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Labor Mobility Barriers and Agricultural Productivity in China: Analysis Based on a General-Equilibrium Roy Model

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With sustainable economic growth and structural transformation, labor productivity in China's agricultural sector has gradually improved. However, significant gaps remain compared to the nonagricultural sector and agriculturally advanced economies. To explain these disparities in sectoral productivity, we develop a two-sector general-equilibrium Roy model incorporating mobility barriers, such as China's hukou policy. These barriers result in labor without comparative advantages in agriculture being trapped in the agricultural sector, which lowers both the quality of labor and productivity in agriculture. Additionally, the phenomenon of insufficient per capita arable land further hampers the growth of agricultural labor productivity. We then calibrate the model's parameters using sector-level data and conduct quantitative analysis. The results show that the mobility barrier across sectors declines between 2002 and 2021, which explains 28% of the rise in the agricultural labor productivity of China. These findings underscore the importance of further reducing labor mobility barriers to promote the improvement of agricultural productivity and accelerate urban-rural integration.

Key Words: Mobility barrier; Labor selection; Agricultural productivity.
JEL Classification Numbers: J24, O15, R23.

1. INTRODUCTION

As the world's largest developing country, China has experienced rapid economic growth and structural change since its reform and opening up (Brandt et al., 2008). Despite significant improvements in labor productivity in both the agricultural and nonagricultural sectors, the productivity difference between these two sectors remains large. As shown in Figure 1,

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the ratio of labor productivity in the agricultural sector to the nonagricultural sector is still lower than 0.30 in 2021. In addition, the productivity of China's agricultural sector is much lower than that of developed countries. For instance, the 2021 agricultural labor productivity in the United States is 11.36 times as high as that in China, while the productivity difference in the nonagricultural sector is a factor of only 5.23.[1] In that China's agricultural labor share remains high, understanding this phenomenon is critical for understanding the income gap between China and developed countries (Lagakos and Waugh, 2013).

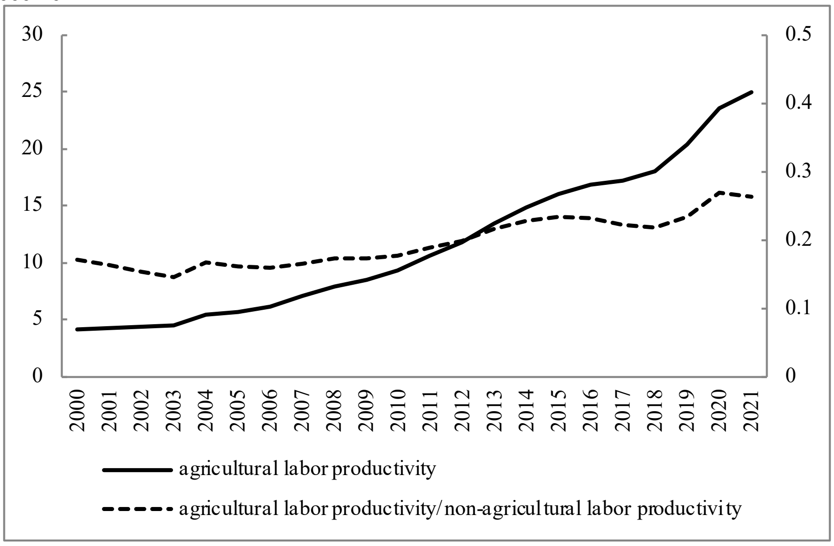
Note that the aforementioned problem is not unique to China. Studies show that the cross-country labor productivity difference in the agricultural sector is much larger than the nonagricultural sector (Donovan, 2012; Gollin et al., 2013; Restuccia et al., 2008). Caselli (2005) constructs purchasing power parity (PPP)-adjusted labor productivity of 79 countries and finds that the ratio of agricultural labor productivity between the 90th and 10th percentile countries is as high as 45 times, while the labor productivity difference in the nonagricultural sector is merely a factor of four. That is, the variation in agricultural productivity across countries is over 10 times as much as that in nonagricultural productivity.

Recent literature provides some explanations for the vast gap in agricultural labor productivity between poor and rich countries. Restuccia et al. (2008) and Donovan (2012) find that high agricultural labor productivity is positively associated with the extent of intermediate input use. Thus, the barriers to modern intermediate inputs in developing countries contribute to large cross-country differences in agricultural labor productivity. Lagakos and Waugh (2013) explain patterns with the self-selection of heterogeneous workers and propose that subsistence requirements induce workers who are relatively unproductive at agricultural work to select for the agriculture sector in poor countries. As a result, an economy-wide efficiency difference predicts that productivity differences are roughly twice as large in agriculture as they are in non-agriculture sectors. Adamopoulos et al. (2022) and Chen (2017) point out that land misallocation across farms reduces aggregate agricultural productivity in developing countries. Moreover, the friction further amplifies the productivity effect of distortionary policies by affecting occupational choices that worsen average ability in agriculture.

In contrast to the cross-country analysis in the existing literature, this paper studies the impacts of the labor mobility barrier on the selection of heterogenous workers across sectors and agricultural productivity in China. Labor mobility across sectors is inhibited in China's unique institutional

[1]Statistics are from the World Bank World Development Indicators database, the China Statistical Yearbook, and the U.S. Bureau of Economic Analysis.

