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Labor Force Participation and Structural Change

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Abstract

Structural transformation can affect not only where people work, but also whether they participate in market work. We study this margin in China, where rapid movement out of agriculture coincided with a large decline in labor force participation. Using census and rural household data, we show that the post-2000 decline was concentrated among rural individuals and broad-based across demographic groups and regions. We develop a quantitative model in which rural household members choose between market work and home production, subject to mobility barriers. Quantitatively, the model closely matches the observed decline without targeting it: agricultural productivity growth releases labor from agriculture and substantially reduces participation, while non-agricultural productivity growth only partially offsets this effect, as mobility barriers limit labor reallocation.

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Keywords: labor force participation, home production, structural change, labor supply, labor mobility, within-household labor allocation, productivity growth, China.

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1 Introduction

Economic development is typically accompanied by a large reallocation of labor from agriculture to non-agricultural sectors, a process known as structural change (Herrendorf et al., 2014). This pattern is observed both across countries and within countries over time. However, most of the structural-change literature focuses on where workers are employed, conditional on being in the labor force. Less attention has been paid to how participation in the labor force itself evolves during structural change. This distinction matters because labor released from agriculture may move into non-agricultural employment, but it may also exit market work altogether.

This paper studies the interaction between structural change and participation in the labor force in China, a country that has experienced rapid structural transformation in recent decades. Between 1982 and 2020, the agricultural employment share among working individuals fell from 68.1 percent to 23.6 percent (National Bureau of Statistics of China, 2021). During the same period, the labor force participation rate fell from 86.4 to 66.1 percent (National Bureau of Statistics of China, 2020). These two facts raise the central questions of the paper. What forces jointly shape structural change and labor force participation? When labor leaves agriculture, under what conditions does it move into non-agricultural employment rather than out of the labor force? More generally, does structural change from agriculture to non-agricultural sectors necessarily imply a decline in labor force participation?

We begin by documenting the decline in labor force participation in China using multiple data sources. The nationwide decline masks two distinct episodes. Between the mid-1990s and 2000, the fall in participation was concentrated in urban areas and was closely associated with the large-scale layoffs that accompanied the reform and privatization of state-owned enterprises. This episode has been well studied, including by Hsieh and Song (2015). After 2000, however, labor force participation changed little in urban areas but declined substantially among rural individuals. The rural decline is less well understood and is the focus of this paper.

We show that the post-2000 decline in rural labor force participation was broad-based rather than concentrated in a single demographic group. Participation fell among both men and women, across age groups, across education groups, and across regions of China. The decline was slightly larger among women and less educated individuals, but the overall pattern is not explained by demographic composition alone. These facts suggest that the decline in rural labor force participation reflected broader economic forces operating during China's structural transformation.

To interpret these patterns, we develop a quantitative framework that combines structural transformation with endogenous labor force participation. Rural household members allocate their time between market work and home production. Conditional on working in the market, they choose among agriculture, rural non-agriculture, and urban non-agriculture. Entry into non-agricultural work is costly: workers face fixed costs as well as proportional barriers that capture migration restrictions, access to public services, and other frictions limiting labor mobility across sectors and locations.

The key mechanism is simple. Because demand for agricultural goods is income-inelastic, agricultural productivity growth reduces the relative price of agricultural output. If the price decline is large enough, the value of the marginal product of agricultural labor, and hence the agricultural wage, can fall despite higher physical productivity. This creates pressure for labor to leave agriculture. Whether those workers remain in the labor force depends on the strength of non-agricultural productivity growth and the severity of labor mobility barriers. If non-agricultural sectors expand sufficiently and workers can move easily into them, structural change need not reduce participation. If, however, non-agricultural sectors cannot fully absorb the labor released from agriculture, either because productivity growth outside agriculture is insufficient or because mobility barriers are severe, some rural individuals may exit market work and shift toward home production.

We calibrate the model to match key moments of the Chinese economy at the beginning of our sample period. Specifically, we match sectoral employment shares and the labor force

participation rate in 2004. We then update the parameters governing sectoral productivity growth, labor mobility barriers, and population composition to match 2019 moments, but we do not target the 2019 labor force participation rate. The model nevertheless predicts a substantial decline in rural labor force participation. In the data, the participation rate falls from 89.1 percent in 2004 to 76.3 percent in 2019. The model predicts a decline to 77.8 percent, close to the observed value. The model also predicts that individuals with lower market ability are less likely to participate in the labor market and more likely to exit over time, consistent with the empirical patterns.

