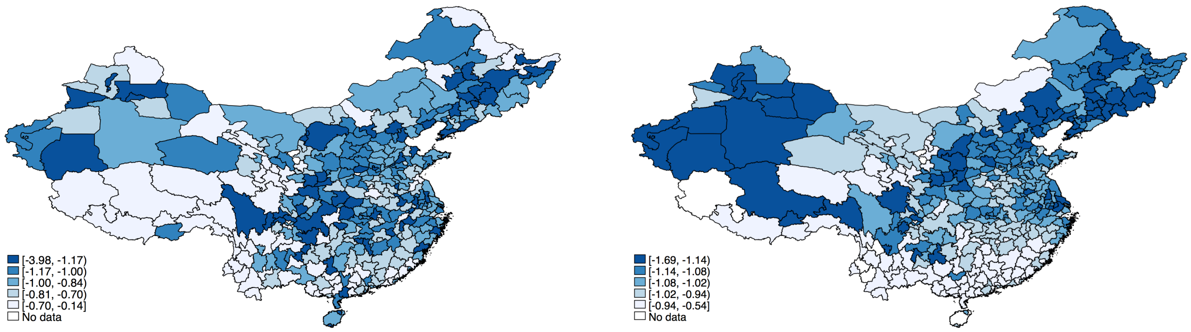
Figure 2: Variation in reductions in tariffs on exports and export growth by industry, using 2001–2010 as an example



Note: This graph uses the data from the World Bank TRAINS dataset. The shaded light-color bars are the change in the log export from 2001 to 2010, and the dark color bars are the percentage point changes in tariff from 2001 to 2010. The industries are at the 2-digit SIC code level, sorted horizontally by the size of exports in 2001.

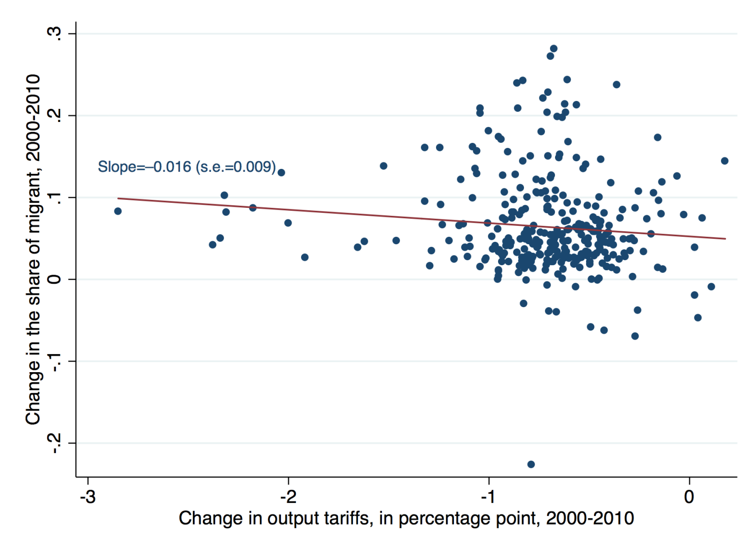
Figure 3: Geographic distribution of prefecture-level changes in tariffs on exports and changes in tariffs through migrant networks, 2001–2010

(a) Own prefecture's tariffs on exports (b) Tariff exposure through migrant networks



Note: This graph shows the geographical distribution of trade shocks from 2001 to 2010, using the industry-level tariff reductions, the prefecture-level industrial compositions, and the prefecture-to-prefecture migration networks. Each polygon is a prefecture. Panel (a) shows the change in a prefecture's own tariff on Chinese exports from 2001 to 2010 ($\tau_{2010}^{own} - \tau_{2001}^{own}$), and Panel (b) show the change in exposure to tariff through migrant networks ($\tau_{2010}^{other} - \tau_{2001}^{other}$). Darker colors mean larger tariff reductions. In Panel (a), one prefecture (Jiyuan Prefecture in Henan Province) is missing because the prefecture is directly administered by the provincial government, and does not have corresponding information in the industrial survey. In Panel (b), there are 5 other prefectures missing (autonomous regions in Hainan Province, Baoshan, Lijiang, and Lincang in Yunnan Province, and Ngari in Tibet Province) because the 0.095% sample does not have their cross-prefecture migration information.

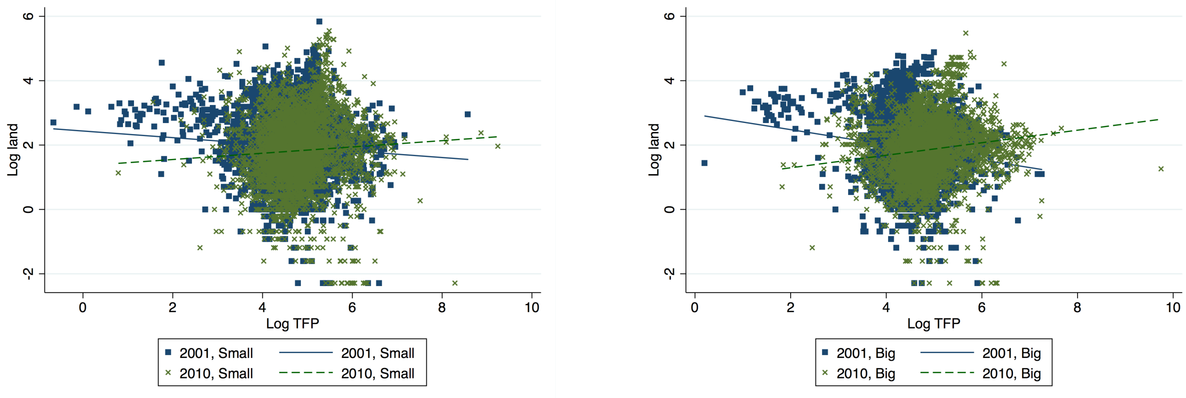
Figure 4: The relationship between prefecture-level trade exposure in the manufacturing sector and changes in the share of migrants, 2000–2010



Note: This figure shows the relationship between the declines in output tariffs and the changes in the share of migrants from 2000 to 2010, from a migrant destination's perspective. Each dot is a prefecture. The horizontal axis shows the percentage point change in output tariffs in the manufacturing sector in a prefecture ($\tau_{i2010} - \tau_{i2000}$), and the vertical axis shows the change in the share of migrants. The pattern is robust to using binned scatter plots and dropping outliers on the left, see Appendix C.2.1.

Figure 5: The correlation between land and TFP at the household-level, in villages with larger versus smaller shocks, 2001–2010

(a) Villages with small shocks, 2001 and 2010 (b) Villages with big shocks, 2001 and 2010



Note: This figure shows the correlation between land and TFP across households within villages. Each dot is a household-year observation. The squares represent households in 2001 (with the solid line as the linear fitted line), and the crosses represent the households in 2010 (with the dashed line as the linear fitted line). Panel (a) shows the households in villages that experienced small trade shocks from 2001 to 2010. There are 5,411 households in 2001, and 4,033 households in 2010. Panel (b) shows the households in villages that experienced large trade shocks from 2001 to 2010. There are 4,994 households in 2001, and 4,216 households in 2010. The 2001 to 2010 trade shock is defined as the change in a village's tariff exposure through migrant networks from 2001 to 2010$(\tau_{2010}^{other} - \tau_{2001}^{other})$ interacted with the share of cross-prefecture migrants (s); the shocks above the median magnitude (in absolute values) are defined as large shocks, and the shocks below the median are defined as small shocks.

Table 1: Data sources of occupation and migration-related variables

Source	Questionnaire	Information	Variable
NFP (1995–2010)	Household	# of laborers with occupation as wage earner	% non-agricultural laborers
	Village	# of laborers outside the village	
		within county	
		within province, between county	
		between province	
Pop Census 2000	Individual	Residence prefecture in 2000	Prefecture-to-prefecture migr network
		Residence prefecture in 1995	# of cross-pref migrants
		Registration place of Hukou	
		Other county, same prefecture	# of within-pref migrants

Note: This table summarizes the data sources for occupation and migration-related variables. The first panel shows the information from the NFP Survey from 1995 to 2010. The household questionnaire records how many household members are working as wage earners. This information is aggregated at the village level to construct the share of non-agricultural labor. The village questionnaire has the number of laborers working outside the village. The second panel shows the information from the 2000 population census. The prefecture-to-prefecture migration network is measured using the current (2000) residence prefecture and the past (1995) residence prefecture. Accordingly, we calculate the number of people who moved across prefectures from 1995 to 2000. We compute the number of within-prefecture migrants as the total number of people whose registration place of Hukou in 2000 is the same as the current residence prefecture but in different counties.

Table 2: The impact of tariffs on exports through migrant networks on occupation choices (2001–2010), village level, and tests for pre-trends

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2001–2010	Outcome: share of non-agricultural laborers					
Tariff exposure through migrant network	-0.08***	-0.06***	-0.06**	-0.04*	-0.16***	-0.16***
(2001-2010)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Tariff exposure through migrant network				-0.04		
× % cross-prefecture migration				(0.04)		
Log(land/labor) 2001 × Tariff through migr.					0.05***	
					(0.01)	
2nd land/labor quintile 2001× Tariff through migr.						0.03
						(0.02)
3rd land/labor quintile 2001 × Tariff through migr.						0.03
						(0.02)
4th land/labor quintile 2001 × Tariff through migr.						0.07**
						(0.03)
5th land/labor quintile 2001 × Tariff through migr.						0.10**
						(0.03)
Own prefecture tariff		0.02*	0.02*	0.02	0.03***	0.03***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Village-Year Specific Controls	No	No	Yes	Yes	Yes	Yes
Observations	2,333	2,333	2,333	2,333	1,971	1,971
R-squared	0.85	0.85	0.85	0.85	0.85	0.85
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: 1995–2001	Outcome: share of non-agricultural laborers					
Tariff exposure through migrant network	0.09	0.09	0.09	0.09	0.12	0.13
(2004-2010)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Observations	1,150	1,150	1,150	1,150	1,117	1,117

Note: This table shows the impact of tariff exposure through migrant networks on the occupation choice of residents of a village. All columns control for province-year fixed effects and village fixed effects. In Panel A, the outcome variable is from 2001 to 2010. Column (1) regresses the non-agricultural labor share on tariff exposure through migrant connections. Column (2) adds the own prefecture's tariff on exports. Column (3) adds controls, including the log labor, the log number of households, and the log government transfer +1. Column (4) adds the interaction between tariff exposure through migrant networks and the share of cross-prefecture migrants. Column (5) replaces the interaction term in Column (4) with the interaction between tariff exposure through migrant networks and the 2001 log land-to-labor ratio in agriculture. Column (6) replaces the interaction term in Column (4) with the interaction between tariff exposure through migrant networks and quintiles of the 2001 land-to-labor ratio. The mean (s.d.) of the share of non-agricultural labor is 0.18 (0.14), the mean (s.d.) of the log of land per agricultural worker in 2001 is 1.19 (0.67), and the mean (s.d.) of tariff exposure through migrant networks is 3.07 (0.44). Panel B has the same specification as Panel A, and the difference is that the outcome variable is from 1995 to 2001, and the regressors are from 2004 to 2010. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: The correlation between land-labor ratio and village characteristics, village-level cross-section in 2001

	(1)	(2)	(3)
	% of land leased	Log(land leased+1)	
		Stock	Flow
Log(land/agr labor)	0.04**	1.06***	0.91***
	(0.01)	(0.25)	(0.24)
	(4)	(5)	(6)
	Ruggedness	% non-agr labor	Allocation efficiency
Log(land/agr labor)	-37.39**	0.04*	0.23***
	(16.66)	(0.02)	(0.07)

Note: This table presents the correlation between the land-to-land ratio and village characteristics in 2001. All columns control for province fixed effects. Each column (1–6) represents a separate regression of a characteristic of a village in 2001 on the log land-to-labor ratio in 2001. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: The impact of tariff exposure through migrant networks on land rental outcomes(2001–2010), village level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(land leased+1)				Log(land lease income+1)		Log(# of hhs>1/3 ha)	
	Stock		Flow					
Tariff exposure through migr. network	-0.60***	-0.10	-1.73***	-1.10**	-3.04**	-2.37**	0.15	0.42*
	(0.15)	(0.32)	(0.46)	(0.41)	(1.03)	(0.92)	(0.16)	(0.22)
Tariff exposure through migr. network		-1.40**		-1.78**		-1.87		-0.73**
× % cross-prefecture migration		(0.54)		(0.62)		(1.97)		(0.25)
Own prefecture tariff	-0.09*	-0.14***	0.10***	0.04	-0.27	-0.34	0.01	-0.02
	(0.05)	(0.04)	(0.02)	(0.05)	(0.50)	(0.49)	(0.04)	(0.04)
Observations	2,333	2,333	2,333	2,333	2,333	2,333	2,333	2,333
R-squared	0.83	0.84	0.69	0.70	0.67	0.67	0.95	0.95

Note: This table shows the impact of tariff exposure through migrant networks on the land rental market of a village. All columns control for own prefecture's tariff on exports, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3)(5) and (7) have the same specification as Table 2 Column (3), and Columns (2)(4)(6) and (8) have the same specification as Table 2 Column (4). The mean (s.d.) of the log stock of land leased is 3.03 (1.63), the mean (s.d.) of the log flow of land leased is 1.88 (1.63), the mean (s.d.) of the log income from land leasing is 6.14 (4.17), the mean (s.d.) of the log number of households with relatively large land is 2.95 (1.18). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The impact of tariff exposure through migrant networks on agricultural machinery adoption(2001–2010), village level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Log(agr machine)		Log(# of hhs with positive ag machine & land larger than 1/3 hectare)				Log(wage of hired labor)	
Tariff exposure through migr. network	-0.07	0.34	-0.23	0.18	0.03	0.46	0.16	0.37
	(0.76)	(0.79)	(0.38)	(0.37)	(0.44)	(0.33)	(0.35)	(0.38)
Tariff exposure through migr. network × % cross-prefecture migration		-1.15**		-1.23***		-1.39**		-0.64
		(0.47)		(0.35)		(0.46)		(0.39)
Own prefecture tariff	0.03	-0.01	-0.08	-0.12*	-0.05	-0.10*	0.00	-0.01
	(0.06)	(0.08)	(0.05)	(0.07)	(0.04)	(0.05)	(0.06)	(0.06)
Log(# of hhs with ag machine> 0 & lan<1/3 ha)					0.07	0.07		
					(0.06)	(0.06)		
Observations	2,333	2,333	2,181	2,181	1,413	1,413	1,742	1,742
R-squared	0.87	0.87	0.88	0.88	0.91	0.91	0.67	0.68

Note: This table shows the impact of tariff exposure through migrant network on the capital market of a village. All columns control for own prefecture's tariff on exports, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3)(5) and (7) have the same specification as Table 2 Column (3), and Columns (2)(4)(6) and (8) have the same specification as Table 2 Column (4). The mean (s.d.) of the log agricultural machinery is 10.18 (1.69), the mean (s.d.) of the log number of households with positive value of agricultural machinery and have relatively large land is 2.00 (1.20), and and the mean (s.d.) of the log wage for hired labor is 3.26 (0.75). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The impact of tariff exposure through migrant networks on agricultural productivity (2001–2010), village level

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(village TFP)				Allocation efficiency	
	output weighted		unweighted			
Tariff exposure through migr. network	-0.69***	-0.45**	0.04	0.09	-0.74***	-0.54**
	(0.05)	(0.14)	(0.22)	(0.23)	(0.06)	(0.17)
Tariff exposure through migr. network		-0.69		-0.13		-0.55
× % cross-prefecture migration		(0.59)		(0.08)		(0.55)
Own prefecture tariff	0.01	-0.02	0.00	-0.00	0.00	-0.01
	(0.09)	(0.08)	(0.03)	(0.03)	(0.06)	(0.06)
Observations	2,333	2,333	2,333	2,333	2,333	2,333
R-squared	0.65	0.65	0.84	0.84	0.58	0.58

Note: This table shows the impact of tariff exposure through migrant networks on the village-level productivity and allocation efficiency of a village. All columns control for own prefecture's tariff on exports, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3) and (5) have the same specification as Table 2 Column (3), and Columns (2)(4) and (6) have the same specification as Table 2 Column (4). The mean (s.d.) of the log weighted TFP is 4.52 (0.90), the mean (s.d.) of the log unweighted TFP is 4.75 (0.51), and the mean (s.d.) of allocation efficiency is -0.23 (0.82). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Characteristics of productive farmers and productive non-agricultural workers (2003–2008), individual level

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(TFP) in agriculture			Log (income) from working outside village		
Education	0.035***	0.005***		0.056***	0.039***	
	(0.005)	(0.001)		(0.004)	(0.002)	
Non-agricultural training (=1)	-0.080***	-0.016		0.390***	0.303***	
	(0.026)	(0.013)		(0.020)	(0.016)	
Agricultural training (=1)	0.160***	0.011		-0.155***	-0.044*	
	(0.048)	(0.017)		(0.034)	(0.024)	
Age	0.002**	-0.000**		-0.001	-0.003***	
	(0.001)	(0.000)		(0.001)	(0.001)	
Log (TFP), 2001			0.177***			-0.008
			(0.013)			(0.018)
Village FE	No	Yes	Yes	No	Yes	Yes
Observations	127,029	127,029	165,515	85,104	85,104	63,000
R-squared	0.034	0.556	0.567	0.108	0.310	0.279

Note: This table shows the characteristics of individuals that are correlated with their households' agricultural TFP and their income when they work in non-agriculture. We include individuals who are not currently in school and are aged 16 to 75. All columns control for year fixed effects and the log number of labor in the household. The outcome variable in Columns (1)–(3) is the log TFP, and the outcome variable in Columns (4)–(6) is the log income from working outside the village. Columns (1) and (4) do not include village fixed effects, and Columns (2)(3)(5) and (6) include village fixed effects. The mean (s.d.) of the log TFP is 4.77 (0.64) and the mean (s.d.) of the log income from working outside the village is 8.50 (0.95). The mean (s.d.) of age is 41 (15), the mean (s.d.) of education is 6.90 (2.29), the mean (s.d.) of the share of individuals with occupational training is 0.08 (0.27), and the mean (s.d.) of the share of individuals with agricultural training is 0.07 (0.25). Standard errors are clustered at the village-year level and at the household level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: The impact of tariff exposure through migrant networks on occupation choices (2001–2010), household level

	(1)	(2)	(3)	(4)
	TFP in 2001			
Y: Number of non-agricultural laborers	<Median	≥Median	<Median	≥Median
Tariff exposure through migr. network	-0.40**	-0.28	-0.38**	-0.23
× % cross-prefecture migration	(0.13)	(0.17)	(0.13)	(0.18)
Own prefecture tariff	0.02	0.05	0.02	0.06
	(0.04)	(0.05)	(0.04)	(0.05)
Number of laborers	0.23***	0.23***	0.25***	0.25***
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	55,715	53,904	56,050	54,192
R-squared	0.65	0.63	0.37	0.35
HH FE	Yes	Yes		
Village FE			Yes	Yes

Note: This table shows the responsiveness of households to trade shocks. All columns control for province-year fixed effects. Column (1) regresses the number of non-agricultural labor on the interaction of tariff exposure through migrant networks and the share of cross-prefecture migrants, own prefecture's tariff on exports, and total number of labor. Column (1) controls for household fixed effects, and uses only the households with TFP in 2001 above the median. Column (2) uses the households with TFP in 2001 below the median instead. Columns (3) and (4) replicate Columns (1) and (2), replacing the household fixed effects with village fixed effects. The mean (s.d.) of tariff exposure through migrant network × the share of cross-pref migrants is 1.41 (0.59), the mean (s.d.) of the number of non-agricultural laborers is 0.51 (0.87), and the mean (s.d.) of the number of laborers is 2.70 (1.29). Standard errors are clustered at the village and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: The impact of tariff exposure through migrant network on land allocation (2001–2010), household level

Y: log(land) in year t	(1)	(2)	(3)	(4)
Initial TFP (log TFP in 2001)	0.281***		0.201***	
	(0.039)		(0.041)	
Tariff exposure through migr. network	0.185	0.155		
	(0.157)	(0.169)		
Tariff exposure through migr. network ×Initial TFP	-0.061***	-0.054***		
	(0.013)	(0.015)		
Tariff exposure through migr. network*%cross-pref. migr			0.097	0.422**
			(0.166)	(0.171)
Tariff exposure through migr. network*%cross-pref. migr			-0.079**	-0.152***
× Initial TFP			(0.028)	(0.038)
Own prefecture tariff	-0.033	-0.032	-0.046	-0.044
	(0.043)	(0.040)	(0.042)	(0.040)
Observations	103,027	102,262	103,027	102,262
R-squared	0.631	0.871	0.631	0.871
Province-Year FE	Yes	Yes	Yes	Yes
Village FE	Yes		Yes	
HH FE		Yes		Yes

Note: This table shows the land allocation across households within a village, in response to trade shocks. Column (1) regresses the log land size of households in year t on the household's TFP in 2001, tariff exposure through migrant networks, and the interaction of the two. We control for own prefecture's tariff on exports, province-year fixed effects, and village fixed effects. Column (2) has the same specification, except that we replace village fixed effects with household fixed effects. Columns (3) and (4) replicate Columns (1) and (2), replacing tariff exposure through migrant networks with the interaction of tariff exposure through migrant networks and the share of cross-prefecture migrants. The mean (s.d.) of the log land is 1.78 (0.99). The mean (s.d.) of the log TFP in 2001 is 4.62 (0.64), the mean (s.d.) of the log TFP is 4.72 (0.65), the mean (s.d.) of tariffs on exports through migrant network is 3.07 (0.45), and the mean (s.d.) of the product of tariff exposure through migrant network and the share of cross-prefecture migrants is 1.41 (0.59). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendices

(Not for publication)

A Appendix on Institutional Contexts

A.1 Rural Land Market Regulations

National Laws and Regulations Pertaining Rural Land The first set of laws on land management is at the national level, regarding land in both rural and urban areas.