FIG. 1. Absolute and relative values of agricultural labor productivity in China, 2000-2021



Notes: Data are from the China Statistical Yearbook. Agricultural labor productivity is deflated to 2002 constant prices in thousand yuan.

context. On the one hand, rural migrants have limited access to public services in cities and face high migration costs under the hukou system of household registration (Bosker et al., 2012; Tombe and Zhu, 2019). On the other hand, the land policy in rural areas prevents farmers from trading land in a frictionless market and flowing to the nonagricultural sector (Ngai et al., 2016). We embed the labor mobility barrier into a general-equilibrium Roy model and analyze how the distribution of heterogenous workers determines sectoral productivity. Our theoretical analysis shows that mobility barriers induce many workers who do not have a comparative advantage in agricultural production to select into the sector, which reduces the average ability and land per capita. Thus, low labor productivity in agriculture results. We further conduct a parameter calibration and counterfactual simulation using rich micro and macro data. The quantitative analysis shows that the mobility barrier between sectors declines between 2002 and 2021, which explains 28% of the rise in agricultural labor productivity in China. However, the mobility barrier remains high in 2021 and accounts for 14% of the China-U.S. gap in agricultural labor productivity.

Our paper contributes to the literature examining significant cross-country differences in agricultural labor productivity. Existing studies explain the low agricultural productivity in developing countries from barriers to intermediate inputs, land misallocation, and the selection of unproductive workers into farm production (Adamopoulos et al., 2022; Chari et al., 2021; Chen, 2017; Donovan, 2012; Gao et al., 2021; Lagakos and Waugh, 2013; Restuccia et al., 2008; Sheng et al., 2019). We propose a new explanation for the phenomenon and show that mobility barriers across sectors reduce the average ability and land per capita in agriculture, thus leading to low agricultural labor productivity. Our analysis also provides important implications for other developing countries considering that the mobility barrier between agricultural and nonagricultural sectors is not unique to China.

Our study is also related to literature that quantitatively evaluates the macroeconomic impacts of mobility barriers. Researchers such as Bryan and Morten (2019), Ngai et al. (2019), Tombe and Zhu (2019), and Hao et al. (2020) show that migration costs prevent efficient labor allocation across sectors and regions. As a result, reducing barriers to internal labor migration will lead to aggregate productivity gains. Differing from these spatial studies, we focus on the role of migration costs across sectors in explaining low agricultural labor productivity in developing countries, which helps enrich the understanding of the impacts of mobility barriers.

The paper is structured as follows. Section 2 presents the stylized facts, and section 3 presents the model. Sections 4 and 5 present the theoretical and quantitative analyses, respectively, and section 6 concludes.

2. STYLIZED FACTS

2.1. Cross-sector differences in labor ability and productivity in China

Although labor productivity in China's agricultural sector has been increasing over the past two decades, the productivity gap across sectors remains sizable. According to the China Statistical Yearbook, the ratio of labor productivity between the agricultural and nonagricultural sectors remains below 0.30 in 2021. The cross-sectoral differences in labor ability help shed light on this phenomenon. As a starting point to examine trends over time, we examine 2002 data showing characteristics of rural farmers and rural to urban (rural-urban) migrants from the 2002 China Household Income Survey. As shown in Table 1, rural workers who flow to the nonagricultural sector in urban areas are younger and have a higher proportion of men. In comparison, a large fraction of women and elderly people who are not good at manual farm work choose to stay in rural areas. Many workers who do not have a comparative advantage in farming choose agricultural production, which helps explain the large productivity gap across sectors in China. In addition, the average years of schooling of rural-urban migrants is higher than that of rural farmers. The outflow of rural workers with higher levels of education enlarges the difference in human capital and labor productivity across sectors. Furthermore, the average annual labor income of farmers is less than 30% of that of migrants to urban areas, which indirectly reflects the gap in labor productivity between the agricultural and nonagricultural sectors.

TABLE 1.

Basic characteristics of rural farmers and migrants in China in 2002

	Rural farmers	**Rural-urban migrants**
Average age	40.79	34.79
Proportion of men	0.45	0.57
Average years of schooling	6.71	7.92
Average annual labor income (yuan)	2532	9434

Notes: Data are from the 2002 China Household Income Survey.

Fact 1: In the process of structural transformation in China, many young male workers with high education levels flow into the nonagricultural sector, while women and elderly people who do not have a comparative advantage on farms select into the agricultural sector, resulting in low labor ability in agriculture.

TABLE 2.

Labor productivity differences between China and the United States in 2002 and 2021

	China		**United States**		**USA/China**	
	2002	2021	2002	2021	2002	2021
Agriculture	1188.73	6722.98	50555.04	76357.66	42.53	11.36
Nonagricultural	7751.22	25454.65	102545.39	133231.44	13.23	5.23
Overall	4469.32	21146.37	101528.73	132285.97	22.72	6.26

Notes: Data are from the World Development Indicators database, the China Statistical Yearbook, and the U.S. Bureau of Economic Analysis. Labor productivity is measured in 2015 constant dollars.

2.2. Cross-country difference in labor ability and productivity

Compared with China, the labor productivity difference across sectors is smaller in developed countries. In some countries with developed agriculture, labor productivity in the agricultural sector is even higher than nonagricultural productivity. For instance, agricultural labor productivity in Israel is 11% higher than nonagricultural labor productivity, and agricultural labor productivity in the Netherlands is 36% higher than nonagricultural labor productivity (Gollin et al., 2013). Table 2 compares the labor productivity gap by sector between China and the United States over time. It is shown that overall labor productivity in the United States is 22.72 times as high as that in China in 2002. The ratio of agricultural labor productivity between the two countries is 42.53, which is much higher than the nonagricultural labor productivity difference. By 2021, the overall labor productivity gap between the United States and China had declined to 6.26, and the ratio of agricultural labor productivity between the two countries lowered to 11.36. Although the gap between China and the United States is narrowing, the labor productivity difference in agriculture is still larger than the gap in nonagricultural sectors.

Fact 2: The labor productivity gap between China and developed countries is larger in agriculture than in nonagricultural sectors.