The model's fit supports its use for decomposing the forces behind the decline in labor force participation. We introduce each set of 2019 parameters into the 2004 baseline economy one at a time. Agricultural and non-agricultural productivity growth have opposing effects. Agricultural productivity growth alone reduces the labor force participation rate by 14.2 percentage points, while non-agricultural productivity growth increases it by 8.3 percentage points. When both types of productivity growth operate simultaneously, their effects largely offset each other, and the labor force participation rate increases slightly. The calibrated effective mobility barriers faced by the remaining rural population rise over time, reducing participation by 10.3 percentage points. Changes in hukou composition, which reduce the size of the remaining rural population, raise participation among those who remain by 7.8 percentage points, because the smaller remaining rural population raises the return to agricultural work. Taken together, these forces allow the model to replicate the observed decline in rural labor force participation.

The welfare implications of declining labor force participation are not obvious. A decline in participation need not be welfare-reducing if higher productivity allows households to maintain consumption while devoting more time to home production. But participation may fall for less benign reasons if mobility barriers prevent workers from accessing better opportunities in non-agricultural sectors. Our decomposition is therefore important because it distinguishes between reductions in market work that arise from productivity-driven changes

in household choices and reductions that arise from frictions. The analysis also shows that structural change does not necessarily reduce labor force participation. Its effect depends on the relative strength of push forces from agriculture and pull forces from non-agricultural sectors (Alvarez-Cuadrado and Poschke, 2011), as well as on the barriers that mediate labor reallocation (Lagakos et al., 2020; Adamopoulos et al., 2024).

This paper contributes to several strands of literature. First, it relates to the literature on structural transformation from agriculture to non-agricultural sectors and the nominal agricultural productivity gap.[1] Most studies of structural transformation focus on sectoral employment shares conditional on labor force participation. We instead study how structural change interacts with endogenous participation.

Two closely related papers are Ngai and Pissarides (2008) and Ohnsorge et al. (2026). Ngai and Pissarides (2008) study how structural change and marketization—the reallocation of time from home production to market work—jointly shape long-run trends in market hours using U.S. historical data. Their model features a continuous allocation of time between market work, home production, and non-work activities. We focus instead on the extensive margin of labor supply—whether individuals participate in market work. In concurrent work, Ohnsorge et al. (2026) also emphasize that structural transformation can affect aggregate employment rather than merely reallocating workers across sectors. Using cross-country data, they document declining employment as economies move out of agriculture and show how non-homothetic demand and endogenous labor supply can generate this pattern. We instead ask what determines whether labor released from agriculture is absorbed into non-agricultural employment or leaves market work, emphasizing the interaction between sectoral productivity growth and barriers to labor mobility in the context of China. In contrast to our framework, both Ngai and Pissarides (2008) and Ohnsorge et al. (2026) abstract from labor

[1]For the literature on structural change, see for instance Kongsamut et al. (2001), Ngai and Pissarides (2007), Duarte and Restuccia (2010), Alvarez-Cuadrado and Poschke (2011), Alvarez-Cuadrado et al. (2017), Lagakos and Waugh (2013), Herrendorf et al. (2015), Bustos et al. (2016), Chen (2020b), Porzio et al. (2022), and Dinkelman and Ngai (2022), among others. For the literature on the nominal agricultural productivity gap, see for instance Gollin et al. (2014), Herrendorf and Schoellman (2015), Lagakos et al. (2020), Schoellman (2020), and Gai et al. (2025).

mobility frictions. Duarte and Restuccia (2026) also study the role of changes in aggregate employment in structural transformation, focusing on the rise of services across countries.

Our paper is also related to Bick et al. (2022), who study labor supply across countries at different stages of development. We instead focus on the evolution of labor force participation within a single country over time and quantify the forces shaping this evolution. We also explicitly link participation to the reallocation of labor from agriculture to non-agricultural sectors.

Second, our work contributes to the development literature on rural–urban migration frictions.[2] These frictions play an important role in shaping labor force participation during structural transformation.

Third, because we explicitly model households and allow for within-household specialization between market work and home production, our paper also relates to the macroeconomic literature on household decision-making and home production.[3] Cao et al. (2026) use a related household framework to study gender differences in sectoral reallocation in China. We instead study the participation margin, asking whether labor released from agriculture is absorbed into non-agricultural employment or exits market work.