The *Land Administration Law of the People's Republic of China* was first enacted on January 1, 1987, and was modified in 1988, 1998, and 2004. The 1988 modification legalized the transfer of land use rights. The 1998 modification emphasized forbidding the change of land use type, especially from agricultural land to construction land. Another important change was specifying that "within the term of land contractual operation if the land contracted by individual contractor needs to be adjusted, it must be approved by more than two-thirds of the members of the village meeting or more than two-thirds of the village representatives, and reported to the township (town) government and the county-level agricultural administrative department." The same procedure applies when units or individuals outside the village collective want to contract the farmland. The 2004 modification said that when the government expropriates land for the benefit of public interest, compensations need to be provided correspondingly.

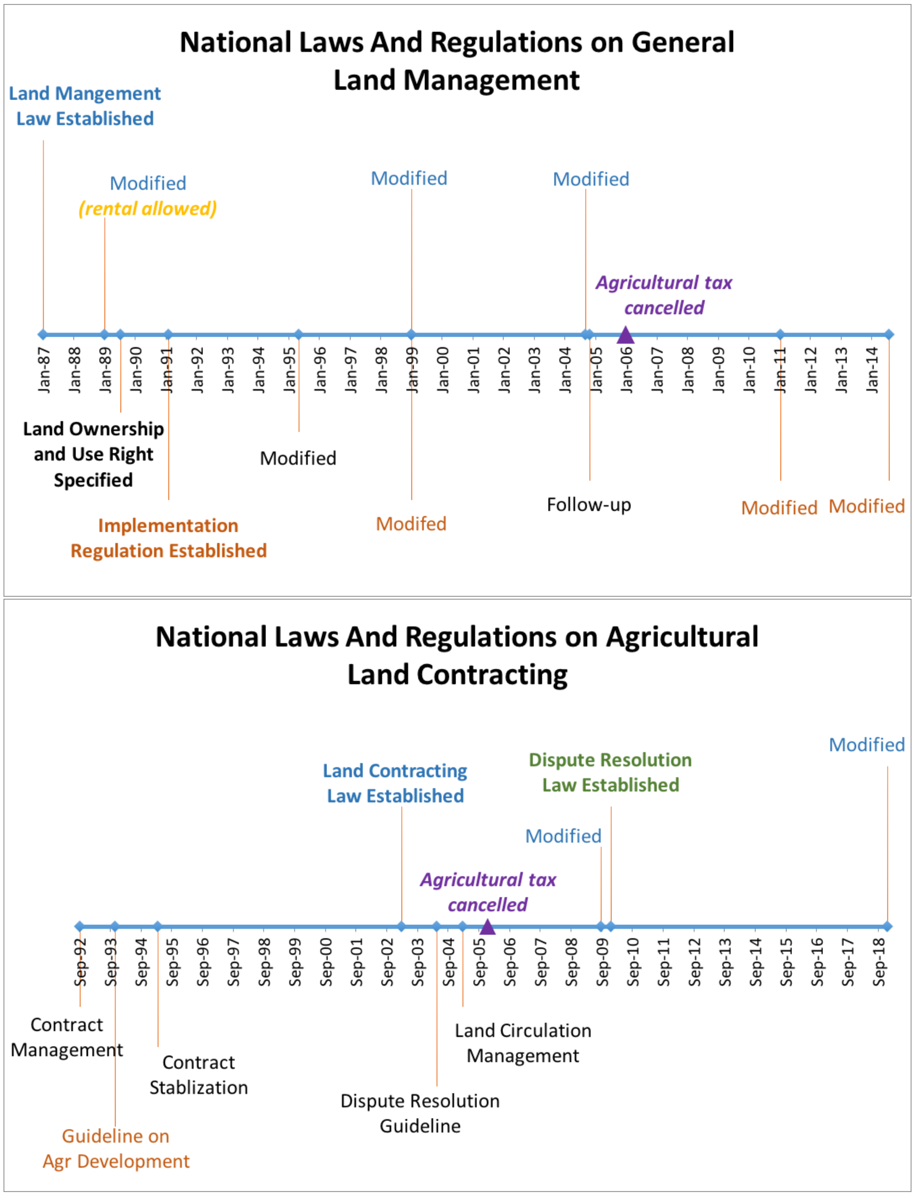
The Land Administration Law has corresponding implementation regulations for details of implementation and interpretation. The first implementation regulation was enacted on February 1, 1991. More details were added in the 1998 modification, and minor changes were made in the 2011 and 2014 modifications. The implementation regulations were supplemented by several other regulations regarding practical issues in land ownership and use rights, in 1989, 1995, and 2004.

The second set of laws and regulations is specific to rural land, especially farmland. The *Law of the People's Republic of China on the Contracting of Rural Land* was enacted on March 1, 2003. It formalized the legal rights of the contractors and the contract issuing party, the principle and procedure of contracting, terms of contracts, the protection of user rights of the contracted land, the protection of the transfer of use rights, and dispute resolution method and legal responsibilities. Importantly, on the issue of out-migration, during the contract period, if the contractor (i.e. the rural household) moves to townships, the land use right remains, and the land can be rented to other households. If the contractor moves to cities and obtains urban Hukou, then the contract terminates, and land is given back to the contract issuing party.

Before that, several regulatory documents addressed some of these aspects, but with fewer details. The 1992 regulation on contract management mentioned that out of thirty-one provinces, seven provinces established local laws on contracting, while seventeen provinces issued related regulations. The 1993 regulation initiated the grain market reform, where the price of grain purchased by the government will be the same as the market price, and at the same time, the government provides a price floor. The 1995 regulation can be seen as the precursor of the 2003 law. There are several important points made: (1) Land contracts should be extended by another 30 years once the term ends; (2) The government encourages long-term contract relations between the village commune and farmers, with the principle that contract land sizes do not respond to changes in the household size; (3) In the case of substantial population changes or land occupation, adjustments at the village level should be agreed by the majority of villagers, and approved by the county government; (4) Land use right transfers are part of contract management, and transfers should have written contracts.

After the 2003 law was enacted, a 2005 notice on land circulation management specified addi-

Figure A.1: Land laws and regulations after the establishment of HCRS



Note: These figures show the timing of the enactment of laws and regulations at the national level on land-related issues, after the establishment of the HCRS. The top graph shows the laws and regulations on general land management, including both urban and rural land. The bottom graph shows the laws and regulations targeted at agricultural land contracting. The ones shown above the timeline are laws, and the ones below the timeline are regulations.

tional execution issues. Minor modifications were made in 2009 and 2018.

Related, the *Law of the People's Republic of China on the Mediation and Arbitration of Rural Land Contract Disputes* was enacted on January 1, 2010. It formalized the procedure of mediation and arbitration and noted that the costs of such dispute resolution are covered by and included in the government budget. This 2010 law was built on the guideline on dispute resolution issued in 2004.

Regional Laws and Regulations Over time, different provinces enacted their own land regulations, within the framework specified by the national government. Chari et al. (2020) use the staggered land reforms carried out by provincial governments after 2003 to investigate the impact of property rights protection on land misallocation and agricultural productivity. In our paper, we control for these province-level policy changes using province-by-year fixed effects.

A.2 Administrative Units in China

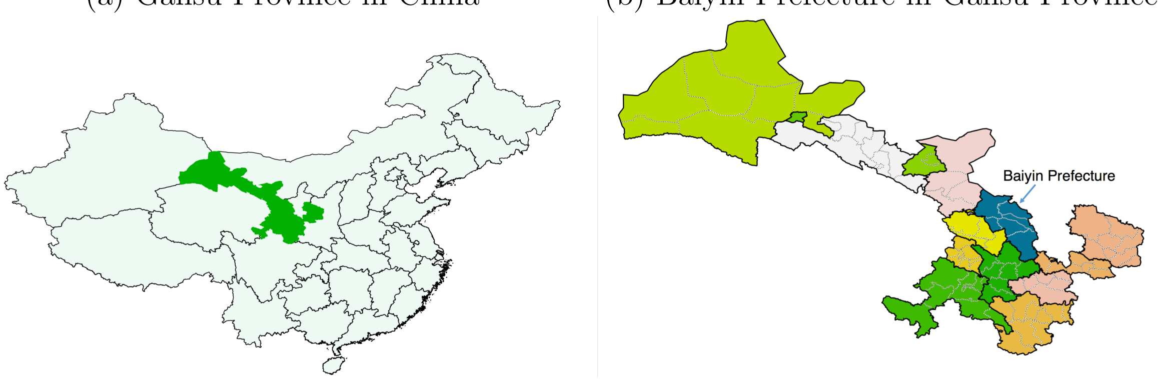
Table A.1: Levels of administrative units, 2000

Level	Number
Province	31
Prefecture	333
County	2,861
Village (1996)	748,340

Note: This table shows the hierarchy of Chinese administrative units. The units ranging from the largest to the smallest are province, prefecture, county, and village. The number of provinces, prefectures, and counties are available in all sample years from the National Bureau of Statistics of China, `data.stats.gov.cn`. The number of villages is available in 1996 only through the First Agricultural Census, `http://www.stats.gov.cn/tjsj/pcsj/nypc/dycnypc/200308/t20030826_39912.html`.

Figure A.2: Example of Baiyin Prefecture in Gansu Province in China

(a) Gansu Province in China (b) Baiyin Prefecture in Gansu Province



Note: This figure shows the hierarchy of Chinese administrative units using Gansu province as an example. Panel (a) shows the location of Gansu Province in China, along with the other 30 provinces. Panel (b) show the location of Baiyin Prefecture in Gansu, along with the other 13 prefectures. The light color borders within the prefectures are county borders.

B Data Appendix

B.1 NFP Data

B.1.1 Sample Size and Coverage

We keep the villages with at least 20 households and at least 20 laborers in total. We also require that there is at least one household with land larger than 1/3 hectare and at least one household with agricultural machinery. Overall, in the 2001 to 2010 period, we have 295 villages, 2,333 village-year observations, and 148,327 household-year observations.

We find no evidence of selective attrition of households. We generate a dummy D_{hvt} that is equal to one if the household h is in a village(v)-year(t) sample, and zero otherwise, given that the village-year is in the sample, and the household is in at least one of the years between 2001 and 2010. Then we run the following regression:

$$D_{h(v)t} = \gamma_0 + \gamma_1 \tau_{v(i)t}^{network} + \gamma_2 \tau_{v(i)t}^{own} + I_{pt} + I_v + \epsilon_{hvt},$$

where $\tau_{v(i)t}^{own}$ and $\tau_{v(i)t}^{network}$ are village v's exposure to its own prefecture i's tariff and tariff exposure through migrant networks, respectively, I_{pt} are province-year fixed effects, and I_v are village fixed effects.

The regression result is shown in Table B1. There is no significant effect of either own prefecture's output tariff and tariff exposure through migrant networks. A joint test of $\gamma_1 = \gamma_2 = 0$ generates a F-statistics of 0.06, and a p-value of 0.94. Thus, we fail to reject that there is no selective attrition.

Table B1: Tariffs and household attrition

	(1) Dummy(=1 if the household is in the sample)
Tariff exposure through migrant connections	-0.55
	(1.57)
Own prefecture tariff	-0.36
	(1.16)
Constant	0.90***
	(0.08)
Observations	171,959
R-squared	0.18

Note: The table shows the regression results of sample attrition. The outcome variable is a dummy that is equal to one if a household shows up in a year, conditioning on the village shows up in the year, and the household ever shows up in the 2001–2010 sample. The regressors are the village's own prefecture's output tariff and tariff exposure through migrant networks. Province-year fixed effects and village fixed effects are controlled. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

B.1.2 Individual-Level Characteristics

Table B2: The industry distribution of people with agriculture/non-ag as occupation, using the 2003–2010 individual data

	(1)	(2)	(3)	(4)
	Agricultural labor		Non-ag laborer	
Industry	Freq	Percent	Freq	Percent
Agriculture	251,042	66%	2,732	3%
Industry	16,588	4%	38,397	39%
Construction	9,131	2%	15,119	15%
Transportation	9,923	3%	5,042	5%
Service	24,177	6%	17,833	18%
Other	66,831	18%	19,809	20%
Total	377,692		98,932	

Note: This table presents the distribution of industries for agricultural and non-agricultural laborers, using the information from individual questionnaires in the NFP Survey from 2003 to 2010.

Table B3: Cross tabulation of individuals with non-agricultural training and agricultural training (2003–2008)

		Agricultural training	
		No	Yes
Non-agricultural training	No	87%	5%
	Yes	6%	2%

Note: This table tabulates the status of individuals in terms of agricultural training and non-agricultural training, using the NFP Survey data on individuals from 2003 to 2008. We include individuals who are not currently in school and are aged 16 to 75. There are 256,184 observations in total.

B.1.3 Perpetual Inventory Method for Capital

Initial-year real capital. Keep the initial year y_o of each household to enter the dataset. Assume that capital is zero for all households in 1986 and that for all years between 1986 and y_o, the capital growth rate of each household is the same as the national annual growth rate of capital. With the annual price index of capital (setting the 1995 index as 1) and the capital book value in y_o, impute the real investment for years between 1986 and y_o. Then reconstruct the capital stock in these years taking into account depreciation, with a depreciation rate of 0.04.[46] The result is the real value of capital stock in y_o.

Subsequent-year real capital. If capital is missing (or zero) in year t, and not missing (or zero) in year $t-1$, then use the capital growth rate from t to $t-1$ to impute for year t. If capital is also

[46] This is the sample mean of the depreciation rate of all NFP households from 1995 to 2002. There is no such information from 2003 onward.

missing (or zero) in year $t-1$, use the $t-2$ for imputation. Then calculate the real investment. First, generate the nominal investment as the difference in nominal capital in years t and $t-1$. If the year $t-1$ capital is missing, use the closest non-missing year to calculate the annual difference. Second, deflate the nominal investment with the price index to generate real investment. Third, use the depreciation rate and nominal capital to generate nominal depreciation. Generate net nominal investment as the difference between nominal investment and nominal depreciation. Then use the price index to deflate the net nominal investment to generate net real investment. Fourth, use the y_o real capital and the net real investment to generate real capital series.

B.1.4 TFP Estimation

Our main TFP estimation specification is as follows,

$$\log(y_{hvt}) = \alpha \log(d_{hvt}) + \beta \log(k_{hvt}) + \gamma \log(l_{hvt}) + \delta \log(m_{hvt}) + I_h + I_{vt} + \epsilon_{hvt},$$

where y_{hvt} is the output value of crops. An alternative way is to the value-added as the outcome variable, defined as the difference between the output value and the intermediate input value ($y_{hvt} - m_{hvt}$), so

$$\log(V_{hvt}) = \alpha^V \log(d_{hvt}) + \beta^V \log(k_{hvt}) + \gamma^V \log(l_{hvt}) + I_h + I_{vt} + \epsilon^V_{hvt},$$

and again the TFP is measured as the residual

$$\hat{\phi}^V_{hvt} = \log(v_{hvt}) - \hat{\alpha}^V \log(d_{hvt}) - \hat{\beta}^V \log(k_{hvt}) - \hat{\gamma}^V \log(l_{hvt}).$$

The identification assumption of the TFP estimation is that the input choices are uncorrelated with the idiosyncratic productivity shocks ϵ_{hvt}. However, if the household has information on the shock and makes the input choices correspondingly, the estimation is biased. For example, if a household member has an adverse health shock, the household may choose to work on smaller land, supply less labor, and use less capital and intermediate goods. One solution is to use lagged input choices to instrument the current ones (Arellano and Bover 1995), and the identification assumption is that the lagged input choices are uncorrelated with the current period productivity shock. Another method is to follow Levinsohn and Petrin (2003) and use intermediate inputs as a proxy for productivity shocks.

Table B4 shows the results of various TFP estimation methods. Column (1) uses the output method, and the estimated output elasticity is 0.346 for land, 0.249 for labor, 0.018 for capital, and 0.271 for intermediate inputs. The labor and capital estimates are similar as in Chari et al. (2020) with by-crop quantity-based estimation, while the land estimate is smaller, closer to Chow (1993) and Cao and Birchenall (2013). The sum of the coefficients is 0.88, and the F-test rejects constant return to scale. Column (2) uses the value-added method, and the coefficients for labor, land, and capital are larger than in Column (1). Columns (3) and (4) use the output method, where Column (3) instruments all inputs with lagged values, and Column (4) instruments only labor and intermediate inputs, assuming that these two inputs are easily adjustable. The coefficients are similar to Column (1) for labor, smaller for capital, and larger for intermediate inputs.