In Table 3, we further use educational attainment as a proxy for labor quality and make a cross-country comparison. Results show that the average years of schooling for agricultural workers in China is much lower than that in developed countries. Moreover, the gap in educational attainment between the agricultural and nonagricultural sectors in China is much higher than the difference in developed countries. These data imply that the cross-sector labor quality difference is larger in China.

TABLE 3.

Average years of schooling by country and sector

Country	Year	Average years of schooling		
		Agriculture	Non-agriculture	Difference between the two sectors
China	2000	6.79	10.06	3.27
China	2010	7.57	10.31	2.74
Israel	1995	9.13	10.93	1.80
United States	2000	11.55	13.18	1.63
Germany	2009	11.80	12.90	1.10
Netherlands	2011	13.80	14.80	1.00

Notes: Data for China are from the census, and data for other countries are from Gollin et al. (2013).

Fact 3: The cross-sector labor quality difference is larger in China than the gap in developed countries.

The above three facts suggest that the selection of heterogenous workers helps explain the low agricultural labor productivity in China. The restrictions imposed by China's hukou system on labor mobility induce many women and elderly people who do not have a comparative advantage on farms to choose the agricultural sector, while young male workers with higher education levels select the nonagricultural sector, which worsens the average ability in agriculture. Based on these stylized facts, we theoretically and quantitatively study the impacts of mobility barriers on the selection of heterogenous workers and agricultural labor productivity in China.

3. MODEL

In this section, we build a two-sector general-equilibrium Roy model with an occupational choice of heterogeneous workers and labor mobility barriers across sectors. The economy consists of two sectors, agriculture (a) and non-agriculture (n). There is one unit continuum of workers who differ in ability. Each worker is endowed with a vector of individual ability denoted $\{\varepsilon_a^i, \varepsilon_n^i\}$. Individual abilities are drawn from a distribution $F(\varepsilon_a, \varepsilon_n)$. The heterogeneous labor chooses the sector in which to maximize utility in the presence of mobility barriers.

3.1. Production

3.1.1. Nonagricultural sector

A representative firm in the nonagricultural sector produces goods with a constant return to scale technology. The production function is

$$Y_n = A_n H_n, \tag{1}$$

where A_n represents total factor productivity (TFP), and H_n represents the number of effective labor units in the nonagricultural sector. The firm chooses the optimal amount of labor input to maximize its profit. Taking the nonagricultural good as the numeraire, the equilibrium wage per unit of effective labor in the nonagricultural sector is

$$w_n = A_n \tag{2}$$

3.1.2. Agricultural sector

Following Adamopoulos and Restuccia (2014), the production unit in the agricultural sector is a farm, which is a technology requiring the inputs of a farm operator and the land. The production function of farm i is

$$y_a^i = (A_a \varepsilon_a^i)^\beta l_i^{1-\beta}, \tag{3}$$

where A_a is the TFP in the agricultural sector, y_a^i is the real output of the farm i, and ε_a^i denotes the ability of the farm operator. In addition, l_i represents the land input of farm i.

Given the price of agricultural goods p_a and the rental price of land r, farmer i chooses the amount of land input to maximize profits[2]:

$$\max_{l_i} p_a y_a^i - r l_i. \tag{4}$$

The first-order conditions imply that the land input and real output for farm i are

$$l_i = \left[\frac{(1-\beta)p_a}{r}\right]^{\frac{1}{\beta}} A_a \varepsilon_a^i, \tag{5}$$

$$y_a^i = \left[\frac{(1-\beta)p_a}{r}\right]^{\frac{1-\beta}{\beta}} A_a \varepsilon_a^i. \tag{6}$$

Assuming that the land income belongs to the farm operator, the income of farmer i is given by $I_a^i = p_a y_a^i$. Let $w_a \equiv A_a p_a^{\frac{1}{\beta}} \left[\frac{(1-\beta)}{r}\right]^{\frac{1-\beta}{\beta}}$, the income of farmer i can be expressed as $I_a^i = w_a \varepsilon_a^i$.

Let Ω^a represent the set of workers employed in the agricultural sector and Ω_n denote the set of workers employed in the nonagricultural sector. The total output of the agricultural sector can be expressed as

$$Y_a = \int_{i \in \Omega^a} y_a^i dF_i. \tag{7}$$

The total number of effective labor units in each sector s is defined as

$$H_s = \int_{i \in \Omega^s} \varepsilon_s^i dF_i, \quad s \in \{a, n\}. \tag{8}$$

The total number of workers employed in each sector s is defined as

$$N_s = \int_{i \in \Omega^s} dF_i, \quad s \in \{a, n\}. \tag{9}$$

3.2. Workers

3.2.1. Preferences

Assume that the utility of worker i is given by

$$U_i = v \log(c_a^i - \overline{a}) + (1-v)\log(c_n^i) \tag{10}$$

[2]To simplify the analysis, we assume no distortions in the agricultural land market. For studies on land misallocation in agriculture, see Adamopoulos et al. (2022). Land misallocation is reflected by lower agricultural TFP in our paper.

where c_a^i and c_n^i represent the consumption of agricultural and nonagricultural goods, and $\overline{a}$ represents a subsistence consumption requirement. v measures the relative taste for nonagricultural goods consumption. The nonhomothetic preference implies that the income elasticity of demand for agricultural goods is less than one.