Given our focus on China, the paper also connects to the literature on Chinese growth and development.[4]

The rest of the paper proceeds as follows. Section 2 documents the empirical patterns of labor force participation in China over recent decades. Section 3 presents the quantitative framework. Section 4 discusses the calibration strategy. Section 5 presents the main quantitative results. Section 6 concludes.

[2]See, for instance, Kung (2002), Munshi and Rosenzweig (2016), Giles and Mu (2018), Kinnan et al. (2018), Ngai et al. (2019), Hamory et al. (2021), and Chen et al. (2026), on various frictions impeding rural–urban migration.

[3]See, for instance, Rogerson (2008), Moro et al. (2017), Ngai and Petrongolo (2017), Bridgman et al. (2018), Greenwood et al. (2023), and Gottlieb et al. (2025), among others.

[4]See, for instance, Brandt and Zhu (2010), Song et al. (2011), Brandt et al. (2013), Feng et al. (2017), Tombe and Zhu (2019), Hao et al. (2020), Liu et al. (2021), Fang and Herrendorf (2021), Chen and Kung (2022), Cao et al. (2024), Chen and Zha (2025), and Brandt et al. (2026), among others.

2 Empirical Patterns

We begin by documenting the evolution of labor force participation over recent decades. Our main focus is the period after 2000, when the decline in participation was concentrated among rural individuals and when micro data allow us to examine the characteristics of those leaving the labor force. We use two complementary data sources. Population census data allow us to place the post-2000 rural decline in a longer national perspective, including the earlier urban decline associated with state-sector restructuring in the late 1990s. The Rural Fixed Point Survey then allows us to study the post-2000 rural decline in greater detail and to examine whether it was concentrated among particular demographic groups.

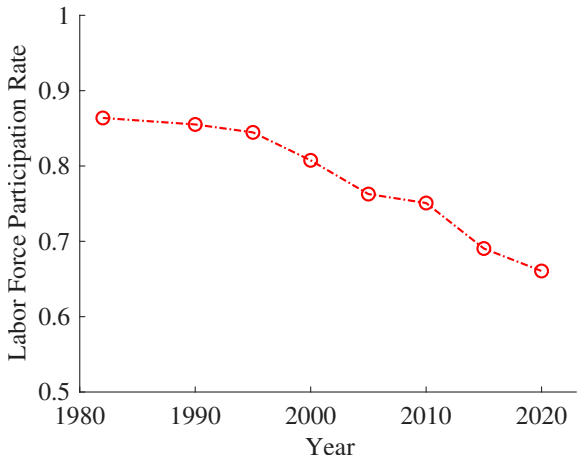
2.1 Labor Force Participation from Population Census Data

The population census provides the broad national picture. We use the 1982-2020 waves of China Population Census conducted by the National Bureau of Statistics of China (National Bureau of Statistics of China, 2020). These data are representative of individuals across the country, including both urban and rural residents and individuals with agricultural and non-agricultural hukou status. We observe individual characteristics such as age, gender, education, and place of residence. In the census, individuals are asked if they worked for at least one hour in the previous week, which we use to classify individual participation in the labor force. Because of data limitations, we cannot distinguish between unemployment and being out of the labor force. Given our focus on long-run changes, short-run fluctuations in unemployment at business-cycle frequencies are less central to our analysis.

Figure 1 shows that the nationwide labor force participation rate declines in the sample period from 86.4 percent in 1982 to only 66.1 percent in 2020.[5] The decline is particularly significant after mid-1990s. Figure 2 shows the labor force participation rate by location of residence since the year 1990 when we have the information of residence. We divide

[5]It should be noted that in the 1982 and 1990 population censuses, individuals were asked directly whether they had a job. Beginning with the 2000 census, labor force participation was instead defined on the basis of working hours.