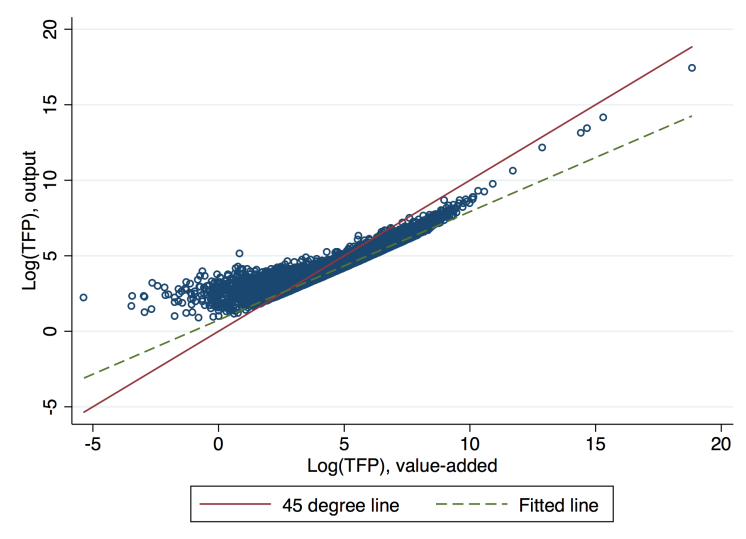
Table B4: TFP estimation, output method, and value-added method, 1995–2010

	(1)	(2)	(3)	(4)
	OLS		IV, log(output value)	
	Log(output value)	Log(value-added)	All inputs Lagged	Labor and intermediate lagged
Log(labor days in agriculture)	0.249***	0.343***	0.242***	0.261***
	(0.013)	(0.017)	(0.010)	(0.011)
Log(capital)	0.018***	0.024***	0.008***	0.010***
	(0.003)	(0.003)	(0.002)	(0.001)
Log(land)	0.346***	0.486***	0.248***	0.161***
	(0.014)	(0.017)	(0.010)	(0.007)
Log(intermediate input costs)	0.271***		0.466***	0.511***
	(0.014)		(0.012)	(0.012)
Observations	245,610	243,281	215,024	217,037
R-squared	0.892	0.846	0.385	0.371
Sum of the coefficients	.88	.85	.96	.94
CRS F-value	83.7	103.7	47.7	194.0
CRS p-value	0	0	0	0

Note: This table presents the results of TFP estimation using different methods. Column (1) uses the output method, where the log output value is regressed on the log land size, the log labor days, the log capital, and the log value of intermediate inputs. Column (2) uses the value-added method, where the log value-added (output value minus the input value) is regressed on the log land size, the log labor days, and the log capital. Column (3) uses the output method, and instruments all inputs with lagged values. Column (4) only instruments the log labor days in agriculture and the log intermediate input with lagged values. All columns control for village-year fixed effects and household fixed effects. Standard errors are clustered at the village and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Figure B1 shows the relationship between the TFP using the output method and the value-added method, both with OLS estimation. The relationship is quite linear, and the fitted line has a smaller slope compared to the 45-degree line. We use the output method in the main result in Section 5.1 Table 6, and the results are similar in Appendix C.6 where we use the value-added method.

Figure B1: The relationship between the TFP from the output method and value-added method, OLS



Note: This figure shows the correlation between the TFP calculated using the output method as in Table B4 Column (1) and the TFP calculated using the value-added method as in Table B4 Column (2). The solid line represents the 45-degree line, and the dashed line presents the linear fitted line.

The correlations between our main output method TFP and alternative measures are (1) 0.9741 when using all inputs instrumented, (2) 0.9566 when using two inputs instrumented, (3) 0.9723 when using Levinsohn and Petrin (2003) method, and (4) 0.9998 when using a balanced panel of households.

B.1.5 Aggregate Trends in the Agricultural Sector

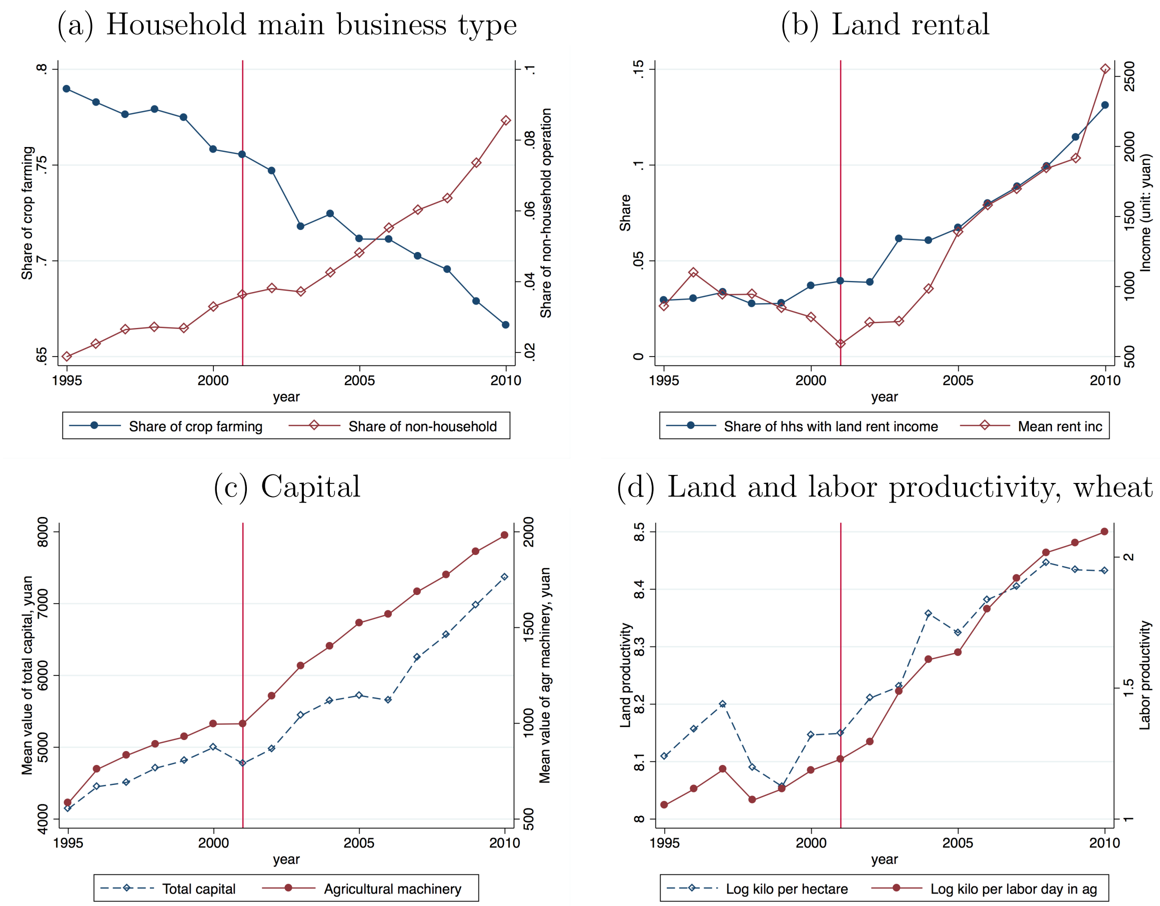
In this section, we present the trends of labor, land, and capital markets for the 1995–2010 period, with trend breaks around 2001. First, more and more households moved out of crop farming and started to work for wages (Figure B2 Panel a). The share of households whose main business was crop farming declined from 79% in 1995 to 75% in 2001 and further declined to 66% in 2010. This decline is mirrored by the increase in the share of households where the entire household worked in non-household business: while the 1995 to 2001 change was less than 2%, the share increased by 5% afterwards.[47]

The land rental market became active mostly after 2001 (Panel b). Less than 5% of households had income from land leasing between 1995 and 2001, and the number increased to 13% in 2010. The size of land-lease income also grew a lot in the post-2001 period, from 550 yuan per household to 2500 yuan in 2010.[48]

[47]Households can be either in the family-run business or in non-household business. Family-run business uses households as the unit of operation, relies entirely or mainly on household members' labor supply, utilizes family-owned or contracted factor inputs, directly organizes the production, does accounting independently, and bears their own gains or losses. There are eight categories for the family-run business: crop farming, forestry, husbandry, manufacturing, construction, transportation, and service.

[48]Appendix C.1 shows that household occupation choices were correlated with how much land they decided to

Figure B2: Trends in the agricultural sector



Note: This figure shows the trends of the agricultural sector, using information from the NFP household-level data. In Panel (a), the solid circles represent the share of households that are in crop farming in a year, and the hollow diamonds represent the share of households that are in non-household businesses. In Panel (b), the solid circles represent the share of households with land-rental income, and the hollow diamonds represent the mean income from land rental, conditioning on having a positive land-rental income. In Panel (c), the solid circles represent the mean value of agricultural machinery, and the hollow diamonds represent the mean value of total capital, both valued in 1995 yuan. In Panel (d), the solid circles represent the log kilo per labor day in agriculture for wheat, and the hollow diamonds represent the log kilo per hectare for wheat.

Alongside the outflow of labor and land rental activities, the amount of capital increased. The dotted line in Panel (c) shows that the average value of total capital stock for households in agriculture increased from 4.8 thousand yuan in 2001 to eight thousand yuan in 2010, with a much smaller change before 2001. Similarly, the value of agricultural machinery had an increase of one thousand yuan after 2001, while the before 2001 changes was less than 0.5 thousand yuan.[49]

The patterns of labor and land productivity growth in Panel (d) were consistent with the increased capital input. Land productivity is defined as the log kilos per hectare, and labor produc-

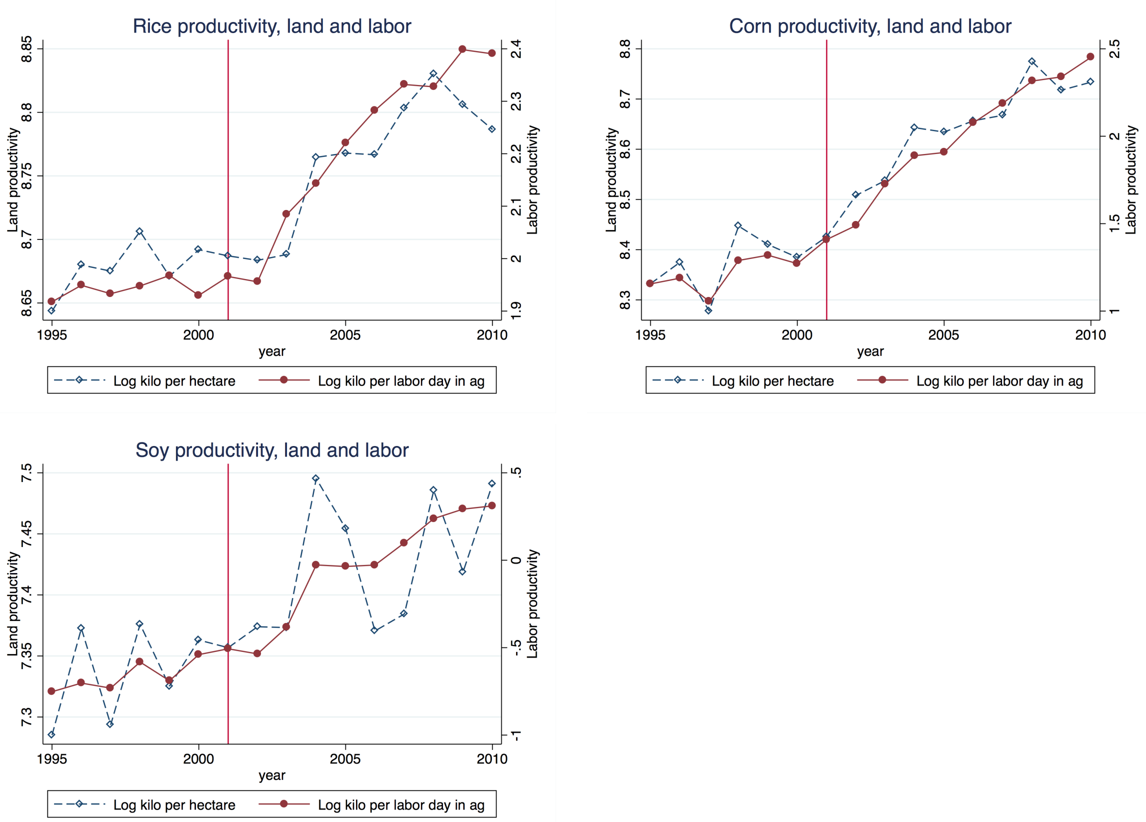
work on. In a household with three laborers, the probability of working on any land was six percentage points smaller when one more household member worked as a non-agricultural laborer; conditional on non-zero land in the agricultural operation, the land size was 25% smaller.

[49]Capital in all years are valued at 1995 yuan using the perpetual inventory method (see Appendix B.1.3 for details). There are eight types of capital in the survey: draft animals, hand farm tools valued at least 50 yuan, agricultural machinery, industrial machinery, transportation machinery, facilities, fixed infrastructure, and others.

tivity is the log kilo per labor day in agriculture. Take wheat as an example, land productivity remained relatively stable before 2001 and experienced a 0.3 log-point increase afterward, and the increase in labor productivity was 0.8 log-point after 2001. On average, a household had 0.5-hectare land in 2001 and 0.48 hectare in 2010. In comparison, a household had 1.8 agricultural laborers in 2001 and 1.3 in 2010. Given the outflow of labor and relatively stable total agricultural land, it is reasonable for labor productivity to increase more than land productivity. Figure B3 shows that the trends were similar for rice, corn, and soybean.

Overall, we find that the agricultural sector experienced an outflow of labor, increased land rental activities, more capital adoption, and higher land and labor productivity through 1995–2010 period, and the change was accelerated after 2001.

Figure B3: Land and labor productivity for rice, corn, and soybean



Note: This figure shows the trends of land productivity and labor productivity for rice, corn, and soybean, using the NFP Survey data. Each dot is a household-year average for households growing the crop. Land productivity is defined as the log output in kilos per hectare and is shown in dashed lines with hollow diamonds. Labor productivity is defined as the log output in kilos per labor day in agriculture and is shown in solid lines with solid circles.

B.1.6 Summary of Statistics of Key Variables

Table B5: Summary of statistics of key variables

VARIABLES	N	mean	sd	min	max
Log(land)	2,333	5.82	0.89	2.30	9.12
Log(land leased+1), stock	2,333	3.03	1.63	0.00	8.54
Log(land leased+1), flow	2,333	1.88	1.63	0.00	8.53
Log(income from land leasing+1)	2,333	6.14	4.18	0.00	14.54
Log(land p.c.)	2,333	1.35	0.71	-1.91	5.18
Log(# of households with land >1/3 ha)	2,333	2.96	1.18	0.00	4.92
% non-agricultural laborer	2,333	0.18	0.14	0.00	0.87
Log(# laborer)	2,333	5.08	0.38	3.22	6.35
Log(# of households)	2,333	4.09	0.36	3.00	5.30
Log(gov transf+1)	2,333	9.18	2.04	0.00	13.60
Log(labor days), hired labor	1,879	5.81	1.73	0.00	12.62
Log(wage), hired labor	1,765	3.43	0.71	-1.39	7.79
Log(agricultural machinery)	2,333	10.18	1.69	0.00	16.65
Log(# HHs with positive ag machinery and land>1/3 ha.)	2,190	2.10	1.20	0.00	4.61
Log(# HHs with positive ag machinery and land<1/3 ha.)	2,016	2.46	1.16	0.00	4.54
Village TFP, weighted	2,333	4.52	0.90	0.01	12.92
Village TFP, unweighted	2,333	4.75	0.51	1.62	6.92
Allocation efficiency	2,333	-0.23	0.82	-6.66	8.02
Cash crop revenue/crop revenue	2,333	0.43	0.30	0.00	1.00
HHs with cash crops/HH with crops	2,333	0.76	0.33	0.00	1.00
Log(# of HHs with cash crops)	2,226	3.53	0.96	0.00	4.94
Vegetable revenue/crop revenue	2,333	0.24	0.25	0.00	1.00
HHs with vegetables/HH with crops	2,333	0.58	0.41	0.00	1.00
Log(# of HHs with vegetables)	2,002	3.18	1.24	0.00	4.85
Log(husbandry output value)	2,266	11.77	1.34	5.03	20.80
Log(# of HHs in husbandry)	2,266	3.17	1.03	0.00	5.05
Log(labor days in husbandry)	2,243	7.68	1.20	2.30	13.72
Own pref. tariff	2,333	3.05	0.92	0.72	8.18
Tariff exposure through migrant connections	2,333	3.07	0.44	1.53	4.47
Tariff exposure through migrant connections × % cross-pref. migr	2,333	1.43	0.58	0.19	3.27

Note: This figure shows the summary of statistics of key variables used in the empirical analysis. Overall, there are 2,333 village-year observations used in the main analysis. Some variables in logs have fewer numbers of observations due to zero values.

B.2 Trade Data

B.2.1 Industry Crosswalk, from 2-digit GB Code to 2-digit SIC Code

The industrial composition from the 2000 Industrial Enterprises Survey, which is conducted on Chinese manufacturing firms with annual sales of more than 500 million RMB and includes basic firm information such as name and address, financial information on sales, export values, fixed capital, wage payment, and total sales costs, and total employment.[50] There are 145,546 firms in 2000 with positive sales revenue and wage information, more than 10 employees, and a valid industry code. The industry code is the 4-digit Chinese Industry Code, which we aggregate to the 2-digit level. The 2-digit Chinese Industry Code is slightly finer than the 2-digit SIC code, with the crosswalk between the codes shown in Table B6. The definitions of primary metal products and fabricated metal products are different in the Chinese industry code and the SIC code, so we combined the two industries into the metal industry.

Table B6: Crosswalk, 2-digit Chinese industry code (GB) to 2-digit U.S. industry code (SIC), manufacturing

GB code	GB description	SIC	SIC description
6	Mining and washing of coal	12	Coal and lignite
7	Extraction of petroleum and natural gas	13	Crude petroleum and natural gas
8	Mining and processing of ferrous metal ores	10	Metallic ores and concentrates
9	Mining and processing of nonferrous metal ores	10	Metallic ores and concentrates
10	Mining and processing of nonmetal ores	14	Nonmetallic minerals, except fuels
11	Mining of other ores	14	Nonmetallic minerals, except fuels
13	Processing of food from agricultural products	20	Food and kindred products
14	Manu. of foods	20	Food and kindred products
15	Manu. of liquor beverages and refined tea	20	Food and kindred products
16	Manu. of tobacco	21	Tobacco products
17	Manu. of textile	22	Textile mill products
18	Manu. of textile fabrics wearing apparel and accessories	23	Apparel and related products
19	Manu. of leather, fur, feather and related products and footwear	31	Leather and leather products
20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products	24	Lumber and wood products, except fuel
21	Manu. of furniture	25	Furniture and fixtures
22	Manu. of paper and paper products	26*	Paper and allied products
23	Printing, production of recording media	27	Printing, publishing, and allied products
24	Manu. of articles for culture, education, art, sport, and entertainment activities	26*	Paper and allied products
25	Processing of petroleum and coking	29	Petroleum refining and related products
26	Manu. of raw chemical material and chemical products	28	Chemicals and allied products
27	Manu. of medicines	28†	Chemicals and allied products
28	Manu. of chemical fibers	28	Chemicals and allied products
29	Manu. of rubber	30	Rubber and miscellaneous plastics products
30	Manu. of plastics products	28‡	Chemicals and allied products
31	Manu. of non-metallic mineral products	32	Stone, clay, glass, and concrete products
32	Smelting and pressing of ferrous metals	300⁎	Metal processing and products
33	Smelting and pressing of non-ferrous metals	300⁎	Metal processing and products
34	Manu. of metal products	300⁎	Metal processing and products
35	Manu. of general purpose machinery	35	Machinery, except electrical
36	Manu. of special purpose machinery	35	Machinery, except electrical
37	Manu. of transportation machinery	37	Transportation equipment
39	Manu. of electrical machinery and equipment	36	Electrical machinery, equipment, and products
40	Manu. of communication equipment, computers and other electric equipment	36	Electrical machinery, equipment, and products
41	Manu. of measuring instruments and machinery	38	Scientific and professional instruments
42	Manu. of artifacts and other manufacturing	39	Miscellaneous manufactured commodities
43	Recycling	91	Scrap and waste material

*https://www.osha.gov/pls/imis/sicsearch.html?p_sic=&p_search=stationery.
†https://www.osha.gov/pls/imis/sicsearch.html?p_sic=&p_search=drug.
‡https://www.osha.gov/pls/imis/sicsearch.html?p_sic=&p_search=plastic.
⁎https://www.osha.gov/pls/imis/sicsearch.html?p_sic=&p_search=metal. Here the SIC 300 will be the weighted average of SIC 33 (Primary metal products) and 34 (Fabricated metal products).