Let y^i denote the income of worker i. The budget constraint of worker i is

$$p_a c_a^i + c_n^i = y^i. \tag{11}$$

Given income and product price, workers make consumption decisions to maximize utility. The optimal consumption decision is given by

$$c_a^i = \overline{a} + \frac{v}{p_a}(y^i - p_a\overline{a}), \tag{12}$$

$$c_n^i = (1-v)(y^i - p_a\overline{a}). \tag{13}$$

3.2.2. Sectoral Choices

Heterogeneous workers choose the employment sector to maximize income. They face mobility barriers when moving from the agricultural sector to the nonagricultural sector because rural migrants are treated differently in the urban labor market and have limited access to local public services under the household registration system in China (Hao et al., 2020; Ngai et al., 2019). If worker i chooses to be employed in the agricultural sector, he receives an income of $I_a^i = w_a\varepsilon_a^i$. If the worker chooses to be employed in the nonagricultural sector, his income is $I_n^i = (1-\tau)w_n\varepsilon_n^i$, where τ denotes the mobility barrier across sectors. The worker will choose the agricultural sector when $I_a^i > I_n^i$. In a converse scenario, the worker will choose the nonagricultural sector. Therefore, the worker's income can be expressed as $y^i = \max\{I_a^i, I_n^i\}$.

Assume that the ability of a worker $\{\varepsilon_a^i, \varepsilon_n^i\}$ is drawn independently from the Fréchet distribution

$$F(\varepsilon_a, \varepsilon_n) = \exp\left[-\sum_{s\in\{a,n\}}\varepsilon_s^{-\theta}\right], \tag{14}$$

where θ controls the dispersion of individual ability. The employment share of workers in the agricultural and nonagricultural sectors is therefore given by

$$\pi_a = \frac{w_a^\theta}{w_a^\theta[(1-\tau)w_n]^\theta}, \tag{15}$$

$$\pi_n = \frac{[(1-\tau)w_n]^\theta}{w_a^\theta + [(1-\tau)w_n]^\theta}. \tag{16}$$

The above equations show that the share of workers employed in the agricultural sector depends on the wage rate in both sectors and the barriers to labor mobility between sectors. Mobility barriers prevent workers from moving to the nonagricultural sector, resulting in a high employment share of agriculture.

3.3. General Equilibrium

The competitive equilibrium of this economy consists of the agricultural product price p_a, the rental price of land r, the wage of effective labor $\{w_a, w_n\}$, the distribution of workers in the two sectors $\{\pi_a, \pi_n\}$, and the total output Y that satisfy the following conditions.

(i) Workers make optimal consumption and employment decisions to maximize utility.

(ii) Firms/farms make optimal input decisions to maximize profits.

(iii) Product market clears, that is, $C_a = Y_a$, $C_n = Y_n$.

(iv) Labor market clears, that is, $\pi_a + \pi_n = 1$.

(v) Land market clears, that is, $T = \int_{i\in\Omega_a} l_i dF_i$, where T denotes total land endowment.

(vi) The total output of this economy is $Y = p_a Y_a + Y_n$.

3.4. Average labor ability and productivity

It is further deduced that the average ability of workers in the agricultural and nonagricultural sectors is

$$E(\varepsilon_a | i \in \Omega^a) = \gamma \pi_a^{\frac{-1}{\theta}}, \tag{17}$$

$$E(\varepsilon_n | i \in \Omega^n) = \gamma \pi_n^{\frac{-1}{\theta}}, \tag{18}$$

where $\gamma = \Gamma\left(\frac{\theta-1}{\theta}\right)$ is a constant. The equations show that the average ability in a sector is negatively related to the employment share of the sector. In the Roy self-selection model, workers choose occupations based on their comparative advantage. When only a few people are employed in a particular occupation, most are highly talented and competent in the occupation. If more people choose this occupation, the average quality of workers will decrease (Hsieh et al., 2016; Roy, 1951). The selection effect suggests that mobility barriers in China induce many workers who are unproductive on farms to choose agriculture, thus worsening the average ability of agriculture.

Given the average ability of workers, the labor productivity of the nonagricultural sectors is

$$Y_n/N_n = A_n E(\varepsilon_n | i \in \Omega^n) = \gamma A_n \pi_n^{\frac{-1}{\theta}}. \tag{19}$$

And the labor productivity of the agricultural sector is

$$Y_a/N_a = A_a^{\beta} \left(\frac{T}{\pi_a}\right)^{1-\beta} [E(\varepsilon | i \in \Omega^a)]^{\beta} = (\gamma A_a)^{\beta} T^{1-\beta} \pi_a^{-\phi}, \tag{20}$$

where $\phi = 1 - \beta(1 - 1/\theta) > 0$. It is implied that agricultural labor productivity is negatively related to the employment share of agriculture. On one hand, given a fixed land endowment T, an increase in the number of agricultural workers will reduce the arable land per capita T/π_a. On the other hand, the average ability of agricultural workers $E(\varepsilon_a | i \in \Omega_a)$ is low when the employment share of agriculture is high due to the selection effect. Furthermore, the ratio of labor productivity in the agricultural to the nonagricultural sector can be expressed as

$$\frac{Y_a/N_a}{Y_n/N_n} = \frac{A_a^{\beta} T^{1-\beta} \pi_n^{1/\theta}}{A_n \gamma^{1-\beta} \pi_a^{\phi}} \tag{21}$$

The equation shows that the cross-sector difference in labor productivity depends on the agricultural land endowment, the difference in TFP, and the distribution of workers between the two sectors.

4. THEORETICAL ANALYSIS

In this section, we conduct a comparative static analysis to examine the impacts of the mobility barrier and agricultural TFP on the selection of heterogenous workers and agricultural labor productivity. We further compare the labor productivity difference between China and the United States to illustrate how the mobility barrier generates cross-country gaps.