Figure 1: Labor Force Participation: Nationwide



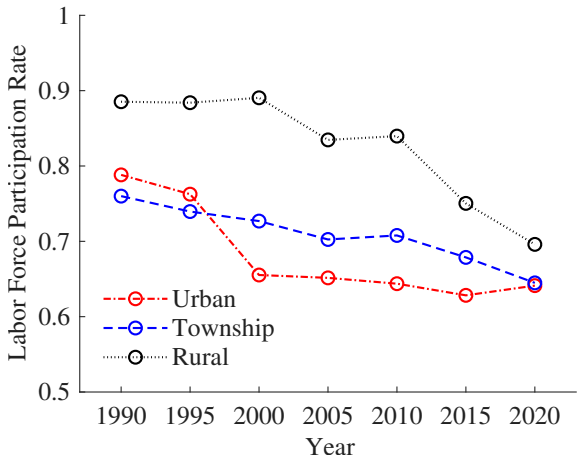
Note: This figure illustrates the nationwide labor force participation rate among individuals aged 16–64 for the years 1982, 1990, 1995, 2000, 2005, 2010, 2015, 2020. Data from the National Bureau of Statistics of China.

individuals into three categories, rural, township, and urban. The decline in labor force participation between 1995 and 2000 is largely driven by urban individuals. This is closely related to the large-scale layoff during the restructuring of the state-owned enterprises in the late 1990s, or breaking the "iron rice bowl" (Hsieh and Song, 2015; He et al., 2018). The labor force participation rate is then rather stable among urban individuals. The decline in labor force participation after 2000, the focus of this paper, is largely driven by rural individuals. We next use our micro data from rural households to take a deeper look at the labor force participation among rural individuals.

2.2 Labor Force Participation from Fixed Point Survey

Our second data source is the Rural Fixed Point Survey (FPS), conducted annually by the Research Center for the Rural Economy (RCRE) under the Ministry of Agriculture of China (Research Center for Rural Economy, Ministry of Agriculture (China), 2020). The Rural Fixed Point Survey is a nationally representative panel data set that is nationally representative of individuals with rural *hukou*, providing information on individual characteristics

Figure 2: Labor Force Participation by Location of Residence



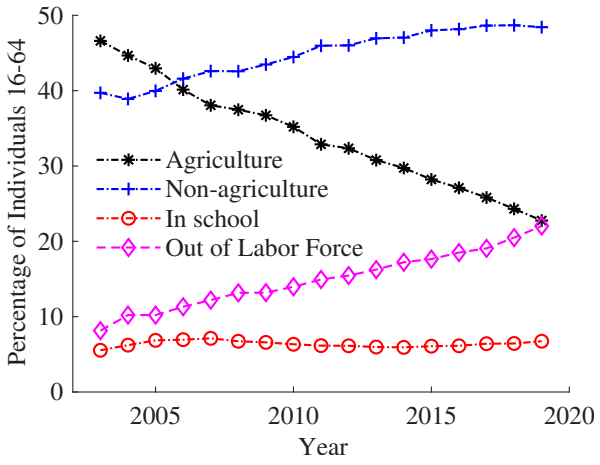
Note: This figure illustrates the labor force participation rate by location of residence, for the years 1990, 1995, 2000, 2005, 2010, 2015, 2020. Data from the National Bureau of Statistics of China.

including age, education, gender, and importantly, the number of working days in a year and the sector and occupation of work. We classify an individual as in the labor force if they work for at least 30 days during the year. Our results are not sensitive to this threshold. The detailed data cleaning process is described in Appendix A. The FPS data started in 1986, but individual-level labor supply data are not available until 2003. We focus on the data period up until the year 2019, right before the widespread COVID-19 disrputions.

Figure 3 shows the employment status among rural individuals aged 16–64. We classify individuals into four groups: working in agriculture, working in non-agriculture, in school, and out of labor force but not in school. The pattern of structural transformation from agriculture to non-agriculture is clear: The employment share in agriculture declines from 46.6 to 22.8 percent in our sample period, while the employment share in non-agriculture increases from 39.7 percent to 48.4 percent. The share of individuals in school is more or less constant.[6] The share of individuals out of the labor force but not in school (the pink line with diamonds) increases substantially from 8.1 percent to 23.6 percent. Understanding

[6]Although years of schooling is rising for later cohorts, their share of the working-age rural population is falling because of earlier declines in fertility.