[50] The 1995 Industrial Enterprise Survey data is not available.

B.2.2 Trade Elasticity

Table B7: The relationship between tariff reductions and export values, industry level

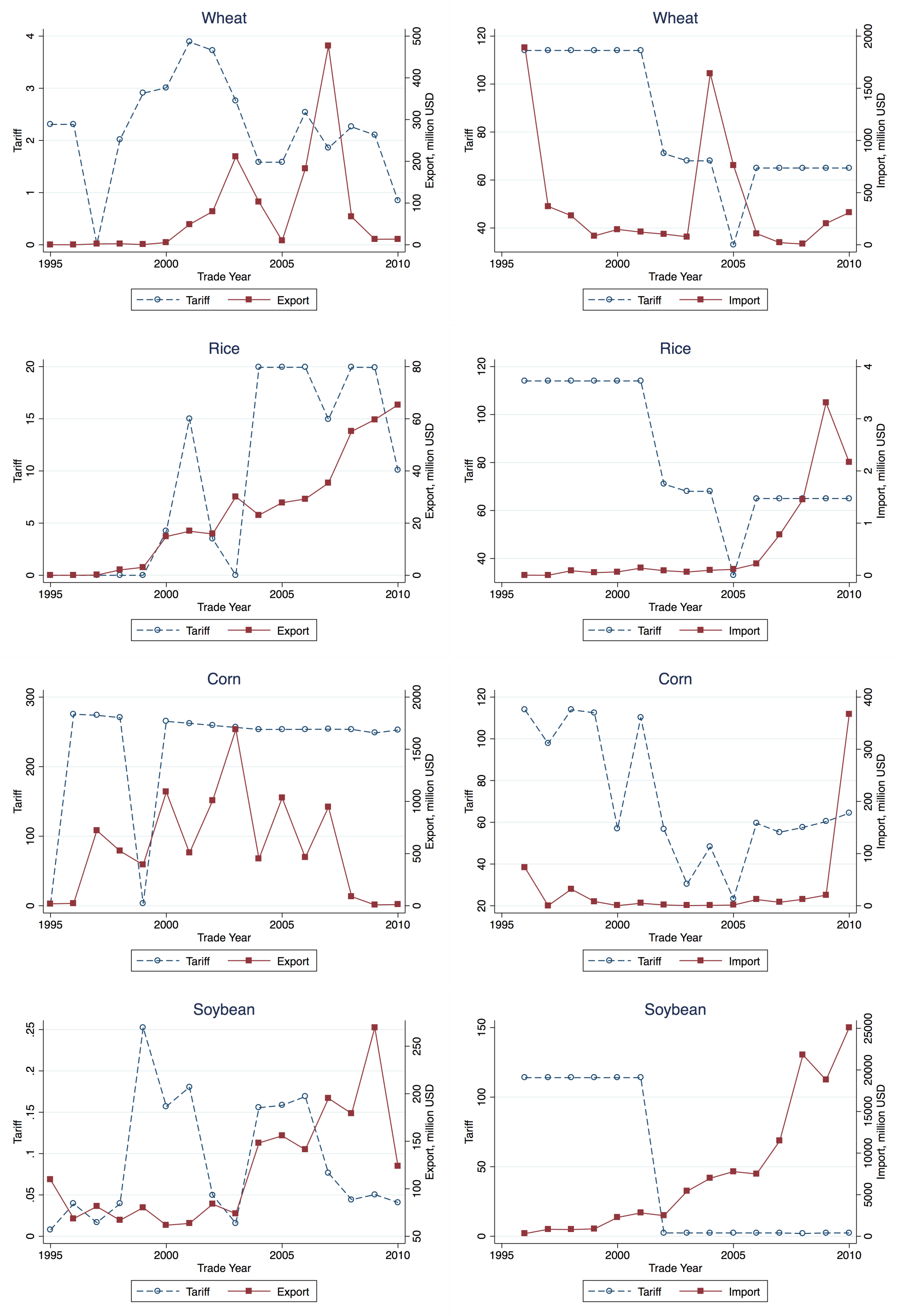
	(1) Log export (2001–2010)	(2) Log export (2004-2010)	(3) Log export (1995-2001)
Tariff on exports, 2001-2010	-7.80***		13.77
	(2.68)		(10.76)
Log export, 1995-2001		0.02	
		(0.07)	
Constant	16.25***	15.79***	14.34***
	(0.07)	(1.09)	(0.27)
Observations	260	234	234
R-squared	0.99	0.99	0.96

Note: This table shows the relationship between export value and tariffs in different periods and the relationship between post-2001 export values and the post-2001 export values. All columns control for industry fixed effects and year fixed effects. In Column (1), the log exports from 2001 to 2010 are regressed on tariffs in corresponding years. In Column (2) the log exports from 2004 to 2010 are regressed on exports from 1995 to 2001, i.e., the lagged exports. In Column (3) the log exports from 1995 to 2001 are regressed on tariffs from 2001 to 2010. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

B.2.3 Agricultural Trade

The data on tariffs and national import and exports by crop are from TRAINS, with 3-digit SIC codes matching to the 11 crops in our data. The trends of tariffs, imports, and exports are shown in Figure B4 (wheat, rice, corn, and soybean), Figure B5 (cotton, oil crops, sugar crops, and flax), and Figure B6 (tobacco, vegetable, and fruits).

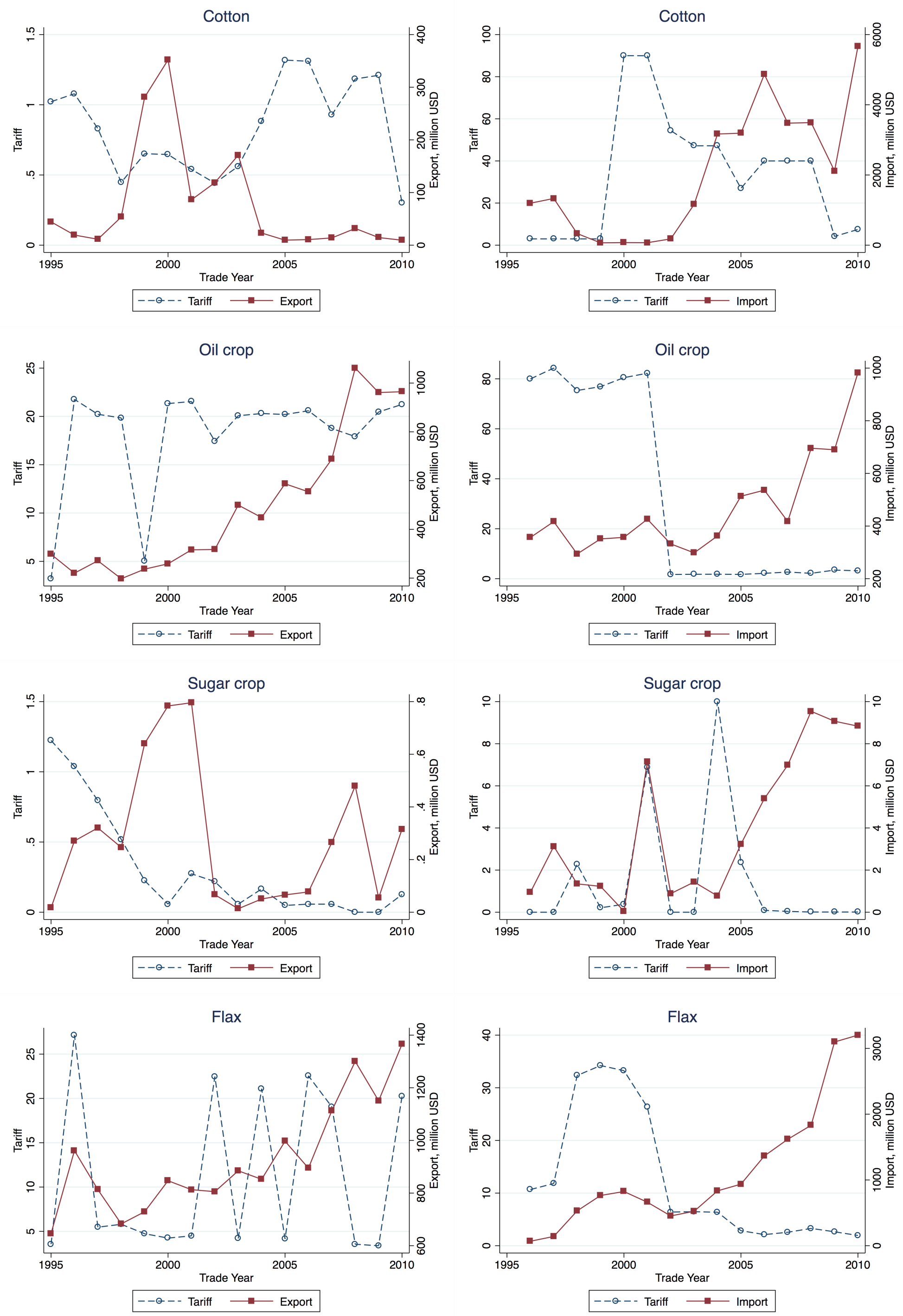
Figure B4: Agricultural trade, 4 major cereal crops



Note: This table presents the trends of Chinese imports, Chinese exports, Chinese tariffs on imports, and tariffs faced by Chinese exports for the four major cereal crops: wheat, rice, corn, and soybean. The data source is the 3-digit SIC code trade data from TRAINS. The lines with hollow dots present tariffs, and the lines with solid squares present trade values.

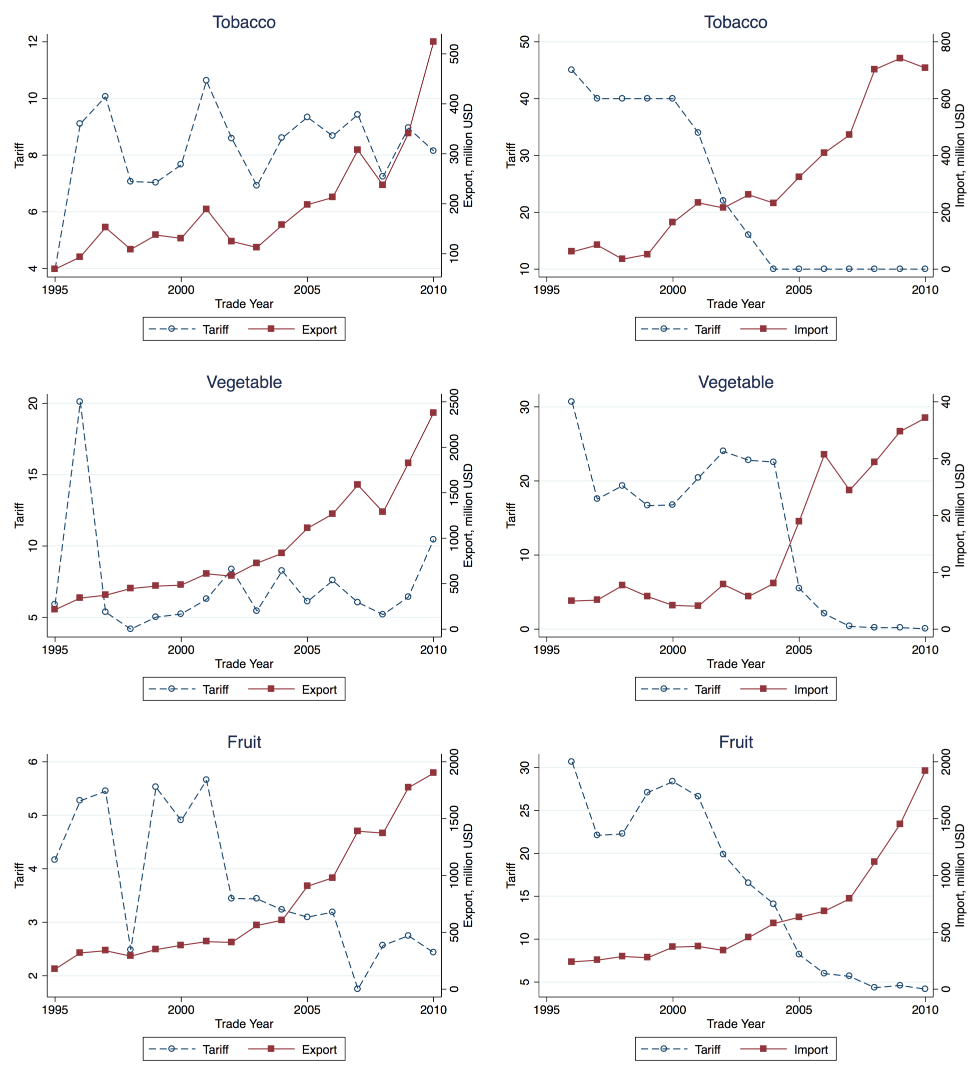
Using this information, we calculate four types of agricultural shocks using the interaction of village-crop area shares in 2001 and crop-year tariffs/trade. The tariff on agricultural exports in

Figure B5: Cash crops (1): cotton, oil crops, sugar crops, flax



Note: This table presents the trends of Chinese imports, Chinese exports, Chinese tariffs on imports, and tariffs faced by Chinese exports for cotton, oil crops, sugar crops, and flax. The data source is the 3-digit SIC code trade data from TRAINS. The lines with hollow dots present tariffs, and the lines with solid squares present trade values.

Figure B6: Cash crops (2): tobacco, vegetable and fruits



Note: This table presents the trends of Chinese imports, Chinese exports, Chinese tariffs on imports, and tariffs faced by Chinese exports for tobacco, vegetables, and fruits. The data source is the 3-digit SIC code trade data from TRAINS. The lines with hollow dots present tariffs, and the lines with solid squares present trade values.

village v and year t is calculated as follows:

$$\tau_{vt}^{EX} = \sum_c \frac{\text{area}_{vc2001}}{\sum_{c'} \text{area}_{vc'2001}} \tau_{ct}^{EX},$$

where τ_{ct}^{EX} is the tariff on Chinese exports for crop c in year t, and area_{vc2001} is the area of crop c in village v and year 2001. We include two types of measures, one for cereal crops only, and another for all 11 crops. The tariff on imports is calculated by replacing τ_{ct}^{EX} with τ_{ct}^{IM}.

Alternatively, we use the market-access type of measures of trade shocks as in Autor et al. (2013). The exposure to agricultural exports in village v and year t is calculated as follows:

$$MA_{vt}^{EX} = \sum_c \frac{\text{area}_{vc2001}}{\sum_{c'} \text{area}_{vc'2001}} \frac{v_{ct}^{EX}}{\sum_{v'} \text{area}_{v'c2001}},$$

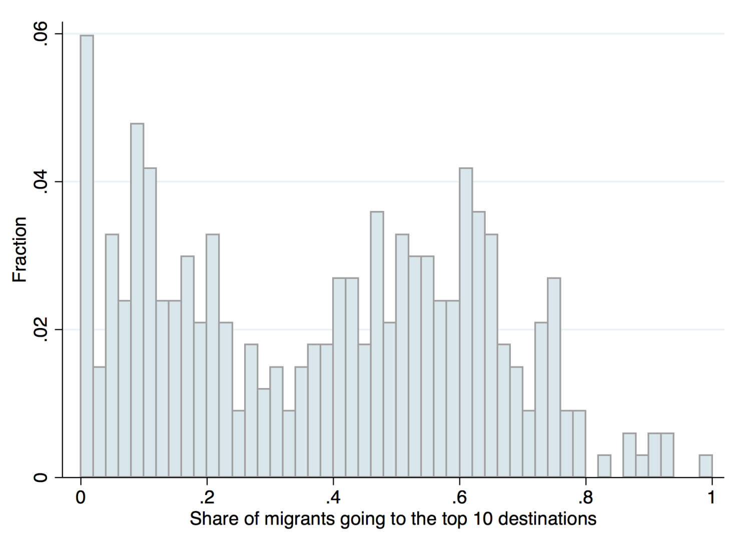
where v_{ct}^{EX} is the Chinese exports for crop c in year t, and area_{vc2001} is the area of crop c in village v and year 2001.

B.3 Migration Network Data

Table B8: Summary of statistics of the 2000 migration network

Variable	Value
Total number of migrants	51,850
Total number of network links	10,491
Per Destination Prefecture	
Median number of migrants	54
Median number of source prefectures	21
Per Source Prefecture	
Median number of migrants	117
Median number of destination prefectures	28

Figure B7: Distribution of the Share of Migrants Moving to the Top 10 Destinations



Note: The top 10 destination prefectures are Shenzhen, Dongguan, Guangzhou, Shanghai, Beijing, Foshan, Chongqing, Wenzhou, Wuhan, and Quanzhou. These 10 prefectures absorbed 38% of total migrants in China in 2000.

B.4 Alternative Measures of Trade Shocks and the Wage Effect

In this section, we present additional evidence related to Section 4. First, we show the robustness of our measure of regional trade shocks. We use tariffs at the 2-digit SIC level to calculate regional trade shocks in Section 4 following Equation (5). In Table B9 Column (1), the outcome variable is the regional trade exposure calculated by dropping θs in Equation (5), and it is highly correlated with our main exposure measure. Column (2) shows that the own prefecture tariff (τ_{it}) calculated using tariffs at the 4-digit SIC level is highly correlated with our main measure. Column (3) shows that our main measure is negatively correlated with trade exposures calculated using measures suggested in Autor et al. (2013), where we replace tariffs (τ_{kt}) with actual export values in Equation (5) and drop θs.

Second, we show that reductions in tariffs led to an increase in wages in Column (4). Thus, migrant destinations with lower tariffs will attract more migrant flows due to this wage effect, consistent with evidence shown in Figure 4.

Table B9: Alternative Measures of Trade Shocks and the Impact of Trade Shocks on Wages

	(1)	(2)	(3)	(4)
Outcome:	Emp weighted	Tariffs at 4-digit industry level	ADH measure	Log wage
Regional trade exposure	0.97***	0.63***	-42.24	-2.53**
	(0.01)	(0.08)	(33.89)	(1.05)
Constant	0.00***	0.01***	16.90***	9.59***
	(0.00)	(0.00)	(1.02)	(0.03)
Observations	3,379	3,379	3,379	1,935
R-squared	1.00	0.83	0.91	0.94

Note: The table shows additional evidence related to Section 4. All columns control for prefecture fixed effects and year fixed effects. The explanatory variable is the regional trade exposure measured using Equation (5). The outcome variable in Column (1) is the regional trade exposure calculated by dropping θs in Equation (5). In Column (2), the outcome variable replicates the measure in Equation (5), but replaces τ_{jt} with the corresponding actual export values and drops θs. The outcome variable in Column (3) is the log wage. Robust standard errors are shown. *** p<0.01, ** p<0.05, * p<0.1.