4.1. The impact of the mobility barrier

Labor is unable to move freely between sectors under the distortional household registration system, which affects the distribution of employment and sectoral labor productivity. The comparative static analysis shows that

$$\partial \pi_a / \partial \tau > 0. \tag{22}$$

This result suggests that an increase in the barrier to labor mobility will cause an increase in the share of employment in agriculture. It is further deduced that

$$\partial (Y_a/N_a)/\partial \tau < 0, \quad \partial \left(\frac{Y_a/N_a}{Y_n/N_n} \right) / \partial \tau < 0. \tag{23}$$

The findings imply that a high mobility barrier contributes to low labor productivity in agriculture, thus enlarging the labor productivity gap between agriculture and non-agriculture sectors. Two mechanisms help explain the finding. First, the mobility barrier prevents workers from moving to the nonagricultural sector and results in an excessive quantity of labor in agriculture, which reduces arable land per capita and agricultural labor productivity. Second, the selection effect amplifies the impact of mobility barrier by worsening the average ability in agriculture. Many workers who do not have comparative advantage in agricultural production select into the agricultural sector, which lowers the average ability of the agricultural workers, thus widening the labor productivity gap between agriculture and non-agriculture.

THEOREM 1. *The mobility barrier induces many workers who are unproductive in agricultural production to select into agriculture, which reduces the average ability and arable land per capita, thus leading to low labor productivity in agriculture.*

Proof. See Appendix. ∎

4.2. The impact of agricultural TFP

Under the nonhomothetic preference, TFP in agriculture affects the distribution of employment and agricultural labor productivity. A comparative static analysis shows that

$$\partial \pi_a / \partial A_a < 0, \quad \partial (Y_a/N_a)/\partial A_a > 0. \tag{24}$$

This finding suggests that an increase in agricultural TFP will reduce the share of employment in agriculture and improve the labor productivity of agriculture. Suppose that agricultural TFP increases from A_a to A_a', the share of agricultural employment will decrease from π_a to π'_a, and the change in agricultural labor productivity is given by

$$\frac{Y'_a/N'_a}{Y_a/N_a} = \left(\frac{A'_a}{A_a}\right)^{\beta} \left(\frac{\pi_a}{\pi'_a}\right)^{\phi} > \left(\frac{A'_a}{A_a}\right)^{\beta} \tag{25}$$

It is shown that an increase in TFP not only improves labor productivity directly but also has an indirect impact on labor productivity by promoting structural change. On the one hand, as the share of agricultural employment decreases, the arable land per capita gradually increases, which helps increase farmer labor productivity. On the other hand, the TFP growth induces workers with a comparative advantage in agricultural production to select into the agricultural sector. Thus, the selection effect amplifies the impact of TFP growth by improving the average ability of agricultural workers.

THEOREM 2. *An increase in agricultural TFP will reduce the share of employment in agriculture and improve the labor productivity of agriculture. The selection effect amplifies the impact of TFP growth by improving the average ability of agricultural workers.*

Proof. See Appendix. ▮

4.3. Cross-country differences in agricultural labor productivity

We further compare the difference in agricultural labor productivity between China and the United States based on the theoretical analysis above. The United States is chosen for comparison not only because it is the most advanced economy in the world but also because it is recognized as a country with few barriers to labor mobility (Hiesh and Klenow, 2009). The superscript U is used to represent the United States and the superscript C is used to represent China. Compared to the United States, China has higher labor mobility barriers ($\tau^C > \tau^U$), less arable land endowment ($T^C < T^U$), and lower agricultural production technology ($A_a^C < A_a^U$). Consistent with the theoretical findings, the employment share of agriculture in China is much higher than the share in the United States. ($\pi_a^C > \pi_a^U$). Moreover, the average ability of agricultural workers in China is lower than the United States under the selection effects.

According to the model, the difference in agricultural labor productivity between the two countries can be expressed as

$$\frac{Y_a^U/N_a^U}{Y_a^C/N_a^C} = \frac{A_a^{U\beta}T^{U(1-\beta)}}{A_a^{C\beta}T^{C(1-\beta)}}\left(\frac{\pi_a^C}{\pi_a^U}\right)^{\phi} > \frac{A_a^{U\beta}T^{U(1-\beta)}}{A_a^{C\beta}T^{C(1-\beta)}}. \tag{26}$$

This result implies that the gap between China and the United States in agricultural labor productivity is greater than their gap in TFP and land endowment. The United States has a developed agricultural production technology and abundant arable land resources. A few workers who are most talented at operating farms select into the agricultural sector and engage in large-scale and mechanized production. In contrast, the agricultural production technology in China is less developed, and the barriers to labor mobility across sectors are high. Many workers who are unproductive on farms choose to stay in the agricultural sector, which lowers the average ability and arable land per capita. As a result, the difference in the average ability and per capita land of agricultural workers widens the gap between China and the United States in agricultural labor productivity.

Corollary 1. *China's employment share of agriculture is significantly higher than the United States due to less developed agricultural production technology and higher mobility barriers across sectors. The selection of heterogenous workers implies that the gap between China and the United States in agricultural labor productivity is larger than the gap between the two countries in TFP and land endowment.*

5. QUANTITATIVE ANALYSIS

5.1. Parameter calibration

In the quantitative analysis part, we use a richer model that allows for correlation between individual ability draws and different degrees of productivity dispersion in the two sectors. Following Lagakos and Waugh (2013), the joint distribution of individual abilities is set as follows:

$$G(\varepsilon_a, \varepsilon_n) = C[F(\varepsilon_a), H(\varepsilon_n)] \tag{27}$$

$$F(\varepsilon_a) = e^{-\varepsilon_a^{-\theta_a}}, H(\varepsilon_n) = e^{-\varepsilon_n^{-\theta_n}} \tag{28}$$

$$C[u, v] = \frac{-1}{\rho}\log\left\{1 + \frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}\right\} \tag{29}$$

Where, $C[u,v]$ is the Frank copula function and the parameter ρ determines the correlation between individual abilities in the two sectors. The marginal distributions of individual ability in both sectors $F(\varepsilon_a)$ and $H(\varepsilon_n)$ are Fréchet with dispersion parameters θ_a and θ_n.