Figure 3: Employment Status among Rural Individuals

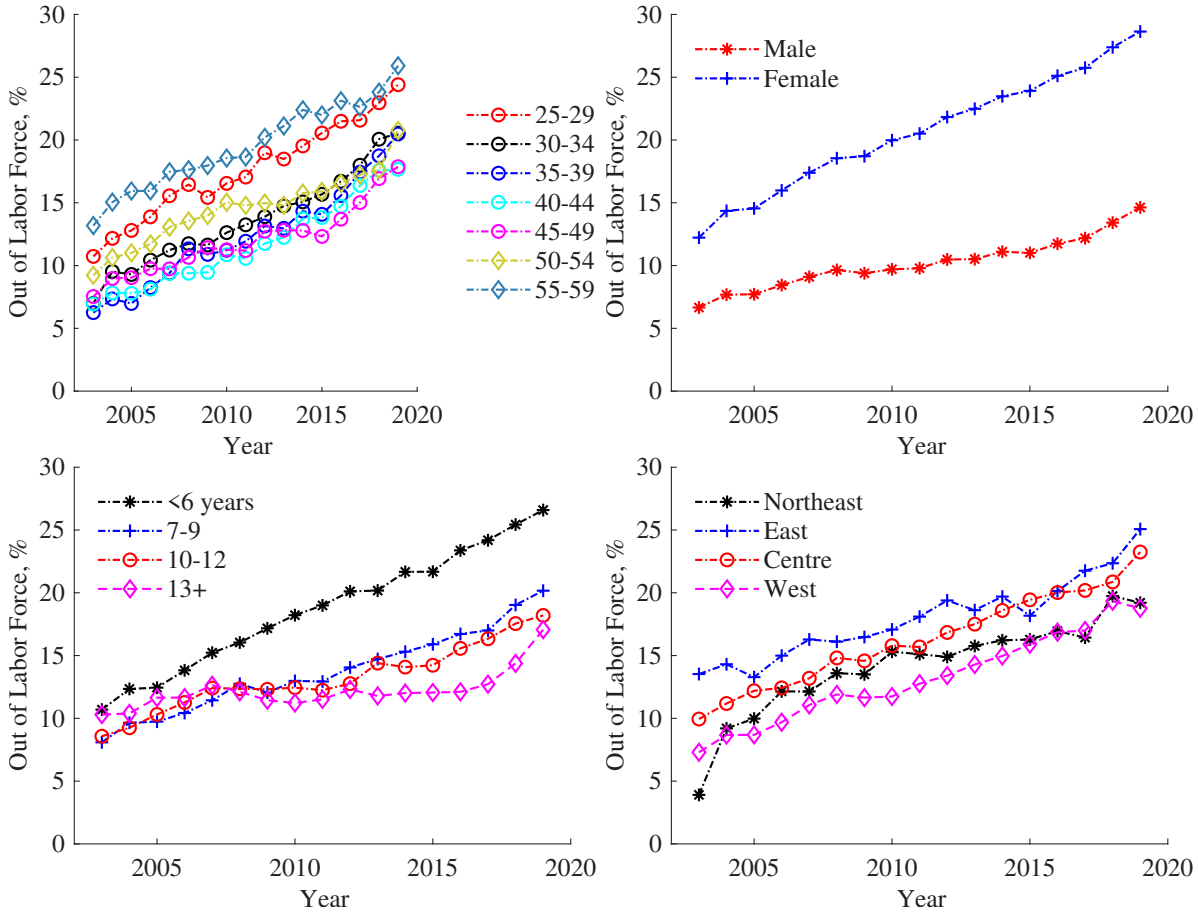


Note: This figure illustrates the employment shares of rural individuals aged 16–64, divided into four groups—working in agriculture, working in non-agriculture, in school, or out of the labor force but not in school—for each year of 2003–2019. Data from the Rural Fixed Point Survey (FPS) by the Research Center for the Rural Economy (RCRE) under the Ministry of Agriculture of China.

this increase is a central objective of the paper.

We now take a deeper look at this pink line, or individuals who are out of the labor force but not in school. In the upper left panel of Figure 4, we show the share of these individuals by age group. The percentage of individuals out of the labor force increases over time, with the magnitude of the increase similar across all age groups from 25 to 59. Hence, the rise in non-participation cannot be attributed to compositional changes in the age of the population through aging. In the upper right panel of Figure 4, we show the share of out-of-the-labor-force individuals by gender. Overall, more females are out of the labor force than males, but the trend is the same: For both males and females, the share of out of the labor force has been increasing steadily over time. The bottom left panel shows the share of individuals out of the labor force by education group. Again, we see an increasing share among all education groups, although the increase is more substantial among those with least education (fewer than 6 years of education). The bottom right panel shows the share of individuals out of the labor force by region, where we classify China into four regions:

Figure 4: Out of Labor Force among Rural Individuals by Group



Note: This figure illustrates the share of rural individuals aged 16–64 who are out of the labor force for each year of 2003–2019. We show the share by age (top left panel), by gender (top right panel), by years of education (bottom left panel), and by region (bottom right panel). Data from the Rural Fixed Point Survey (FPS) by the Research Center for the Rural Economy (RCRE) under the Ministry of Agriculture of China.

northeast, east, centre, and west. Again, we see an increasing share of out of the labor force individuals in all regions.