C Additional Empirical Results

C.1 Occupation Choice and Land Rental, OLS Evidence

Household occupation choice was correlated with how much land they decided to work on. Table C1 Column (1) shows that in a household with 3 laborers, the probability of working on any land was 6 percentage points smaller when one more household member worked as a non-agricultural laborer. Columns (2) and (3) add village-year fixed effects and household fixed effects, and the coefficients are smaller than in Column (1), significant at the 1% level. Column (4) indicates that one more household member working as a non-agricultural laborer is correlated with a 25-percentage-point decline in the land size; while statistically significant, the numbers are again smaller with village-year fixed effects and household fixed effects.

Table C1: The relationship between non-agricultural laborer share and land, 2001–2010

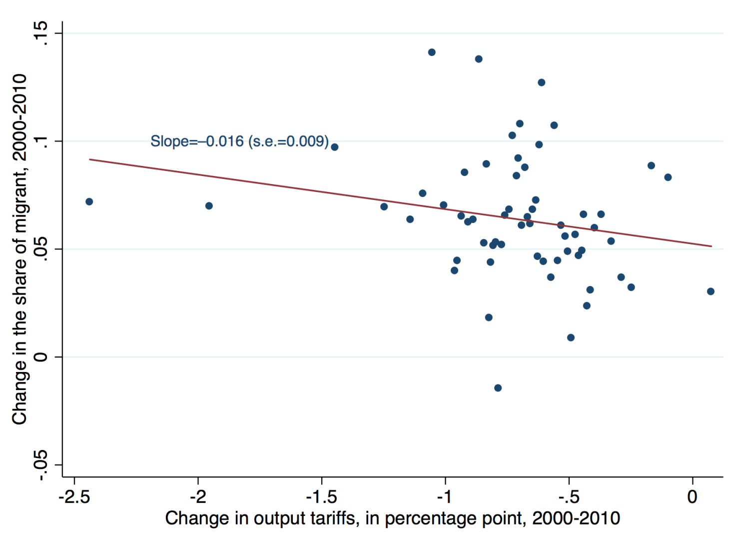
	(1)	(2)	(3)	(4)	(5)	(6)
	Any land (=1)			Log(land size)		
% non-ag laborer	-0.18***	-0.15***	-0.13***	-0.84***	-0.21***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.22)	(0.03)	(0.02)
Log(# labor)	0.08***	0.08***	0.03***	0.35***	0.40***	0.19***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.02)
Constant	0.84***	0.84***	0.88***	1.54***	1.40***	1.59***
	(0.01)	(0.00)	(0.00)	(0.17)	(0.03)	(0.02)
Observations	144,675	144,675	142,513	128,884	128,883	126,528
R-squared	0.04	0.25	0.69	0.06	0.70	0.90
Year FE	Yes			Yes		
Village-Year FE		Yes	Yes		Yes	Yes
HH FE			Yes			Yes

Note: This table shows the results on the correlation between the household non-agricultural labor share and the land in the agricultural operation, using the NFP Survey data on households. Column (1) regresses the dummy for whether the household has any land in agricultural operation on the share of non-agricultural labor and the log number of labor, controlling for year fixed effects. Column (2) replaces the year fixed effects with village-year fixed effects. Column (3) adds household fixed effects. Columns (4)–(6) replicates the results in Columns (1)–(3), using the log land size as the outcome variable. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.2 Evidence at the Destination-Prefecture Level

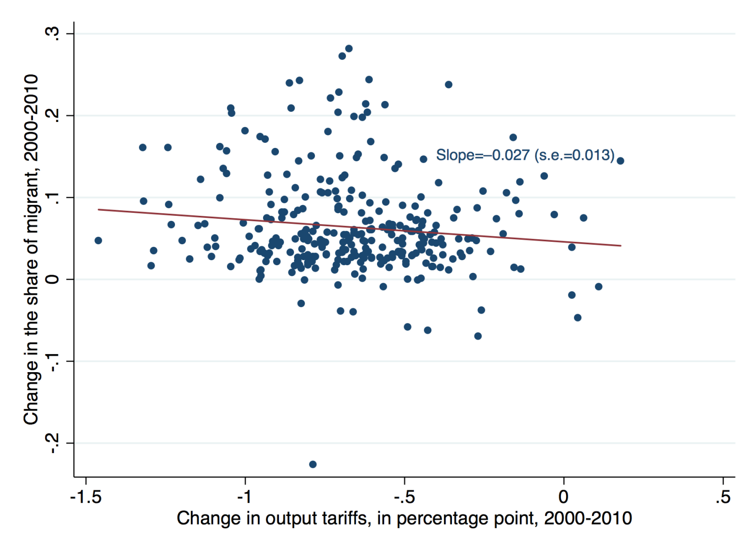
C.2.1 Robustness of the Scatter Plot on Destination Migration Flows

Figure C1: Prefectures with larger declines in output tariffs in the manufacturing sector experienced larger increases in the share of migrants, 2000–2010, binned scatter plot



Note: This figure shows the relationship between the declines in output tariffs and the changes in the share of migrants from 2000 to 2010, using the output tariffs and the number of migrants using the 2000 and 2010 censuses. Each dot is a prefecture group, defined by the size of the change in output tariffs, with 60 groups in total. The horizontal axis shows the percentage point change in output tariffs in the manufacturing sector in a prefecture ($\tau^{own}_{2010} - \tau^{own}_{2000}$), and the vertical axis shows the change in the share of migrants.

Figure C2: Prefectures with larger declines in output tariffs in the manufacturing sector experienced larger increases in the share of migrants, 2000–2010, dropping outliers on the left



Note: This figure shows the relationship between the declines in output tariffs and the changes in the share of migrants from 2000 to 2010, using the output tariffs and the number of migrants using the 2000 and 2010 censuses. Each dot is a prefecture. The horizontal axis shows the percentage point change in output tariffs in the manufacturing sector in a prefecture ($\tau_{2010}^{own} - \tau_{2000}^{own}$), and the vertical axis shows the change in the share of migrants. Here 12 outliers out of 318 on the left-hand side are dropped.

C.3 Alternative Tests of Pre-Trends

An alternative way of testing the pre-trends is to use the following year-by-year regression,

$$\tau_{v(i)t}^{o} = \gamma_o + \gamma_1 \tau_{v(i)2001}^{o} + \Pi Z_{v1995\text{–}2001} + I_p + \xi_v, \tag{10}$$

where $o = own, network$, $t = 2002, ..., 2010$, and $Z_{v1995-2001}$ is a vector of changes of village-level variables from 1995 to 2001, including changes in the share of non-agriculture labor, land rental, agricultural capital, and TFP, and I_p are province fixed effects. As shown in Table C2, for $o = network$ and $o = own$, we fail to reject the hypothesis of $\Pi = 0$ for 17 out of the 18 tests for $t = 2002, ..., 2010$, when two outlier villages are excluded. Results in Section 5 are not affected by dropping the two outlier villages. Thus, we find no evidence of differential trends of key outcome variables for villages with different sizes of trade exposures.

Table C2: P-values for F tests on pre-trends

Year	2010	2009	2008	2007	2006	2005	2004	2003	2002
p-value for $o = own$	0.61	0.33	0.73	0.36	0.47	0.30	0.07	0.64	0.30
p-value for $o = network$	0.27	0.47	0.21	0.24	0.16	0.34	0.47	0.13	0.51

Note: This table presents the p-value for the joint test of coefficients for $\Pi = 0$ in Equation 10. Each cell represents the p-value for the joint test from one regression.

C.4 Robustness of the Occupation Choice

C.4.1 Controlling for Other Trade Shocks

First, we provide evidence of the absence of agricultural trade effects in this section. Table C3 adds a measure of agricultural trade shocks as controls, and the specification is the same as in Section 5.1 Table 2 Column (1). Column (1) is a direct replication of all villages with no missing agricultural trade shock measures. Columns (2) and (3) add the agricultural tariff shocks, for four cereal crops and for all eleven crops, respectively. Columns (4) and (5) use market-access-based trade exposure measures. In all last four columns, the coefficients on the agricultural trade shocks are insignificant, and the coefficients on manufacturing tariff exposures (through migrant networks and own) are the same as in Column (1).

Another potential concern is whether the tariff reduction was the only trade shock induced by China's WTO accession. For example, Pierce and Schott (2016), Handley and Limão (2017), and Erten and Leight (2021) emphasize the importance of the reduction in tariff uncertainty between the United States and China. They argue that the United States applied MFN tariffs on Chinese exports even before the WTO accession. However, before 2001, there was great uncertainty regarding the U.S. trade policy: the MFN status had to be approved each year by the Senate and the House; otherwise, the Column 2 tariff would be applied to Chinese exports.

To address this concern, we construct the U.S. uncertainty-related tariff. We use the 2000 customs data by firm, eight-digit Harmonized System (HS) category, and destination country, then combine it with the information on the 2000 Column 2 tariffs and MFN tariffs by eight-digit HS category by the United States from Handley and Limão (2017).[51] With these data, the potential U.S. tariff on prefecture i in 2001 is:

$$\tau^{US}{}_{i2001} = \sum_p \frac{export^{US}_{p,i,2000}}{\sum_{p'} export^{US}_{p,i,2000}} Column2^{US}_{p,2000},$$

where i is a prefecture, p is a six-digit HS category, $export^{US}_{p,i,2000}$ the exports from Chinese prefecture i to the United States in category p in 2000, $Column2^{US}_{p,2000}$ is the U.S. Column 2 tariff on category p in 2000. The U.S. tariff on prefecture i in year $t = 2002, ..., 2010$, is

$$\tau^{US}{}_{it} = \sum_p \frac{export^{US}_{p,i,2000}}{\sum_{p'} export^{US}_{p,i,2000}} MFN^{US}_{p,t},$$

where $MFN^{US}_{p,2000}$ is the U.S. MFN tariff.

Then we have a village's exposure to its own prefectures' output tariff as

$$\tau^{own,US}_{vit} = \tau^{US}_{it},$$

and its exposure to tariffs through migrant connections as

$$\tau^{other,US}_{vit} = \sum_{j \neq i} \frac{m_{ij}}{\sum_{j' \neq i} m_{ij'}} \tau^{US}_{jt},$$

where m_{ij} is the number of migrants who are from prefecture i and reside in prefecture j in 2000.

[51] We convert the eight-digit HS codes to six-digit ones in both datasets to increase the matching probability.

Table C3: Occupation choice results, controlling for the agricultural trade shocks and uncertainty shock

Y: % non-ag laborer	(1)	(2)	(3)	(4)	(5)	(6)
		Agricultural tariff		Agricultural market access		Uncertainty
		Cereal	All	Cereal	All	
Tariff exposure through migr. network	-0.09***	-0.09**	-0.09***	-0.09***	-0.09***	-0.06**
	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Own prefecture tariff	0.02**	0.02**	0.02*	0.02**	0.02**	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Agricultural export shock		-0.07	-0.11	0.06	-0.02	
		(0.16)	(0.19)	(0.10)	(0.03)	
Agricultural import shock		-0.09	-0.02	0.00	-0.00	
		(0.05)	(0.03)	(0.01)	(0.00)	
Uncertainty, own pref.						-0.11***
						(0.03)
Uncertainty, through migr. network						0.15
						(0.13)
Observations	1,964	1,964	1,964	1,964	1,964	2,333
R-squared	0.85	0.85	0.85	0.85	0.85	0.85

Note: This table shows the robustness of the result in Table 2 Column (3). Column (1) replicates Table 2 Column (3), restricting the sample to the villages that had non-missing crop area information in 2001. Columns (2) and (3) add agricultural export and import shocks calculated from agricultural tariff reductions, including only cereal crops and all crops, respectively. Columns (4) and (5) use agricultural export and import shocks using the market access approach, including only cereal crops and all crops, respectively. Column (6) replicates Table 2 Column (3), adding the uncertainty shocks. All columns control for the log labor, the log number of households, the log government transfer+1, province-year fixed effects, and village fixed effects. The mean (sd) of the share of non-agricultural labor is 0.19 (0.15). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

In Table C3 Column (6), we control for the U.S. uncertainty-related tariffs, both in a village's own prefecture and through migrant connections. We find that the coefficients for the actual tariffs in the first two rows are exactly the same as in Table 2 Column (1), meaning that our actual tariff results are robust. We don't find a significant effect of exposure to U.S. uncertainty-related tariffs through migrant connections. One-standard deviation larger decline in own prefecture's U.S. uncertainty-related tariff resulted in a one-percentage-point larger increase in the share of non-agricultural labor. This result is consistent with the finding in Erten and Leight (2021), but contrary to our actual own prefecture effect.

C.4.2 Village-Level Results for Occupation Choice and Out-Migration

Section 5.1 Table 2 uses the share of non-agricultural labor in a village as the outcome variable to investigate the impact of trade exposure on rural residents' occupation choice. Table C4 uses data from the village questionnaire, with the specification being the same as in Table 2 Column (1). Column (1) shows that a one-standard-deviation larger decline in tariff exposure through migrant networks led to a 17% larger decline in the share of households whose sole business was agriculture. Columns (2)–(4) focus on the share of labor working outside the village. Column (2) shows that a one-standard-deviation larger decline in tariff exposure through migrant connections led to a 10% larger increase in the share of labor working outside the village. The effect is mainly driven by within-province migration (Column 3) instead of between-province migration (Column 4). The decline in tariff also led to a decline in the share of excess labor, but the effect is not statistically significant (Column 5). Excess labor is defined in labor units. It is calculated as $\frac{\text{total labor} \times 300 - \text{total labor days}}{300}$.

Table C4: Occupation choice and out-migration, village questionnaire result, 2001–2010

	(1)	(2)	(3)	(4)	(5)
	% in agr.		% out of village		% excess labor
		Any	within prov.	between prov.	
Tariff exposure through migr. network	0.17***	-0.10*	-0.12**	0.02	0.03
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Own prefecture tariff	0.01	-0.01**	-0.02*	0.00	0.01
	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	2,255	2,257	2,256	2,257	2,253
R-squared	0.86	0.80	0.78	0.88	0.70
Mean (sd) Y	0.50 (0.31)	0.27 (0.18)	0.17 (0.14)	0.10 (0.13)	0.08 (0.11)

Note: This table shows the labor market outcomes in response to the trade shocks, using NFP Survey data from village questionnaires. All columns control for the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. All columns have the same specification as Table 2 Column (3). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.4.3 Controlling for the Crop Patterns

Table C5: Results on occupation choices, controlling for concurrent crop patterns

Y=% non-ag laborer	(1) Wheat	(2) Rice	(3) Corn	(4) Soybean
Tariff exposure through migr. network	-0.06**	-0.06**	-0.06**	-0.06**
	(0.02)	(0.02)	(0.02)	(0.02)
Own prefecture tariff	0.02*	0.02	0.02	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Share of output value coming from crop X	0.13*	0.03	0.01	0.02
	(0.06)	(0.05)	(0.04)	(0.06)
Observations	2,333	2,333	2,333	2,333
R-squared	0.85	0.85	0.85	0.85
Province-Year FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of tariff exposure through migrant networks on the occupation choice pattern when we control for the share of output value coming from one of the four major crops. All columns control for own prefecture's output tariff, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. The average value share of wheat is 11%, rice 23%, corn 19%, and soybean 4%. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: Results on occupation choices, controlling for initial crop patterns

Y=% non-ag laborer	(1) Wheat	(2) Rice	(3) Corn	(4) Soybean
Tariff exposure through migr. network	-0.09***	-0.10***	-0.09***	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
Own prefecture tariff	0.02**	0.02**	0.02***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
2001 crop share × Year FE	Yes	Yes	Yes	Yes
Observations	1,971	1,971	1,971	1,971
R-squared	0.85	0.85	0.85	0.85
Province-Year FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of tariff exposure through migrant networks on the occupation choice pattern when we control for the share of output value coming from one of the four major crops in the initial year (interacted with year fixed effects). All columns control for own prefecture's output tariff, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. The average initial value share of wheat is 13%, rice 24%, corn 16%, and soybean 5%. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.5 Capital Adoption, Remittance Results

In this section, we show how investment in fixed capital is correlated with income from different sources, both on the extensive margin and on the intensive margin. In Table C7, the outcome variable in Panel A is the log of household expenditure on the purchase of productive fixed assets plus one, and the regressors are the share of income from different sources. In Panel B, the outcome variable is the probability of having a positive investment. All columns control for the log total income, household fixed effects, and year fixed effects.

When the share of income from wages increases by 10 percentage points, the investment decreases by 4%, which is 7% of the mean growth rate of the investment. The probability of investment decreases by 0.5 percentage point, which is 6% of the mean of investment probability. On the other hand, income from farm operations and from government agricultural subsidies increase both the size of the investment and the probability of investment.

Table C7: Correlation of expenditure on capital investment with income from various sources, 1995–2010

	(1)	(2)	(3)	(4)	(5)
	Wage	Farm	Land rent	Interest	Government
Panel A: Y = Log(investment+1)					
Share of income from...	-0.41***	0.29***	0.17	0.20	0.75***
	(0.04)	(0.04)	(0.10)	(0.29)	(0.22)
Panel B: Y= I(investment>0)*100					
Share of income from...	-4.80***	3.44***	1.85	1.72	9.12***
	(0.64)	(0.63)	(1.50)	(3.12)	(2.96)
Mean (sd) share of income from...	0.22 (0.28)	0.62 (0.33)	0.01 (0.05)	0.005(0.003)	0.02 (0.05)

Note: This table shows the correlation between investment in fixed capital and the share of income from different sources. The outcome variable in Panel A is the log of investment +1, and the outcome variable in Panel B is the probability of having a positive investment. All columns control for the log total income, household fixed effects, and year fixed effects. The mean (sd) of the log expenditure on capital +1 is 0.57 (1.99), and the mean (sd) of the probability of investing in expenditure is 0.08 (0.27). Standard errors are clustered at the village and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.6 Robustness of the TFP Results

The TFP results are similar using the value-added method, compared to the results in Table 6 with the output method.

Table C8: The effect of trade exposures on village-level TFP, value-added method

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(village TFP)				Allocation efficiency	
	output weighted		unweighted			
Tariff exposure through migr. network	-0.68***	-0.39	0.03	0.11	-0.70***	-0.49
	(0.16)	(0.21)	(0.34)	(0.35)	(0.14)	(0.27)
Tariff exposure through migr. network		-0.81		-0.23		-0.59
× % cross-prefecture migration		(0.71)		(0.13)		(0.66)
Own prefecture tariff	0.04	0.02	0.02	0.01	0.02	0.00
	(0.12)	(0.11)	(0.04)	(0.04)	(0.09)	(0.08)
Observations	2,332	2,332	2,332	2,332	2,332	2,332
R-squared	0.67	0.67	0.85	0.85	0.59	0.59

Note: This table shows the equivalence of results with Table 6 when we use the TFP from the valued-added method instead of the TFP from the output method. All columns control for the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3) and (5) have the same specification as Table 2 Column (3), and Columns (2)(4) and (6) have the same specification as Table 2 Column (4). The mean (sd) of the log weighted TFP is 5.32 (1.13), the mean (sd) of the log unweighted TFP is 5.61 (0.68), and the mean (sd) of allocation efficiency is -0.29 (0.97). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

An alternative measure of agriculture productivity is labor productivity (Lagakos and Waugh 2013). In Table C9, we measure the household-level agriculture productivity as

$$\hat{\phi}^L_{h(v)t} \equiv \log(y_{h(v)t}) - \log(d_{h(v)t}),$$

where $\log(y_{h(v)t})$ is the log of the value of agriculture output in household h, village v, and time period t, and $\log(d_{h(v)t})$ is the labor days in agriculture. Then, we calculate the corresponding measures of output-weighted village level TFP, unweighted TFP, and allocation efficiency according to Equations (3) and (4), by replacing $\hat{\phi}_{h(v)t}$ with $\hat{\phi}^L_{h(v)t}$.