We use micro-level wage data from the 2002 China Household Income Survey (CHIP). The parameters $\{\theta_a, \theta_n, \rho\}$ are chosen to match three moments: the variance of the log wage in agriculture, the variance of the log wage in non-agriculture, and the covariance of the log wages in the two sectors. Specifically, the variance of the log wage in each sector is closely related to the dispersion of individual ability, while the correlation of abilities in the two sectors determines the covariance of the log wages in the two sectors.

In CHIP 2002, the hourly wage rate for a rural household is calculated by the total income of the household and the agricultural production time of all workers in the household. The hourly wage rate for hired agriculture and non-agriculture workers is calculated directly from the annual income of each worker and the annual hours worked. We remove samples with income below the minimum wage and define a farmer as a worker who spends more than half of his time in agricultural production. Some farmers have been involved in nonagricultural production, which allows us to observe the wages of farmers in both sectors. The data show that the standard deviation of the log of agricultural wages in China is 0.5, the standard deviation of the log of nonagricultural wages is 0.6, and the covariance of the log of farmers' wages in the two sectors is 0.1. From the parameter calibration, we have $\theta_a = 2.68$, $\theta_n = 2.09$, and $\rho = 0.64$. Thus, the individual abilities in the two sectors are positively correlated with a linear correlation coefficient of about 0.1.

The parameter v measures the relative preference of workers for agricultural products. Duarte and Restuccia (2010) show that the share of agricultural employment converges to the parameter v in the long run. Following the existing literature, we set the parameter v to 0.03. Adamopoulos et al. (2022) find that the share of labor income in China's agricultural output is 0.54. Based on their estimates, we set the parameter β to 0.54.

In this paper, we set the Chinese economy in 2002 as the initial equilibrium. According to the China Statistical Yearbook, the employment share of agriculture in 2002 is 0.5, and the ratio of labor productivity between the agricultural and nonagricultural sectors is 0.15. Given that the arable land per capita in rural areas is 2 mu,[3] we calibrate the total arable land

[3]Mu is a Chinese unit of land measurement that is commonly 666.7 square meters.

TABLE 4.

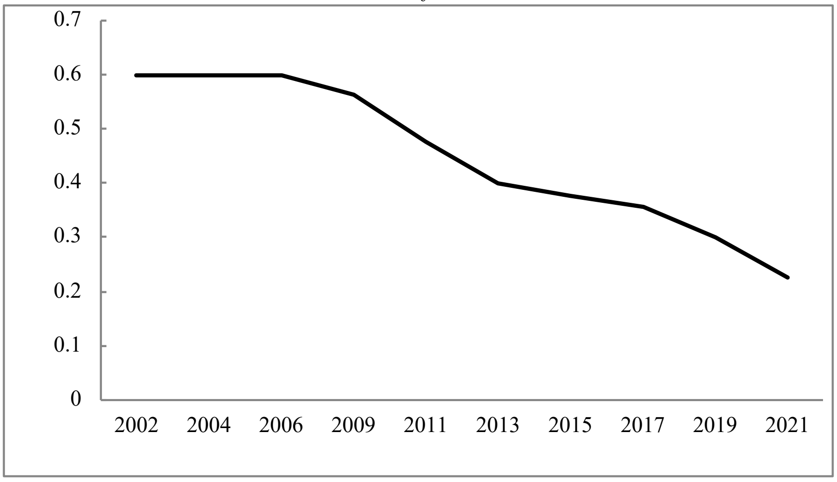
Parameter calibration and initial equilibrium (2002)

Parameters	Value	Targets
θ_a	2.68	Standard deviation of the log of agricultural wages
θ_n	2.09	Standard deviation of the log of nonagricultural wages
ρ	0.64	Covariance of the log of farmers' wages in both sectors
v	0.03	Convergence value of employment share of agriculture in the long run
β	0.54	Share of labor income in agricultural output
τ	0.60	Difference in labor productivity between agriculture and non-agriculture in 2002
A_n	1	Normalization
$p_a A_a$	0.28	Employment share of agriculture in 2002
T	1	Arable land per capita in rural areas in 2002
$p_a \overline{a}$	0.19	Optimal consumer decision and product market clearing conditions

endowment T to 1. To accurately estimate labor market distortions, it is necessary to control for differences in the human capital of workers in the two sectors. The human capital of sector s is measured by educational attainmentand the return to education r_s, i.e. $h_s = h_0 e^{r_s e_s}$ (Herrendorf and Schoellman, 2018). We obtain the average years of schooling for the agricultural and nonagricultural workers from the China Population and Employment Statistics Yearbook and calculate the return to education for both sectors using micro-level data from the 2002 CHIP. After controlling for human capital differences, the ratio of labor productivity between the agricultural and nonagricultural sectors in 2002 becomes 0.31. The nonagricultural TFP in 2002 is normalized to 1. By matching the employment share of agriculture and the cross-sector labor productivity difference, we have $p_a A_a = 0.28$, $\tau = 0.60$. Furthermore, from the optimal consumption decision and the product market clearing condition, we have $p_a \overline{a} = 0.19$. Table 4 summarizes the parameter calibration and initial equilibrium of this paper.

Based on the same approach, we calculate the barriers to labor mobility in 2003-2021. As shown in Figure 2, the barriers to labor mobility between sectors in China decrease from 0.60 in 2002 to 0.22 in 2021. As China lifts restrictions on the household registration system, rural migrants have better access to employment opportunities and public services in urban areas. In the meantime, the restrictions on the transfer of land-use rights in rural areas are relaxed, which makes it easier for rural workers to flow to nonagricultural sectors. Hence, the barriers to labor mobility across sectors gradually decline during this period.