We conclude that the decline in labor force participation exists among rural individuals of all age groups, of both genders, of all education groups, and in all regions of China, although females and less educated individuals experience slightly larger declines in labor force participation.

2.3 A Comparative Perspective

The decline in labor force participation in China raises the question of whether this pattern is specific to China or reflects a broader feature of structural transformation. To provide perspective, we compare China with two groups of economies. The first group consists of large or middle-income economies undergoing structural transformation in recent decades, including India, Indonesia, Viet Nam, Malaysia, Thailand, the Philippines, Brazil, Mexico, and Türkiye. The second consists of earlier East Asian industrializers—Japan, Korea, and Taiwan—that experienced rapid movement out of agriculture before China. Because these countries reached comparable stages of development in different calendar periods, we use country-specific windows rather than imposing a common period on all countries, subject to data availability. Table 1 reports labor force participation rates from the International Labour Organization (2026) for age 15 and above.

The comparison reveals no uniform relationship between structural transformation and aggregate labor force participation. China's participation rate fell from 78.7 percent in 1982 to 70.3 percent in 2018, a decline of 8.5 percentage points.[7] Japan and Türkiye also experienced sizable declines, while participation changed relatively little in Taiwan, India, Brazil, Viet Nam, and the Philippines. By contrast, participation increased in Korea, Indonesia, Malaysia, and Mexico. Thailand experienced an even larger decline than China. Thus, the movement of labor out of agriculture can be accompanied by declining, stable, or rising

[7]The labor force participation rate reported by the ILO is not directly from the census data and hence it differs slightly from our calculation.

aggregate participation.

China's experience appears to reflect a combination of high initial labor force participation, rapid movement out of agriculture, and incomplete absorption into non-agricultural market work. Viet Nam provides a useful contrast: It also began with high participation but experienced only a modest subsequent decline. This contrast suggests that high initial participation alone is insufficient; subsequent participation dynamics may also depend on the pace of agricultural exit, the expansion of non-agricultural employment, and the barriers workers face in accessing those opportunities.

Cross-country comparisons should nevertheless be interpreted cautiously. Statistical systems differ in their treatment of unpaid family work, own-use production, and subsidiary activities, and the country windows are not identical. We therefore view Table 1 as descriptive evidence on broad within-country changes rather than as a formal test of the model. The main takeaway is that structural transformation affects not only where individuals work, but potentially also whether they remain attached to market work.

3 A Model of Labor Supply and Structural Change

The model has three purposes. First, it generates structural change through non-homothetic demand for agricultural and non-agricultural goods. Second, it makes labor force participation endogenous by allowing household members to allocate time between market work and home production. Third, it limits the reallocation of rural labor into non-agricultural employment through fixed and proportional mobility barriers. Together, these ingredients allow agricultural productivity growth to release labor from agriculture without requiring that all released labor be absorbed into non-agricultural employment.

The framework is designed to capture the choices facing rural households during China's structural transformation. Individuals living in villages may work locally in agriculture, work locally in rural non-agriculture, migrate to urban non-agriculture, or remain out of market

Table 1: Labor Force Participation Across Countries

Country	Window	Labor Force Participation Rate (%)		
		Start	End	Change
China	1982–2018	78.7	70.3	−8.5
Japan	1953–1980	70.0	63.3	−6.7
Korea	1960–2000	50.1	61.6	+11.5
Taiwan	1978–2000	58.8	57.7	−1.1
India	1994–2025	58.1	55.3	−2.8
Brazil	1989–2025	64.2	63.2	−1.0
Indonesia	1977–2023	64.8	67.9	+3.1
Viet Nam	1996–2024	75.8	72.4	−3.4
Malaysia	1982–2022	64.8	69.3	+4.5
Thailand	1978–2025	81.6	67.0	−14.6
Philippines	1978–2023	63.9	60.4	−3.5
Mexico	1991–2026	57.9	59.5	+1.5
Türkiye	1988–2025	58.5	53.5	−5.0

Note: This table reports labor force participation rates at the beginning and end of the indicated period, together with the corresponding change. Changes are calculated using unrounded values. Data are from the ILO.

work and devote time to home production. Moving into non-agricultural employment is costly, reflecting barriers across sectors and locations. These barriers play a central role in determining whether released from agriculture is absorbed by non-agricultural sectors or instead exits market work.