Table C9 shows a similar effect as Table 6.

Table C9: The effect of trade exposures on village-level productivity, labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(village TFP)				Allocation efficiency	
	output weighted		unweighted			
Tariff exposure through migr. network	-0.79***	-0.53**	-0.09	0.08	-0.69***	-0.61**
	(0.11)	(0.18)	(0.22)	(0.26)	(0.14)	(0.21)
Tariff exposure through migr. nework		-0.71		-0.47*		-0.24
× % cross-prefecture migration		(0.45)		(0.21)		(0.44)
Own prefecture tariff	-0.02	-0.04	-0.01	-0.03	-0.01	-0.02
	(0.07)	(0.06)	(0.04)	(0.05)	(0.04)	(0.03)
Observations	2,333	2,333	2,333	2,333	2,333	2,333
R-squared	0.73	0.73	0.85	0.86	0.49	0.49

Note: This table shows the equivalence of results with Table 6 when we use the labor productivity instead of the TFP from the output method. All columns control for the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3) and (5) have the same specification as Table 2 Column (3), and Columns (2)(4) and (6) have the same specification as Table 2 Column (4). The mean (sd) of the log weighted TFP is 3.63 (0.89), the mean (sd) of the log unweighted TFP is 3.64 (0.75), and the mean (sd) of allocation efficiency is -0.00 (0.61). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.7 Additional Robustness

C.7.1 Shift-Share Equivalence Results at the Migrant-Destination Level

In this section, we present the equivalence results of the shift-share design suggested by Borusyak et al. (2022). Specifically, we convert the agricultural sector outcomes (and corresponding control variables in the regressions) to the destination-prefecture level and show the equivalence of coefficient estimates. We focus on the main regression specification where the main regressor is the tariff exposure through the migrant network, controlling for own prefecture tariff, village-year specific controls (i.e., log labor, log number of households, log government transfer+1), province-year fixed effects, and year fixed effects. The outcomes of interests are the share of non-agricultural laborers, the land leasing transaction that happened within a year, agricultural machinery values, and the output-weighted TFP.

The results are shown in Table C10. The main results report standard error clustered at the year level, consistent with the specification in Section 5. At the bottom of the table, we show p-values using bootstrapped standard errors, and standard errors clustered at the destination-province level and at the year level. Overall, the coefficient estimates are the same as in the main results, and the significance levels are similar.

Table C10: Equivalence Results at the Destination-Prefecture Level

	(1) % non-agricultural laborer	(2) Log(land leased+1) Flow	(3) Log (agr machine)	(4) Log(village TFP) output weighted
Tariff exposure through migrant network	-0.06**	-1.73**	-0.07	-0.69**
(at destination prefecture level)	(0.02)	(0.73)	(0.92)	(0.25)
Observations	3,379	3,379	3,379	3,379
Bootstrap	0.07	0.01	0.94	0.06
Clustered at the province level and at the year level	0.00	0.01	0.93	0.04

Note: This table replicates the results of the effect of trade exposure on various agricultural outcomes at the village level in Section 5, using the regressors and regresees converted to the destination prefecture level. Column (1) replicates Table 2 Column (3), Column (2) replicates Table 4 Column (3), Column (3) replicates Table 5 Column (1), and Column (4) replicates Table 6 Column (1). Standard errors are clustered at the year level in the top panel, and p-values using bootstrapped standard errors and standard errors clustered at the province level and at the year level are reported at the bottom of the table. *** p<0.01, ** p<0.05, * p<0.1.

C.7.2 Controlling for the Share of Migrants Going to the Top 10 Destinations

Table C11: Controlling for the initial share of migrants going to top 10 destinations

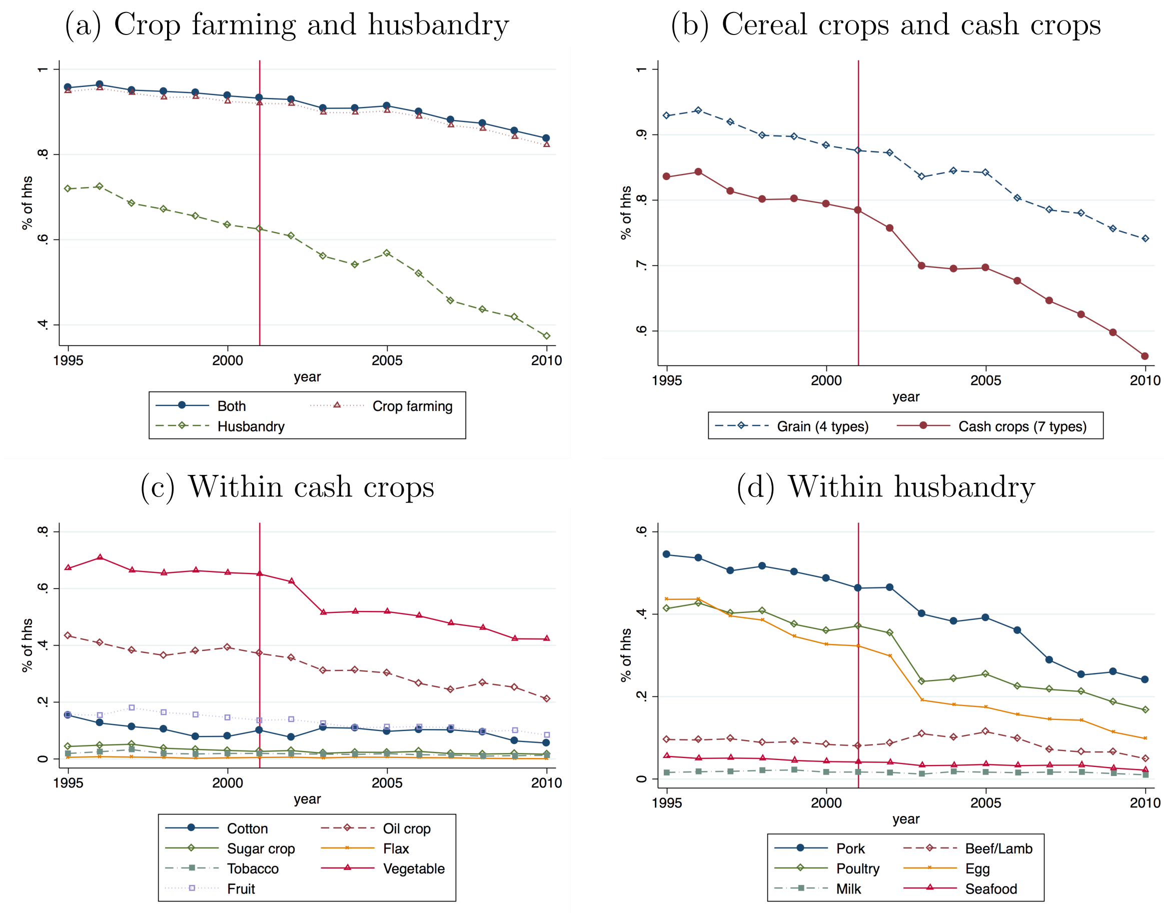
	(1) % non-agricultural laborer	(2) Log(land leased+1) Flow	(3) Log (agr machine)	(4) Log(village TFP) output weighted
Tariff exposure through	-0.06**	-1.74***	-0.12	-0.79***
migrant network	(0.02)	(0.43)	(0.79)	(0.14)
Top 10 share × Time trend	0.01	0.02	0.12	0.22*
	(0.01)	(0.13)	(0.07)	(0.11)
Observations	2,333	2,333	2,333	2,333
R-squared	0.85	0.69	0.87	0.65

Note: This table replicates the results of the effect of trade exposure on various agricultural outcomes at the village level in Section 5, when we control for linear trends interacted with the share of migrants going to the top 10 destination prefectures in 2000. Column (1) replicates Table 2 Column (3), Column (2) replicates Table 4 Column (3), Column (3) replicates Table 5 Column (1), and Column (4) replicates Table 6 Column (1). All columns control for own prefecture's output tariff, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. The average share of people moving to the top 10 destination prefectures is 29%. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.8 Crop Mix and Husbandry

In this section, we provide some facts on crop mix and husbandry, as well as the impact of trade on these outcomes. Figure C3 shows the trend of the share of households in each type of production. Overall, the share declined for all types, especially after 2001.

Figure C3: Crop mix and husbandry



Note: This figure shows the trends of husbandry and crop farming, using the NFP Survey data on households. Panel (a) depicts the share of households in either crop farming or husbandry (the solid line with solid circles), the share of households in crop farming only (the dotted line with hollow triangles), and the share of households in husbandry only (the dashed line with hollow diamonds). Panel (b) depicts the share of households growing grains (the dashed line with hollow diamonds), and the share of households with cash crops (the solid line with solid circles). Panel (c) shows the share of households with different types of cash crops. Panel (d) shows the share of households with different types of husbandry. Oil crops include peanuts, sesame, rapeseed, sunflower, benne, and castor bean. Sugar crops include sugar cane and beets.

Table C12 presents the effect of trade on cash crop production. A one-percentage-point larger decline in tariff exposure through migrant networks led to an 11% larger decline in the share of households with cash crops among all crop farming households (Columns 3 and 4); similar effects can be found in the number of households in cash crop farming (Columns 5 and 6). We find no significant effect on the revenue share of cash crops.

Table C12: Cash crop effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Cash crop revenue /crop revenue		# HHs with cash crops /HH with crops		Log(# of HHs) with cash crops	
Tariff exposure through migrant connections	-0.04	-0.05	0.11***	0.11**	0.20*	0.13
	(0.08)	(0.07)	(0.03)	(0.03)	(0.11)	(0.17)
Tariff exposure through migr. network		0.02		0.02		0.20
× % cross-prefecture migration		(0.08)		(0.09)		(0.42)
Own prefecture tariff	-0.02	-0.01	0.01	0.01	-0.00	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.08)	(0.09)
Observations	2,333	2,333	2,333	2,333	2,221	2,221
R-squared	0.92	0.92	0.89	0.89	0.87	0.87
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the effect of tariff exposure through migrant connections on cash crop farming. All columns control for own prefecture's output tariff, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3) and (5) have the same specification as Table 2 Column (3), and Columns (2)(4) and (6) have the same specification as Table 2 Column (4). The mean (sd) of the revenue share of cash crops is 0.42 (0.30), the mean (sd) of the household share of cash crops is 0.76 (0.33), and the mean (sd) of the log number of households with cash crops is 3.53 (0.95). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

Similar effects are found in Table C13 with vegetable production. Households left vegetable production more in villages with a larger increase in trade exposures.

Table C13: Vegetable effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Vegetable revenue /crop revenue		# HHs with vegetable /HH with crops		Log(# of HHs) with vege production	
Tariff exposure through migr. network	0.01	-0.02	0.16*	0.14	1.12***	0.87***
	(0.06)	(0.07)	(0.07)	(0.09)	(0.13)	(0.20)
Tariff exposure through migr. network × % cross-prefecture migration		0.06		0.05		0.72
		(0.06)		(0.13)		(0.57)
Own prefecture tariff	-0.00	-0.00	0.01	0.01	-0.02	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.08)	(0.09)
Observations	2,333	2,333	2,333	2,333	1,993	1,993
R-squared	0.92	0.92	0.90	0.90	0.87	0.87

Note: This table shows the effect of tariff exposure through migrant networks on vegetable farming. All columns control for own prefecture's output tariff, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3) and (5) have the same specification as Table 2 Column (3), and Columns (2)(4) and (6) have the same specification as Table 2 Column (4). The mean(sd) of the revenue share of vegetables is 0.42 (0.30), the mean (sd) of the household share of vegetables is 0.76 (0.33), and the mean (sd) of the log number of households with vegetables is 3.53 (0.95). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

We find no significant effect on husbandry, as shown in Table C14.

Table C14: Husbandry effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Log (husb. output)		Log (# of HHs in husb.)		Log(labordays in husb.)	
Tariff exposure through migr. network	0.21	0.20	0.25	0.42	-0.00	0.13
	(0.26)	(0.23)	(0.32)	(0.35)	(0.48)	(0.58)
Tariff exposure through migr. network × % cross-prefecture migration		0.05		-0.46		-0.37
		(0.47)		(0.31)		(0.51)
Own prefecture tariff	0.12	0.12	0.07	0.06	0.10	0.09
	(0.07)	(0.08)	(0.04)	(0.04)	(0.09)	(0.08)
Observations	2,263	2,263	2,263	2,263	2,241	2,241
R-squared	0.79	0.79	0.87	0.87	0.82	0.82

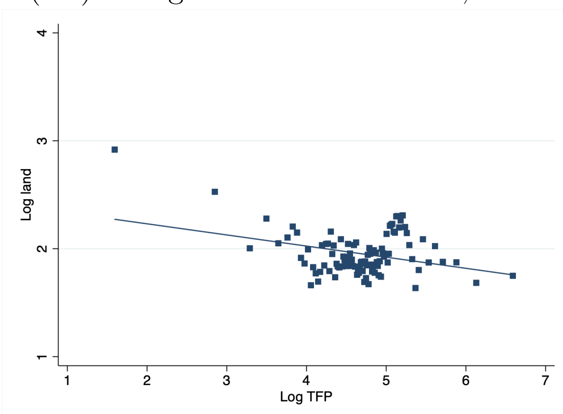
Note: This table shows the effect of tariff exposure through migrant networks on husbandry. All columns control for own prefecture's output tariff, the log labor, the log number of households, the log government transfer +1, province-year fixed effects, and village fixed effects. Columns (1)(3) and (5) have the same specification as Table 2 Column (3), and Columns (2)(4) and (6) have the same specification as Table 2 Column (4). The mean (sd) of the log value of husbandry is 11.77 (1.33), the mean (sd) of the log number of households with husbandry is 3.16 (1.04), and the mean (sd) of the log labor days in husbandry is 7.67 (1.21). Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

C.9 Additional Household-Level Results

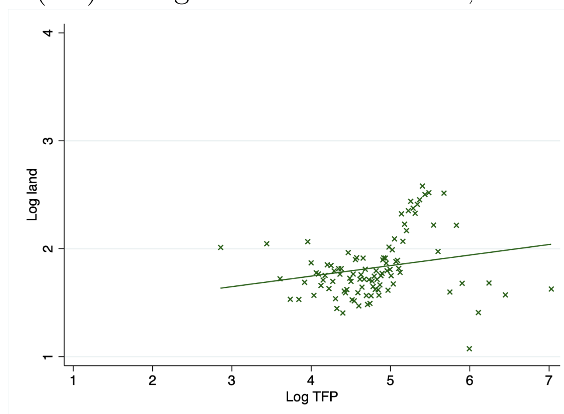
C.9.1 Land Reallocation Binscatter Plots

Figure C4: The correlation between land and TFP at the household-level, in villages with larger versus smaller shocks, 2001–2010, binscatter plots

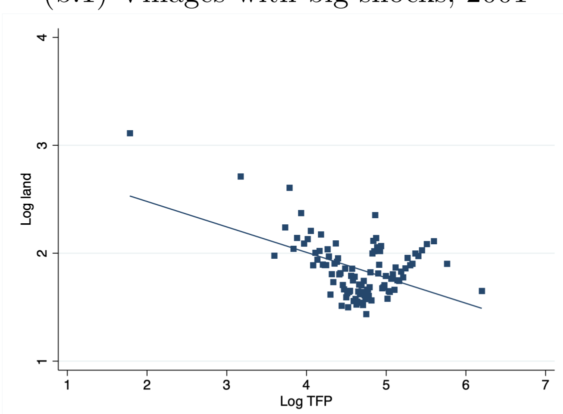
(a.1) Villages with small shocks, 2001



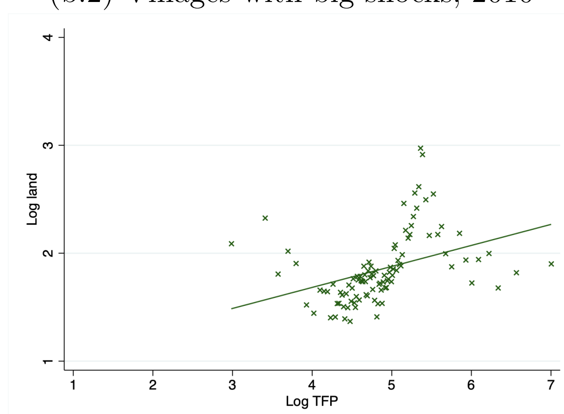
(a.2) Villages with small shocks, 2010



(b.1) Villages with big shocks, 2001



(b.2) Villages with big shocks, 2010



Note: This figure replicates the results in Figure 5 by using bin scatter plots.

C.9.2 Land Reallocation Results with Current TFP

Table C15 replicates the results of Table 9, by replacing the TFP in 2001 with the concurrent TFP. Given the high serial correlation of TFP over time, the results are very similar to the ones in Table 9.

Table C15: Land allocated result with current TFP, 2001–2010

Y: log(land)	(1)	(2)	(3)	(4)
Log(TFP)	0.267***	0.135***	0.215***	0.091***
	(0.055)	(0.034)	(0.045)	(0.025)
Tariff exposure through migr. network	0.184	0.144		
	(0.142)	(0.138)		
Tariff exposure through migr. network× Log(TFP)	-0.062***	-0.049***		
	(0.016)	(0.010)		
Tariff exposure through migr. network*%cross-pref. migr			0.135	0.057
			(0.186)	(0.158)
Tariff exposure through migr. network*%cross-pref. migr			-0.100**	-0.076***
× Log(TFP)			(0.032)	(0.019)
Own prefecture tariff	-0.016	-0.017	-0.027	-0.026
	(0.035)	(0.036)	(0.035)	(0.036)
Observations	119,760	117,671	119,760	117,671
R-squared	0.648	0.885	0.648	0.885
Village-Year FE	Yes	Yes	Yes	Yes
Village FE	Yes		Yes	
HH FE		Yes		Yes

Note: This table replicates Table 9, replacing TFP in 2001 by TFP in the contemporaneous year t. Standard errors are clustered at the province and the year level. *** p<0.01, ** p<0.05, * p<0.1.

D Model Appendix

In this section, we present a simple two-sector open-economy model with agricultural land market frictions. We calibrate the key model parameters using 1995, 2001, and 2010 NFP Survey data and conduct several quantitative exercises. Importantly, we back out: (1) the correlation between agricultural and non-agricultural productivity; (2) the size of agricultural land market frictions; (3) the economy-wide average productivity in agriculture and non-agriculture. Using this information, we investigate the interaction between the push factors driving out-migration (i.e., the reduction in land market frictions) and the pull factors of out-migration (i.e., relative productivity growth in the two sectors).