FIG. 2. Barriers to labor mobility across sectors from 2002 to 2021



5.2. Counterfactual analysis

5.2.1. Impact of the decline in mobility barriers from 2002 to 2021

In recent years, the employment share of agriculture has gradually decreased, and agricultural labor productivity has improved along with the progress of technology and the reduction of institutional distortions in China. Data show that the share of agricultural employment in China decreases from 0.5 in 2002 to 0.23 in 2021. Meanwhile, agricultural labor productivity measured by the real value added per worker in constant 2002 prices increases from 4419 yuan to 24990 yuan. The decline in the mobility barrier during the period contributes to productivity growth by improving land per capita and the average ability in agriculture. First, the reduction in migration costs encourages more of the rural population to choose the nonagricultural sector in urban areas, which improves arable land per capita in agriculture. In addition, as the employment share of agriculture falls, workers who have a comparative advantage in agricultural production are more likely to select into the agricultural sector, thus improving the average ability in agriculture.

In this section, we combine the model with sector-level data to quantitatively evaluate the impact of the labor mobility barrier on structural changes and agricultural labor productivity in China. The quantitative study proceeds in the following three steps. First, given a fixed land endowment, the agricultural and nonagricultural TFP growth rate from 2002 to 2021 is calibrated by matching the labor productivity by sector over the period. Second, we take the Chinese economy in 2002 as the initial equilibrium and conduct a counterfactual experiment by increasing the TFP of the agricultural and nonagricultural sectors to the 2021 level while keeping the labor mobility barrier fixed at 0.60. Third, we calculate the contribution of the decline in mobility barrier to agricultural labor productivity growth by comparing the new equilibrium with the initial equilibrium.

The quantitative results are summarized in Table 5, which shows that the decline in labor mobility barriers from 2002 to 2021 reduces the employment share of agriculture by 6.12 percentage points and increases agricultural labor productivity by 130%. During the period, the actual employment share of agriculture decreases by 27 percentage points and the labor productivity of agriculture increases by 4.66 times. It is implied that the decline in mobility barriers explains 23% of the change in agricultural employment share and 28% of the increase in agricultural labor productivity. Therefore, removing the labor mobility barriers helps facilitate a structural change and agricultural productivity growth in China.

TABLE 5.

Impact of the mobility barrier on agricultural labor productivity in China

	Growth in China from 2002 to 2021		**China-US difference in 2021**	
	Agricultural labor productivity growth	Share of growth	Agricultural labor productivity growth	Share of growth
All changes	466%	1.00	1036%	1.00
TFP and land	336%	0.72	888%	0.86
Endowment changes				
Mobility barrier changes	130%	0.28	148%	0.14

5.2.2. The decomposition of the agricultural labor productivity gap between China and the United States.

Generally speaking, the United States has higher labor mobility than Europe and can be seen as a country with few labor market distortions. In this section, we compare the differences in agricultural labor productivity between China and developed countries using the United States as an example. As shown in Table 2, the difference between China and the United States in agricultural labor productivity is larger than their difference in nonagricultural sectors. In 2021, nonagricultural labor productivity in the United States is 5.23 times as high as that in China, but their labor productivity difference in the agricultural sector is a factor of 11.36.

In our theoretical framework, the gap between China and the United States in agricultural labor productivity is determined by their differences in TFP,[4] land endowment, and labor mobility barriers. Compared to the United States, workers in China face higher mobility barriers across sectors. The Roy model suggests that the mobility barrier induces many workers who do not have a comparative advantage on farms to choose the agricultural sector, resulting in insufficient arable land per capita and low average ability. Hence, the difference in the mobility barriers between China and the United States helps explain their large gap in agricultural labor productivity.

In this section, we use counterfactual simulations to decompose the China-U.S. gap in agricultural labor productivity and quantitatively assess the impact of labor mobility barriers. The quantitative analysis proceeds in three steps as follows. First, assuming no distortions in the U.S. labor market ($\tau^U = 0$), the differences between China and the United States in land endowment and sector-level TFP are determined by matching their 2021 differences in agricultural and nonagricultural labor productivity. Second, we use the Chinese economy in 2021 as the initial equilibrium and conduct a counterfactual simulation by increasing the land endowment and sector-level TFP to the level of the United States while holding the mobility barrier fixed at 0.23. Third, we decompose the differences between China and the United States in agricultural labor productivity by comparing the initial equilibrium and the new equilibrium.

The simulations show that China's agricultural labor productivity will increase by 8.88 times if land endowment and sector-level TFP are raised to the level of the United States. Further removing the mobility barrier across sectors in China will increase agricultural labor productivity by 10.36 times. It is implied that 86% of the agriculture labor productivity gap between China and the United States can be explained by their differences in land endowment and TFP, and the remaining 14% of the gap can be explained by the labor mobility barrier in China. Therefore, reducing labor mobility barriers is beneficial to narrowing the gap between China and developed countries in agricultural labor productivity.

[4] Sector-level TFP is determined by a variety of factors, including production technology, degree of mechanization, level of human capital, and efficiency of land and capital allocation. This paper focuses on the impact of labor mobility barriers and subsumes other factors that affect agricultural labor productivity into TFP.