The population is organized into families living in villages, townships, and urban centers. At each date, two goods are produced: an agricultural good (a) and a non-agricultural good (n). Agricultural production is limited to villages, while production of the non-agricultural good can occur either in rural townships or urban centers, denoted by rural (r) and urban (u), respectively. The agricultural sector produces the agricultural good that is for consumption. Outputs from the two non-agricultural sectors are combined into a final non-agricultural consumption good. Village households can work locally in agriculture and the rural non-agricultural sector, or migrate to the cities to work in the urban non-agricultural sector. Township and urban households work only in the corresponding non-agricultural sector.

Our analysis focuses on the occupation, location, and participation decisions of individuals and families living in villages.

3.1 Description

3.1.1 Preferences and Endowments

The preferences are summarized by the following utility function:

$$u = \log(c) + \omega \log(c^h) - \kappa,$$

where c is market consumption, c^h is home production, and κ is disutility from sectoral choice that will be introduced later on. ω governs the relative importance between market goods and home-produced goods.

We follow Comin et al. (2021) and specify market consumption c as an aggregation of consumption of the agricultural good c^a and that of non-agricultural good c^n:

$$\phi^{\frac{1}{\varepsilon}} c^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}} (c^a)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\phi)^{\frac{1}{\varepsilon}} c^{\frac{(1-\varepsilon)\mu_n}{\varepsilon}} (c^n)^{\frac{\varepsilon-1}{\varepsilon}} = 1.$$

We assume $\mu_a \leqslant \mu_n$, and hence the income elasticity is larger for the non-agricultural good, implying a structural transformation from agriculture to non-agriculture with income growth.

Village families are at the core of our analysis. Village families can work in agricultural, rural non-agricultural, or urban non-agricultural sectors. There is a unit measure of village families each comprising J individuals. Each individual family member is endowed with one unit of time that can be used to supply labor or to produce at home, and a pair of abilities (s, h), where s is the earning ability in agriculture and h is that in non-agriculture. Individuals are subject to labor mobility frictions.

There is an exogenous mass N_r of township families and N_u of urban families. They are homogeneous and they can only work in the rural and urban non-agricultural sectors,

respectively. Their only decision is to choose consumption and labor supply. Each is endowed with one unit of time that can be used to supply labor with average ability $\bar{h}$ or to produce at home.

The endowments of capital and land are denoted as K and L, respectively. The factor income of capital is rebated to all households uniformly, while the factor income of land is uniformly rebated to villagers.

3.1.2 Technologies

The non-agricultural good is produced using the constant returns to scale technology

$$Y^k = A^k (K^k)^{\alpha} (H^k)^{1-\alpha}, \quad k \in \{r, u\},$$

where A^k is the productivity parameter of the rural (r) and urban (u) non-agricultural sectors and K^k and H^k are capital and total labor input in efficiency units in the corresponding sector. The output from these two non-agricultural sectors are aggregated into a non-agricultural good for consumption

$$Y^n = \left(\varphi (Y^r)^{\frac{\rho-1}{\rho}} + (1-\varphi)(Y^u)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}.$$

The agricultural good is produced by combining capital (K^a), land (L^a), and total labor input in efficiency units (H^a):

$$Y^a = A^a (K^a)^{\alpha_a} (L^a)^{\gamma_a} (H^a)^{1-\alpha_a-\gamma_a}.$$

3.1.3 Markets

A large number of firms operate each of the agricultural, rural non-agricultural, and urban non-agricultural technologies in competitive markets. We set the final non-agricultural good as the numeraire and normalize its price to one. We denote by w^r the competitive price of

efficiency units of labor in the rural non-agricultural sector and w^u the price in the urban non-agricultural sector. We denote by p the relative price of the agricultural good, q the rent of land, and w^a the competitive price of efficiency units of labor in the agricultural sector. Capital can be used in any sector, with its rental rate denoted as r.