Our two-sector economy model shares many features with Adamopoulos et al. (2022). The key differences are as follows. First, instead of the closed-economy setup, we model a small open economy where the agricultural and non-agricultural prices are determined in the international market. This allows us to focus on the supply side of the economy and abstract from demand-side factors such as non-homothetic preferences and subsistence constraints for the consumption of agricultural goods. Second, Adamopoulos et al. (2022) model the household-level frictions in the agricultural sector as a random variable that is correlated with the household's agricultural productivity, and the size of the friction is such that no land rental activity happens in equilibrium. In contrast, we provide a micro foundation for the source of misallocation in the form of land market transaction costs as in Chari et al. (2020). Third, we calibrate the model parameters with data from different years to document changes in the key parameter values and to conduct counterfactual analysis using these changes. Note that the modeling of the non-agriculture sector is simplistic since it ignores the population that is always urban and only includes the population that moved from rural (agricultural sector) to urban (non-agricultural sector). In this sense, we also differ from Adamopoulos et al. (2022) since we do not match any aggregate moments but only focus on the part of the economy covered by the NFP Survey.

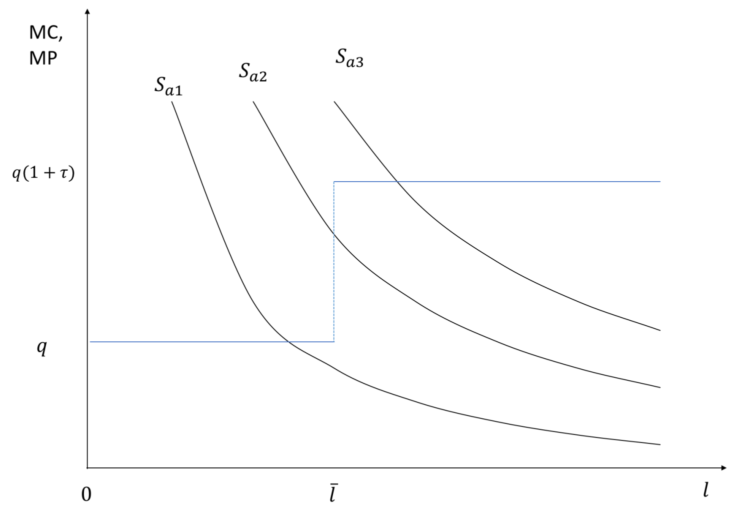
D.1 Model Setup

Environment The economy is a small open economy with two sectors, one agricultural sector (a) and one non-agricultural sector (n). The relative price of the agricultural goods is p_a, and the non-agricultural good price is normalized to 1. Both prices are determined exogenously on the international market. There is a continuum of individuals with measure 1. Each individual i is endowed with a pair of productivity levels in the two sectors (s_{ai}, s_{ni}), land $\bar{l}_i$, and one unit of labor that is inelastically supplied. We assume that land is equally distribution across individuals, so $\bar{l}_i = \bar{l}$. The cost of capital r is determined exogenously on the world market. An individual chooses the sector with a higher income, so $I_i = \max\{I_{ai}, I_{ni}\}$, where I_i is the income of an individual, I_{ai} is the income in agriculture, and I_{ni} is the income in non-agricultural. Let $H_n = \{i : I_{ai} < I_{ni}\}$, and $H_a = \{i : I_{ai} \geq I_{ni}\}$.

Production The agricultural sector operates with individual farms that exhibit decreasing return to scale with respect to capital and land,

$$y_{ai} = (A_a s_{ai})^{1-\gamma}(l_i^{\alpha} k_i^{1-\alpha})^{\gamma},$$

Figure D1: Marginal costs and products of land for farmers with different s_{ai}



where y_{ai} is the agricultural output in farm i, A_a is the agricultural productivity that is common across individuals, l_i and k_i are the land input and capital input, respectively. γ is the span-of-control parameter that governs the returns to scale, as in Lucas (1978).

The land market features a transaction cost in renting. If farmers use less than their endowed land $\bar{l}$, the rental rate is q. If they need to rent land from other farmers, the rental rate is $q(1+\tau)$. Thus, there is a kink in the marginal cost curve. Think about three types of farmers with different agricultural productivity: $s_{a1} < s_{a2} < s_{a3}$. As shown in Figure D1, the marginal product of land for a Type I farmer at $\bar{l}$ is smaller than the rental rate q, so a Type I farmer will use the land up to the point where $MPL_1 = q$, and rent out the rest of land. The marginal product of land for a Type II farmer at $\bar{l}$ is between q and $q(1+\tau)$, so a Type II farmer will use exactly $\bar{l}$. For a Type III farmer with $MPL_{l_3=\bar{l}} > q(1+\tau)$, he/she will rent in land from other farmers.

A farmer maximizes profit by choosing the optimal inputs,

$$\max_{k_i,l_i} \pi_i = p_a y_{ai} - rk_i - C(l_i),$$

where r is the rental rate of capital, and $C(l_i)$ is the cost of land, which takes the following form:

$$C(l_i) = \begin{cases} ql_i & \text{if } l_i \leq \bar{l}, \\ q\bar{l} + q(1+\tau)(l_i - \bar{l}) = q(1+\tau)l_i - q\tau\bar{l} & \text{if } l_i > \bar{l}. \end{cases}$$

Production in the non-agricultural sector employs a constant returns to scale technology that uses effective labor only,

$$Y_n = A_n Z_n,$$

where Y_n is the non-agricultural output, A_n is non-agricultural productivity that is common to all individuals, and Z_n is the total amount of effective labor used. Thus,

$$Z_n = \int_{i \in H_n} s_{ni} di,$$

where H_n is the set of individuals who chooses to work in the non-agricultural sector. The total number of workers in the non-agricultural sector is

$$N_n = \int_{i \in H_n} di.$$

Occupation choice If a person chooses the agricultural sector, he receives the profit from running the farm. A person always receives the factor payment $q\bar{l}$ no matter which sector he works in. Thus, agricultural income $I_{ai} = \pi_i + q\bar{l}$. If a person chooses the non-agricultural sector, he receives a wage of w_n. Thus, the non-agricultural income $I_{ni} = w_n s_{ni} + q\bar{l}$. The transaction cost τ represents the friction in the land rental market, so $\tau(l_i - \bar{l})$ is simply lost for $l_i > l$ and no agent gets it as income. The occupation choice is represented by

$$o(s_{ai}, s_{ni}) = \begin{cases} 1 & \text{if } i \in H_a, \\ 0 & \text{if } i \in H_n. \end{cases}$$

D.2 Definition of Equilibrium

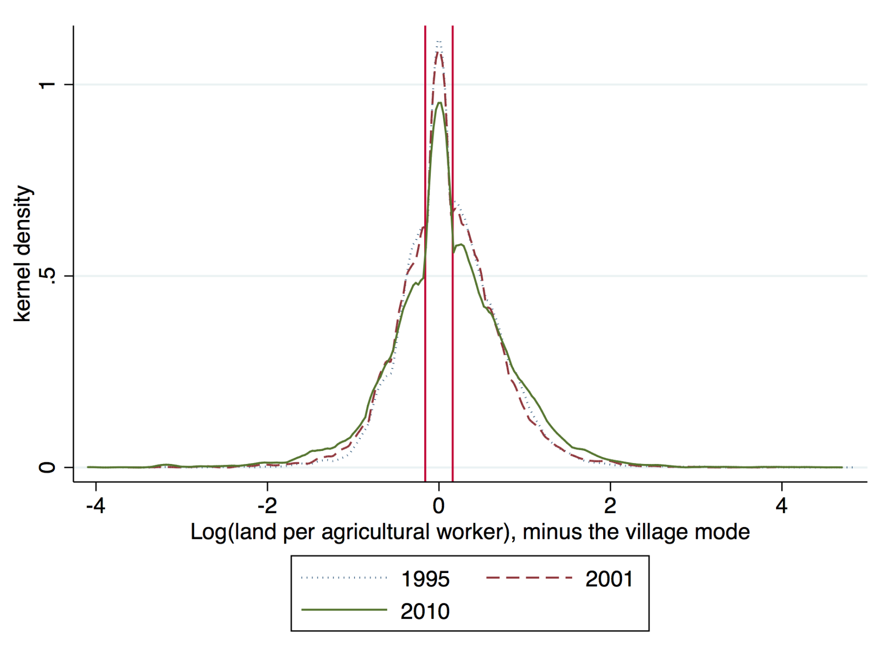
Given international prices for goods and capital, $\{p_a, r\}$, a competitive equilibrium is a land price q, an allocation for each farm $\{l_i, k_i, y_{ai}\}$, and allocation for the non-agricultural firm $\{Y_{n,} N_n\}$, an occupation choice $\{o(s_{ai}, s_{ni})\}$, a consumption allocation $\{(c_{ai}, c_{ni})\}$ for each individual such that: (1) individuals maximizes their utility; (2) firms maximize their profit; (3) farmers maximize their profits; (4) individuals maximizes their income by choosing their occupation; and (5) the land market and labor market clear.

D.3 Model Analysis

The model implies that in any cross-section, there exist three types of farmers: Type I with land smaller than the endowment, Type II with land at the endowment, and Type III with land larger than the endowment. Importantly, given the bunching at the endowment point, we should observe an empirical mass point.

We define the empirical mass point to be the village mode. In Figure D2, we plot the distribution of the log land per agricultural worker (subtracting the village-year mode) in 1995, 2001, and 2010. The household-level land is divided by the number of agricultural workers to construct data at the individual level. We find that in all three years, there appears to be a discontinuity in the distribution of the log land per agricultural worker at –0.16 and 0.16. Thus, we allow fuzziness in the definition of the village mode and define observations with the value between –0.16 and 0.16 as at the village mode. Then the observations to the left of the village mode are Type I farmers, the ones in the village mode are Type II farmers, and the ones to the right of the mode are Type III farmers. We find that the variance of the distribution of land per agricultural worker increased from 2001 to 2010, while the 1995–2001 change was very small.

Figure D2: The distribution of land per agricultural worker outspread over time



Note: This figure shows the distribution of the log land per agricultural worker in 1995, 2001, and 2010, using the NFP Survey household-level data. The distribution is for individuals in a year. To convert household-level information to individual-level information, we divide the total land in agricultural operation by the number of agricultural workers in the household and duplicate the observation by the number of agricultural workers. Then we take the village-year mode as the village-year level land endowment and deduct it from the log land per capita. The dotted line is for 1995, the dashed for 2001, and the solid for 2010. The vertical lines are at -0.16 and 0.16 on the x-axis.

Assume that the ability (s_{ai}, s_{ni}) follows a bi-variate log-normal distribution with mean $(0, 0)$ and variance

$$\Sigma = \begin{pmatrix} \sigma_a^2 & \sigma_{an} \\ \sigma_{an} & \sigma_n^2 \end{pmatrix}.$$

The correlation between the agricultural and non-agricultural ability is $\rho_{an} = \frac{\sigma_{an}}{\sigma_a \sigma_n}$.

The first-order condition of the non-agricultural sector gives

$$w_n = A_n. \tag{11}$$

Denote the marginal product of land for individual i as q_i. The first-order conditions for land and capital in the agricultural sector are

$$l_i = A_a (\gamma p_a)^{\frac{1}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} \left(\frac{\alpha}{q_i}\right)^{\frac{1-\gamma(1-\alpha)}{1-\gamma}} s_{ai}, \tag{12}$$

$$k_i = A_a (\gamma p_a)^{\frac{1}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{1-\alpha\gamma}{1-\gamma}} \left(\frac{\alpha}{q_i}\right)^{\frac{\alpha\gamma}{1-\gamma}} s_{ai}. \tag{13}$$

The profit of farmer i and farm output are

$$\pi_i = A_a \frac{1-\gamma}{\gamma} (\gamma p_a)^{\frac{1}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} \left(\frac{\alpha}{q_i}\right)^{\frac{\alpha\gamma}{1-\gamma}} s_{ai}, \tag{14}$$

$$y_i = A_a (\gamma p_a)^{\frac{\gamma}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} \left(\frac{\alpha}{q_i}\right)^{\frac{\alpha\gamma}{1-\gamma}} s_{ai}, \tag{15}$$

For Type II farmers, they are at the kink, $l_i = \bar{l}$, and $q_i \in (q, q(1+\tau)]$, and the value of q_i is determined by plugging $l_i = \bar{l}$ into Equation 12. Type I farmers have $l_i < \bar{l}$ and $q_i = q$. Type III farmers have $l_i > \bar{l}$ and $q_i = q(1+\tau)$. Thus, for all individuals, $q_i = q\phi_i$, with $1 \le \phi_i \le 1+\tau$.

With the new representation, we can re-write the expressions for l_i, k_i and π_i as follows,

$$l_i = l\phi_i^{-\frac{1-\gamma(1-\alpha)}{1-\gamma}} s_{ai}, \tag{16}$$

$$k_i = k\phi_i^{-\frac{\alpha\gamma}{1-\gamma}} s_{ai},$$

$$\pi_i = \pi\phi_i^{-\frac{\alpha\gamma}{1-\gamma}} s_{ai},$$

$$y_i = y\phi_i^{-\frac{\alpha\gamma}{1-\gamma}} s_{ai},$$

where $l = w_a\alpha\gamma/q$, $k = w_a(1-\alpha)\gamma/r$, $\pi = (1-\gamma)w_a$, $y = \frac{w_a}{p_a}$, and

$$w_a \equiv A_a \gamma^{\frac{\gamma}{1-\gamma}} p_a^{\frac{1}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} \left(\frac{\alpha}{q}\right)^{\frac{\alpha\gamma}{1-\gamma}}$$

are common for all farmers. The terms with ϕ_i represent the extent of distortion for the farmers, and they are decreasing functions with respective to ϕ_i, meaning that the distortions are larger for households who want to utilize larger lands. Holding the non-agricultural ability constant, these farmers are the ones with higher agricultural productivity.

Given the log normal distribution of (s_{ai}, s_{ni}), define the following terms

$$u_{ai} \equiv \log(s_{ai}),$$

$$u_{ni} \equiv \log(s_{ni}).$$

Thus, $E(u_{ai}) = E(u_{ni}) = 0$, $Var(u_{ai}) = \sigma_a^2$, $Var(u_{ni}) = \sigma_n^2$, $cov(u_{ai}, u_{ni}) = \sigma_{an}$. Also, $u_{ni} - u_{ai}$ follows a normal distribution with mean 0 and variance $\sigma^2 \equiv \sigma_a^2 + \sigma_n^2 - 2\sigma_{an}$.

The probability of individual i choosing the agricultural sector is

$$
\begin{aligned}
n_a^i &= \Pr(I_{ai} \geq I_{ni}) \\
&= \Pr(\pi_i \geq w_n s_{ni}) \\
&= \Pr(\log(\pi_i) \geq \log(w_n s_{ni})) \\
&= \Pr(\log((1-\gamma) w_a \phi_i^{-\frac{\alpha\gamma}{1-\gamma}} s_{ai}) \geq \log(w_n s_{ni})) \\
&= \Pr(\log(s_{ni}) - \log(s_{ai}) \leq \log((1-\gamma) w_a \phi_i^{-\frac{\alpha\gamma}{1-\gamma}}) - \log(w_n)) \\
&= \Pr(\frac{u_{ni} - u_{ai}}{\sigma} \leq \frac{b_a^i - b_n}{\sigma}),
\end{aligned}
$$

where $b_a^i \equiv \log((1-\gamma) w_a \phi_i^{-\frac{\alpha\gamma}{1-\gamma}})$, and $b_n \equiv \log(w_n)$.

Depending on the equilibrium value of l_i, n_a^i can take three forms. For Type I farmers, $\phi_i = 1$, $b_a = b_1$. For Type III farmers, $\phi_i = 1 + \tau$, $b_a = b_3$. For Type II farmers, we first solve the ϕ_i from Equation (16),

$$
\phi_i = \left(\frac{w_a \alpha \gamma s_{ai}}{q \bar{l}} \right)^{\frac{1-\gamma}{1-\gamma(1-\alpha)}}
$$

As a result,

$$
\begin{aligned}
n_a^i &= \Pr(\log((1-\gamma) w_a \phi_i^{-\frac{\alpha\gamma}{1-\gamma}} s_{ai}) \geq \log(w_n s_{ni})) \\
&= \Pr(\log((1-\gamma) w_a \left(\frac{w_a \alpha \gamma s_{ai}}{q \bar{l}} \right)^{-\frac{\alpha\gamma}{1-\gamma(1-\alpha)}} s_{ai}) \geq \log(w_n s_{ni})) \\
&= \Pr(\log((1-\gamma) w_a^{\frac{1-\gamma}{1-\gamma(1-\alpha)}} \left(\frac{\alpha\gamma}{q \bar{l}} \right)^{-\frac{\alpha\gamma}{1-\gamma(1-\alpha)}} s_{ai}^{\frac{1-\gamma}{1-\gamma(1-\alpha)}}) \geq \log(w_n s_{ni})) \\
&= \Pr(\log(s_{ni}) - \frac{1-\gamma}{1-\gamma(1-\alpha)} \log(s_{ai}) \leq \log((1-\gamma) w_a^{\frac{1-\gamma}{1-\gamma(1-\alpha)}} c) - \log(w_n)) \\
&= \Pr(\frac{u_{ni} - \widetilde{u}_{ai}}{\widetilde{\sigma}} \leq \frac{b_2 - b_n}{\widetilde{\sigma}}),
\end{aligned}
$$

where $\widetilde{u}_{ai} \equiv \frac{1-\gamma}{1-\gamma(1-\alpha)} u_{ai}$, $\widetilde{\sigma}^2 \equiv \left(\frac{1-\gamma}{1-\gamma(1-\alpha)} \right)^2 \sigma_a^2 + \sigma_n^2 - 2 \frac{1-\gamma}{1-\gamma(1-\alpha)} \sigma_{an}$, $b_2 \equiv \log((1-\gamma) w_a^{\frac{1-\gamma}{1-\gamma(1-\alpha)}} c)$, and $c \equiv \left(\frac{\alpha\gamma}{q\bar{l}} \right)^{-\frac{\alpha\gamma}{1-\gamma(1-\alpha)}}$.

Now we want to solve for the range of s_{ai} for the three situations. In Equation 16, set $l_i = \bar{l}$, and $\phi_i = 1$, we solve

$$
s_{ai} = \frac{\bar{l} q}{w_a \alpha \gamma} \equiv \underline{s},
$$

and set $l_i = \bar{l}$, and $\phi_i = 1 + \tau$, we solve

$$s_{ai} = \frac{\bar{l}q}{w_a \alpha\gamma}(1+\tau)^{\frac{1-\gamma(1-\alpha)}{1-\gamma}} \equiv \bar{s}.$$

Thus, for any individual to choose agriculture over non-agriculture, the probability is

$$\begin{aligned}
N_a &= \Pr(\frac{u_{ni} - u_{ai}}{\sigma} \leq \frac{b_1 - b_n}{\sigma}, \frac{u_{ai}}{\sigma_a} \leq \frac{\log(\underline{s})}{\sigma_a}) \\
&+ \Pr(\frac{u_{ni} - \widetilde{u}_{ai}}{\widetilde{\sigma}} \leq \frac{b_2 - b_n}{\widetilde{\sigma}}, \frac{\log(\underline{s})}{\sigma_a} < \frac{u_{ai}}{\sigma_a} \leq \frac{\log(\bar{s})}{\sigma_a}) \\
&+ \Pr(\frac{u_{ni} - u_{ai}}{\sigma} \leq \frac{b_3 - b_n}{\sigma}, \frac{u_{ai}}{\sigma_a} > \frac{\log(\bar{s})}{\sigma_a}) \\
&= P(A) + P(B) + P(C).
\end{aligned}$$

D.4 Calibration

We calibrate the key model parameters using 1995, 2001, and 2010 NFP Survey data. First, we assume that the ability (s_{ai}, s_{ni}) follows a bi-variate log-normal distribution with mean $(0,0)$ and variance Σ and is fixed over time. The variance-covariance matrix Σ is important in the migrant selection analysis. Second, we want to recover the land market transaction cost τ. Third, the average productivity in the two sectors (A_a, A_n) is useful in analyzing the relative productivity changes in the two sectors.