6. CONCLUSIONS

China has experienced rapid structural transformation and economic growth since its reform and opening up. Nevertheless, labor productivity in the agricultural sector has grown relatively slowly due to policy distortions such as the household registration system and the land system. A considerable agricultural productivity gap remains compared to developed countries. In this paper, we build a two-sector general-equilibrium Roy model to investigate the impact of mobility barriers on the selection of heterogenous workers across sectors and agricultural labor productivity in China. Our theoretical analysis shows that mobility barriers prevent workers from moving to the nonagricultural sector. Many workers who do not have comparative advantage in agricultural production select into the agricultural sector, which reduces the average ability of farm workers and arable land per capita, resulting in low agricultural labor productivity.

Our quantitative study shows that the mobility barrier between sectors declined from 2002 to 2021, which explains 28% of the rise in the agricultural labor productivity of China. However, the mobility barrier remains high in 2021, and accounts for 14% of the China?U.S. gap in agricultural labor productivity. The findings suggest that further reducing the labor mobility barrier would promote structural change and agricultural productivity growth in China.

Our studies have important policy implications for achieving high-quality agriculture development in China. To improve the labor productivity of agriculture, effective measures should be taken to lift the restrictions on labor mobility. First, the government should further reform the household registration system, protect the legitimate rights of rural migrants, and ensure that rural migrants have the same access to local public services as urban natives. Second, the government should speed up the reform of the land system, promote the transfer of land use rights, and improve the allocation efficiency of land resources. In addition, innovation in agricultural technology is the key to improving TFP and promoting high-quality agricultural development. To this end, the government should adopt measures to accelerate the mechanization and modernization of agricultural production in China.

APPENDIX

Proof of Theorem 1: From the clearing condition for the land market, we have $r = (1-\beta)p_a(A_aH_a/T)^{\beta}$, where $H_a = \gamma\pi_a^{\eta}, \eta = 1 - 1/\theta$. On this basis, the output and wage of the two sectors can be expressed as: $Y_a = \gamma^\beta A_a^\beta T^{1-\beta}\pi_a^{\beta\eta}$, $Y_n = \gamma A_n(1-\pi_a)^\eta$, $w_a = p_a\gamma^{\beta-1}A_a^\beta T^{1-\beta}\pi_a^{(\beta-1)\eta}$ and $w_n = A_n$. Plug them into equation (15) and the equilibrium condition of consumption $p_a = \frac{vY_n}{(1-v)(y_n-\overline{a})}$. Then the comparative static analysis yields

$$\begin{aligned} a_1\frac{\partial\pi_a}{\partial\tau} - b_1\frac{\partial p_a}{\partial\tau} &= c_1 \\ d_1\frac{\partial\pi_a}{\partial\tau} + e_1\frac{\partial p_a}{\partial\tau} &= 0 \end{aligned}$$

where $a_1 = w_a^\theta + [(1-\tau)w_n]^\theta + (1-\beta)\eta\theta(1-\pi_a)w_a^\theta/\pi_a$, $b_1 = \theta\pi_n w_a^\theta/p_a$, $c_1 = \theta\pi_a[(1-\tau)w_n]^{\theta-1}$, $d_1 = (1-v)\beta\eta p_a Y_a/\pi_a + v\eta y_n/\pi_n$ and $e_1 = (1-v)(y_a-\overline{a})$ are all positive numbers. From the above equations, we derive

$$\begin{cases} \frac{\partial\pi_a}{\partial\tau} = \frac{c_1e_1}{a_1e_1+b_1d_1} > 0 \\ \frac{\partial p_a}{\partial\tau} = \frac{c_1d_1}{a_1e_1+b_1d_1} < 0 \end{cases}$$

From equations (19) and (21), it is directly deduced that

$$\partial(Y_a/L_a)/\partial\tau < 0, \quad \partial\left(\frac{Y_a/L_a}{Y_n/L_n}\right)/\partial\tau < 0.$$

The proof is complete.

Proof of Theorem II: The comparative static analysis yields

$$\begin{aligned} a_2\frac{\partial\pi_a}{\partial A_a} - b_2\frac{\partial p_a}{\partial A_a} &= c_2 \\ d_2\frac{\partial\pi_a}{\partial A_a} + e_2\frac{\partial p_a}{\partial A_a} &= -f_2 \end{aligned}$$

where $a_2 = w_a^\theta + [(1-\tau)w_n]^\theta + (1-\beta)\eta\theta(1-\pi_a)w_a^\theta/\pi_a$, $b_2 = \theta\pi_n w_a^\theta/p_a$, $c_2 = \beta\theta\pi_n w_a^\theta/A_a$, $d_2 = (1-v)\beta\eta p_a Y_a/\pi_a + v\eta Y_n/\pi_n$, $e_2 = (1-v)(Y_n-\overline{a})$ and $f_2 = \beta(1-v)p_aY_a/A_a$ are all positive numbers. From the above equations, we can solve for

$$\begin{cases} \frac{\partial\pi_a}{\partial A_a} = -\frac{b_2f_2-c_2e_2}{a_2e_2+b_2d_2} < 0 \\ \frac{\partial p_a}{\partial A_a} = -\frac{a_2f_2+c_2d_2}{a_2e_2+b_2d_2} < 0 \end{cases}$$

where $b_2f_2 - c_2e_2 = \beta(1-v)\theta\pi_n w_a^\theta\overline{a}/A_a > 0$.

Assuming that nonagricultural technology and labor market distortions remain constant, the share of agricultural employment will decrease ($\pi_a' <$

π_a) and the share of nonagricultural employment will increase ($\pi'_n > \pi_n$) if the agricultural TFP increases from A_a to A'_a. From equations (19) and (21), it can be deduced that

$$\frac{Y'_a/L'_a}{Y_a/L_a} = \left(\frac{A'_a}{A_a}\right)^{\beta} \left(\frac{\pi_a}{\pi'_a}\right)^{\phi} > \left(\frac{A'_a}{A_a}\right)^{\beta}.$$

The proof is complete.

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