Based on the definition of the land endowment, we use the information on (1) the probabilities of being Type I, Type II, and Type III farmers, (2) the probability of choosing agriculture over non-agriculture, (3) the variances of land for Type I and Type III farmers, (4) the mean income of workers who switched from agriculture to non-agriculture, (5) the mean value of agricultural output, and (6) the mean output-to-land and output-to-capital ratio to calibrate the variance of the joint distribution of agricultural and non-agricultural ability, Σ, the average productivity (A_a, A_n), and the land market transaction cost τ.

The details of the calibration process are shown below.

Step 1. Simplification First assume that the variance of agricultural ability and non-agricultural ability are the same, i.e., $\sigma_n^2 = \sigma_a^2$. The following terms can be simplified,

$$\sigma^2 \equiv \sigma_a^2 + \sigma_n^2 - 2\sigma_{an} = 2\sigma_a^2 - 2\sigma_{an}.$$

For Type I farmer, denote $X \equiv \frac{u_{ai}}{\sigma_a}$, $Y \equiv \frac{u_{ni} - u_{ai}}{\sigma}$, $a^I \equiv \frac{\log(\bar{s})}{\sigma_a}$, and $b^I \equiv \frac{b_1 - b_n}{\sigma}$. Then we know that $(X, Y) \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$, where $\rho \equiv \frac{1}{\sigma\sigma_a}(\sigma_{an} - \sigma_a^2) = \frac{1}{\sqrt{2\sigma_a^2 - 2\sigma_{an}}}\frac{1}{\sigma_a}(\sigma_{an} - \sigma_a^2) = -\frac{\sqrt{\sigma_a^2 - \sigma_{an}}}{\sqrt{2}\sigma_a}$, and

$$P(A) = P(X \leq a^I, Y \leq b^I).$$

For Type III farmer, denote $a^{III} \equiv \frac{\log(\underline{s})}{\sigma_a}$, $b^{III} \equiv \frac{b_3 - b_n}{\sigma}$, and

$$P(C) = P(X > a^{III}, Y \leq b^{III}).$$

The relationship between the cutoffs is as follows. For (a^I, a^{III}),

$$a^I = \frac{\log(\underline{s})}{\sigma_a} = \frac{1}{\sigma_a} \log \frac{\bar{l}q}{w_a \alpha\gamma},$$

$$a^{III} = \frac{\log(\bar{s})}{\sigma_a} = \frac{1}{\sigma_a} \log \frac{\bar{l}q}{w_a \alpha\gamma}(1+\tau)^{\frac{1-\gamma(1-\alpha)}{1-\gamma}} = a^I + \frac{1-\gamma(1-\alpha)}{1-\gamma} \frac{\log(1+\tau)}{\sigma_a}.$$

For (b^I, b^{III}),

$$b^I = \frac{\log((1-\gamma)w_a) - b_n}{\sigma},$$

$$b^{III} = \frac{\log((1-\gamma)w_a(1+\tau)^{-\frac{\alpha\gamma}{1-\gamma}}) - b_n}{\sigma} = b^I - \frac{\alpha\gamma}{1-\gamma} \frac{\log(1+\tau)}{\sigma}.$$

Also

$$\sigma = \sqrt{2}\sqrt{\sigma_a^2 - \sigma_{an}} = -2\rho\sigma_a.$$

For Type II farmer, denote $Z \equiv \frac{u_{ni} - \widetilde{u}_{ai}}{\widetilde{\sigma}}$, and $b^{II} \equiv \frac{b_2 - b_n}{\widetilde{\sigma}}$. Then we know that $(X, Z) \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_2 \\ \rho_2 & 1 \end{bmatrix} \right)$, where $\rho_2 \equiv \frac{1}{\widetilde{\sigma}\sigma_a}(\sigma_{an} - \frac{1-\gamma}{1-\gamma(1-\alpha)}\sigma_a^2)$, and

$$P(B) = P(a^I < X \leq a^{III}, Z \leq b^{II}).$$

The cutoff b^{II} is related to (a^I, b^I),

$$\begin{aligned} b^I &\equiv \frac{\log((1-\gamma)w_a^{\frac{1-\gamma}{1-\gamma(1-\alpha)}} c) - \log(w_n)}{\widetilde{\sigma}} \\ &= \frac{\sigma \cdot b^I + \frac{\alpha\gamma}{1-\gamma(1-\alpha)} \sigma_a \cdot a^I}{\widetilde{\sigma}}, \end{aligned}$$

where $\widetilde{\sigma} = \left(\frac{1-\gamma}{1-\gamma(1-\alpha)}\right)^2 \sigma_a^2 + \sigma_a^2 - 2\frac{1-\gamma}{1-\gamma(1-\alpha)}\sigma_{an}$.

Step 2. Calibration of Parameters using Values from Literature We take the production function parameters α and γ directly from the literature, as shown in Table D1.

Table D1: Parameter values from the literature

Parameter	Value	Source
α	0.66	Adamopoulos et al. (2022)
γ	0.54	

Step 3. Calibration of the Variance-Covariance Matrix and The Distortion The value to be recovered: $(\rho, \sigma_a^2, a^I, b^I, \tau)$. We use the following five equations to recover them.

1. The probability of being a Type I farmer.

$$P(A) = P(X \leq a^I, Y \leq b^I). \tag{17}$$

2. The probability of being a Type II farmer.

$$P(C) = P(a^I < X \leq a^I + \frac{1-\gamma(1-\alpha)}{1-\gamma}\frac{\log(1+\tau)}{\sigma_a}, Z \leq \frac{\sigma \cdot b^I + \frac{\alpha\gamma}{1-\gamma(1-\alpha)}\sigma_a \cdot a^I}{\widetilde{\sigma}}). \tag{18}$$

3. The probability of being a Type III farmer.

$$P(C) = P(X > a^I + \frac{1-\gamma(1-\alpha)}{1-\gamma}\frac{\log(1+\tau)}{\sigma_a}, Y \leq b^I - \frac{\alpha\gamma}{1-\gamma}\frac{\log(1+\tau)}{\sigma}). \tag{19}$$

4. The variance of land for Type I farmers.

$$\begin{aligned} var(\log(l_i) \mid A) =& var(\log(l_i) \mid X \leq a^I, Y \leq b^I) \\ =& var(\log(s_{ai}) \mid X \leq a^I, Y \leq b^I) \\ =& \sigma_a^2 var(\frac{u_{ai}}{\sigma_a} \mid X \leq a^I, Y \leq b^I) \\ =& \sigma_a^2 var(X \mid X \leq a^I, Y \leq b^I). \end{aligned} \tag{20}$$

5. The variance of land for Type III farmers.

$$\begin{aligned} var(\log(l_i) \mid C) =& var(\log(l_i) \mid X > a^{III}, Y \leq b^{III}) \\ =& \sigma_a^2 var(X \mid X > a^I + \frac{1-\gamma(1-\alpha)}{1-\gamma}\log(1+\tau), Y \leq b^I - \frac{\alpha\gamma}{1-\gamma}\frac{\log(1+\tau)}{\sigma}). \end{aligned} \tag{21}$$

Take the 1995, 2001, and 2010 data. First, we plot the distribution of land per agricultural worker in Figure D2. The data is at the individual level and deducted by the village-year mode. Observations with a value smaller than –0.16 are defined as Type I farmers, and observations with a value larger than 0.16 are defined as Type III farmers. The farmers with a value between –0.16 and 0.16 are Type II farmers.

With the definition of different types of farmers, the following information can be calculated from the data.

Table D2: Data moments

Year	1995	2001	2010
Probability of choosing agriculture	.75	.71	.49
Total number of farmers	21,521	19,564	15,158
Number of Type I farmers	5,963	5,769	4,560
Number of Type II farmers	6,242	5,673	3,966
Number of Type III farmers	9,316	8,122	6,632
Prob of Type I farmers, conditioning on being a farmer	.28	.29	.30
Prob of Type II farmers, conditioning on being a farmer	.29	.29	.26
Prob of Type III farmers, conditioning on being a farmer	.43	.42	.44
Variance of log land, Type I	.097	.136	.237
Variance of log land, Type III	.158	.161	.232

Note: This table shows the data moments in 2001 and 2010, using the NFP Survey household-level data. Type I farmers are the ones with land (minus the village-year mode) smaller than –0.16, Type II farmers are the ones with land (minus the village-year mode) bigger than –0.16 and smaller than 0.16, and Type III farmers are the ones with land (minus the village-year mode) larger than 0.16.

We proceed in the following order using the 2001 information. (1) Guess (ρ, τ, σ_a). (2) Solve the cutoff points (a^I, b^I) from Equations 17 and 19. (3) Solve σ_a from Equation 20. (4) Update σ_a such that the guess and the solution are close. (4) Choose τ such that the difference between LHS and RHS of Equation 18 is the smallest. (5) Choose ρ such that the difference between LHS and RHS of Equation 21 is the smallest.

Table D3: Calibrated parameters

Year	1995	2001	2010
ρ		-0.6429	
σ_a		0.8469	
τ	1.6	1.6	1.2
a^I	-0.3939	-0.3333	-0.1515
a^{III}	0.2840	0.3446	0.4079
b^I	0.8981	0.7541	0.2036
b^{II}	0.8332	0.6987	0.1659
b^{III}	0.1724	0.1191	-0.4016

Note: This table shows the calibrated parameter values following the procedures in Step 3. The 2001 column calibrates all parameter values using the 2001 data. The 1995 and 2010 columns take the value of ρ and σ_a from the 2001 column and calibrate the rest of the parameters with the 1995, and 2010 data, respectively.

Suppose that we now use the variance-covariance matrix calibrated using the 2001 data to back out other parameter values in 1995 and 2010. We proceed in the following order. (1) Guess τ. (2) Solve the cutoff points (a^I, b^I) from Equations 17 and 19. (3) Calculate the difference between the LHS and the RHS of Equation 18, and choose τ such that the difference is the smallest.

Step 4. Calibration of the Remaining Parameters

- Solve (w_a, w_n). Think about the individuals who are (1) Type I farmers in 1995, and (2) Type I workers in 2001. Then we know that the following conditions must be satisfied: $X \leq a^I_{1995}, Y \leq b^I_{1995}, X \leq a^I_{2001}, Y > b^I_{2001}$. Denote the set of these individuals as H. Consider these switchers from 1995 to 2001, then we know that their non-agricultural income is,

$$\begin{aligned} E\log(I^{2001}_{ni} \mid i \in H) = &\log(w^{2001}_n) + E(\log(s_{ni}) \mid i \in H) \\ = &\log(w^{2001}_n) + E(u_{ni} - u_{ai} + u_{ai} \mid i \in H) \\ = &\log(w^{2001}_n) + \sigma E(Y \mid i \in H) + \sigma_a E(X \mid i \in H). \end{aligned}$$

Empirically, given the values of $(a^I_{1995}, b^I_{1995}, a^I_{2001}, b^I_{2001})$, the individuals with $i \in H$ are just the ones who worked in agriculture in 1995 as Type I farmer, and moved to non-agriculture in 2001.
Then w_n solved. Using the cutoff, $b^I = \frac{\log((1-\gamma)w_a) - \log(w_n)}{\sigma}$, then w_a solved.
Similarly, we use the 2001 to 2010 switchers to solve the (w_a, w_n) in 2010.

- Solve (r, p_a). Consider the Type I farmer in 2001. The value of output from farming is

$$\begin{aligned} E\log(p_a y_i \mid A) = &\log(w_a) + p_a \cdot E(\log(s_{ai}) \mid A) \\ = &\log(w_a) + p_a \sigma_a \cdot E(X \mid A). \end{aligned}$$

Then p_a solved.
The ratio of the value of output w.r.t. to inputs is as follows,

$$\frac{p_a y_i}{k_i} = \frac{1}{(1-\alpha)\gamma} r,$$

$$\frac{p_a y_i}{l_i} = \frac{1}{\alpha\gamma} q.$$

then $\{r, q\}$ can be solved.

- (A_a, A_n) can be solved using the following two equations:

$$w_n = A_n,$$

$$w_a = A_a \gamma^{\frac{\gamma}{1-\gamma}} p_a^{\frac{1}{1-\gamma}} \left(\frac{1-\alpha}{r}\right)^{\frac{\gamma(1-\alpha)}{1-\gamma}} \left(\frac{\alpha}{q}\right)^{\frac{\alpha\gamma}{1-\gamma}}.$$

- $\bar{l}$ can be solved using the following equation:

$$a^I = \frac{\log(\underline{s}) - \mu_a}{\sigma_a} = \frac{1}{\sigma_a} \log\left(\frac{\bar{l} q}{w_a \alpha \gamma}\right).$$

Table D4: Calibration of remaining parameters

Panel A: Data moments	2001	2010
Mean of log non-agricultural income for switchers	8.10	9.31
Mean of log agricultural output value for type I farmers	7.33	7.67
Mean agricultural output to land ratio for type I farmers	1271	1777
Mean agricultural output to capital ratio for type I farmers	3.72	4.83
Panel B: Calibrated parameters		
$\bar{l}$	3.65	5.29
p_a	2.64	3.66
r	1.80	3.25
$\log(A_n)$	8.1	9.6
$(1-\gamma)\log(A_a)$	6.8	7.2

Note: This table shows the data moments used and the calibrated parameter values in Step 4. The non-agricultural income includes wage income and income from land leasing, and it is calculated by dividing the household-level income by the number of non-agricultural workers. Switchers are the ones who were working in the agricultural sector in the previous year as Type I farmers and work in the current period as wage earners. The log agricultural output value is calculated as the household-level crop output value (minus the cost of intermediate inputs) divided by the number of agricultural workers.

The calibration results are shown in Table D5. Here, we assume that the variance of agricultural ability and non-agricultural ability are the same. We find that the correlation of the sectoral ability is 0.17, a rather small positive correlation, which is consistent with the empirical results shown in Section 6.1. The land market transaction costs are 1.6 in 2001 and 1.2 in 2010. These costs are substantial and decline over the years, which is in line with the land reforms documented in Chari et al. (2020). The growth of agricultural productivity (from 6.8 in 2001 to 7.2 in 2010) is smaller than the growth in non-agricultural productivity (from 8.1 in 2001 to 9.6 in 2010), indicating strong forces for sectoral labor reallocation.

Table D5: Calibrated parameters

Year	2001	2010
Variance of sector-specific productivity, σ_a^2	0.7172	
Covariance between productivity in different sectors, σ_{an}	0.1243	
Land market transaction cost, τ	1.6	1.2
Agricultural productivity, $(1-\gamma)\log A_a$	6.8	7.2
Non-agricultural productivity, $\log A_n$	8.1	9.6

Note: This table shows the calibrated parameter values.

D.5 Quantitative Exercise

Our quantitative exercise focuses on two aspects. First, we investigate the role of land market transaction costs in determining sectoral employment patterns and economic output. Second, we experiment with different patterns of sectoral productivity growth and highlight the role of manufacturing productivity growth.

The procedure of the counterfactual exercises is as follows:

Step 1. Generate a sample of 1,000,000 individuals with agricultural and non-agricultural ability with the calibrated variance-covariance matrix.

Step 2. Benchmark economy: use the cut-off points calculated from the 2010 data to determine occupation choice and type of farmer. Then calculate the capital and land allocation accordingly. Generate the total land size.

Step 3. Counterfactual. First, guess the price q. Given the vector, determine the cutoff points $(a^I, a^{III}, b^I, b^{II}, b^{III})$. Then do the same exercise as in the BE, such that the land market clears.

Table D6: Counterfactuals for 2010

Aggregate statistics	Benchmark Economy	C1 $\tau = 0$	C2 $A_n^{2010} = A_n^{2001}$
Real agricultural productivity (output per person)	1	1.09	0.69
Share of employment in agriculture	0.49	0.48	0.90
TFP in agriculture	1	1.06	0.91
Real non-agricultural productivity (output per person)	1	0.93	0.36
Average ability in agriculture (in log)	1	1.48	0.34
Average ability in non-agriculture (in log)	1	0.79	1.84
GDP per worker	1	1.02	0.83
Total agricultural capital per agricultural employment	1	1.09	0.69

Note: This table shows the results of the counterfactual analysis for 2010. Column benchmark economy is in 2010, and Columns C1 and C2 represent different counterfactual analyses. In Column C1, we set the distortion to be 0. In Column C2, we set the non-agricultural productivity in 2010 to be the same as the non-agricultural productivity in 2001. Real agricultural and non-agricultural productivity are the output per worker in the agricultural sector and the non-agricultural sector, respectively. TFP in agriculture is defined as $\frac{\sum y_{ai}}{\left(\sum_{i\in H_a} 1\right)^{1-\gamma} \text{land}^{\alpha\gamma} (\sum k_i)^{(1-\alpha)\gamma}}$. The average ability in agriculture is $\frac{\sum_{i\in H_a} s_{ai}}{\sum_{i\in H_a} 1}$, and the average ability in non-agriculture is $\frac{\sum_{i\in H_n} s_{ni}}{\sum_{i\in H_n} 1}$. GDP per worker is defined as the total value of output $p_a \sum y_{ai} + \sum y_{ni}$ divided by the total number of workers.

The results of the counterfactual analysis are shown in Table D6. Column BE shows the aggregate statistics for the baseline economy in 2010. Our first experiment changes the value of the land market transaction cost. In Column C1, we set the 2010 transaction cost to zero and eliminate all distortions in the land market. The demand for land rental increases, leading to increased land rental prices. Low-productivity farmers exit and high-productivity farmers enter, resulting in an increase in the average ability of farmers. On the other hand, the average productivity of non-agricultural workers declines due to the influx of marginal workers who are less productive. Overall, this results in a slight increase in per capita GDP (2%), a slight decrease in the share of agricultural workers (one percentage point), and an increase in the capital per worker in the agricultural sector (9%).

One second experiment changes the non-agricultural productivity. In Column C2, we set the 2010 non-agricultural productivity to be the same as the 2001 non-agricultural productivity. Due to the decline in non-agricultural productivity, the demand for land increases, and the land rental price also increases. The opportunity cost of farming declines, and more people stay in agriculture. This results in a decline in the average agricultural productivity and an increase in the average non-agricultural productivity since only the most productive workers remain in non-agriculture. Overall, the effect is a substantial decrease in per capita GDP (17%), a large increase in the share of agricultural workers (42 percentage points), and a large decline in the capital per worker in the agricultural sector (31%).

In sum, we find a relatively small effect of reducing land-market transaction costs on the overall economy, measured as the per capita GDP and the share of employment in the agricultural sector. The intuition is that given the increased importance of the non-agricultural sector, the distortion in the land market in the agricultural sector was relatively unimportant. This mirrors Chari et al. (2020) where they find no impact of land reforms on out-migration in the 2003–2008 period. However, reducing the distortion still benefited the agricultural sector, in the form of increased capital adoption and agricultural TFP. In contrast, the effect of increasing non-agricultural productivity had a very large impact on sectoral employment patterns and agricultural productivity. Only the most productive farmers remained in agriculture, and they substantially increased the amount of capital used. Overall, the pull factors of out-migration (i.e., relative productivity growth in the two sectors) had much larger impacts than the push factors of out-migration (i.e., the reduction of land market frictions) on both urbanization and agriculture modernization.