3.1.4 Labor Mobility Barriers

Village families and individuals are subject to labor mobility distortions if they work outside agriculture. Labor mobility distortions include an implicit tax on non-agricultural wage income. An individual faces a tax rate of ξ^r if they work in rural non-agriculture locally, and a tax rate of ξ^u if they work in urban non-agriculture. In addition, if an individual chooses to work in rural or urban non-agricultural sectors, then a fixed utility cost of κ^r or κ^u is incurred. In other words, we allow for both fixed and proportional costs of labor mobility. The implicit tax which is proportional to one's income is the more traditional setting in the literature (e.g. Restuccia et al., 2008; Hsieh et al., 2019; Adamopoulos et al., 2024; Lee, 2024). The fixed component is less often used in the literature. Intuitively, the fixed component captures real world costs arising from, for instance, relocation to different regions, finding schools for children, or accessing public services like medical care (Cao et al., 2026). In Appendix C, we discuss in detail the quantitative roles of these two types of costs separately. We note that we allow for the possibility that the barriers to reallocating labor supply from agriculture to the rural and urban non-agriculture sectors may differ (Brandt and Zhu, 2010). These barriers can be catchalls for all the factors that may impede the reallocation of labor to the non-agricultural sectors, inclusive of the land institutions as discussed in Adamopoulos et al. (2024).

3.2 Village Families

We start by describing the occupational choices of village individuals. Each rural individual is endowed with a pair of abilities, with s denoting the ability of working in agriculture and

h denoting the ability of working in non-agricultural sectors. An individual j of household i working full-time in non-agricultural sector $k \in \{r, u\}$ earns wage rate $w^k h_{ij}$ per unit of labor input. If this individual works in agriculture, the income is simply $w^a s_{ij}$. Denote D_{ij}^a as an indicator that equals one if this individual chooses to work in agriculture, and define D_{ij}^r and D_{ij}^u as indicator functions which take the value of one if this individual chooses to work in rural/urban non-agriculture. Denote the effective wage rate after sectoral choice as w_{ij} which is given by

$$w_{ij} = D_{ij}^a w^a s_{ij} + D_{ij}^r w^r (1 - \xi^r) h_{ij} + D_{ij}^u w^u (1 - \xi^u) h_{ij}.$$

If an individual chooses not to work, then $D_{ij}^a = D_{ij}^r = D_{ij}^u = 0$.

Each individual is endowed with one unit of time that can be divided into labor supply (n_{ij}) and leisure/home production ($1 - n_{ij}$). Home production c_{hi} for household i is given by

$$c_i^h = \left[\sum_{j=1}^{J} (1 - n_{ij})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}.$$

The household pools income from its members. Household income y_i is given by

$$y_i = \sum_{j=1}^{J} w_{ij} n_{ij} + r k_i + q l_i + T,$$

where k_i and l_i are the household's shares of capital and land endowment, respectively, and T is the transfer from the government.

The utility maximization problem can then be written as

$$\max_{c_i^a, c_i^n, \{n_{ij}, D_{ij}^a, D_{ij}^r, D_{ij}^u\}_{j=1}^J} \log(c_i) + \omega \log(c_i^h) - \kappa_i,$$

subject to

$$\phi^{\frac{1}{\varepsilon}} c_i^{\frac{(1-\varepsilon)\mu_a}{\varepsilon}} (c_i^a)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\phi)^{\frac{1}{\varepsilon}} c_i^{\frac{(1-\varepsilon)\mu_n}{\varepsilon}} (c_i^n)^{\frac{\varepsilon-1}{\varepsilon}} = 1,$$

$$c_i^h = \left[\sum_{j=1}^{J} (1 - n_{ij})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}},$$

$$\kappa_i = \sum_{j=1}^{J} \left(D_{ij}^r \kappa_i^r + D_{ij}^u \kappa_i^u \right),$$

$$pc_i^a + c_i^n = \sum_{j=1}^{J} w_{ij} n_{ij} + rk_i + ql_i + T_i.$$

The solution of this problem is detailed in Appendix B.

3.3 Township and Urban Households

The township and urban households maximize the same utility function. Denote the consumption and labor supply of the township households as c_r^a, c_r^n, and n_r, respectively. Similarly, the urban households' consumption and labor supply are denoted as c_u^a, c_u^n, and n_u. These households play no substantive role in the model and are included only to ensure that the model's aggregate quantities match those in the national accounts.

3.4 Equilibrium

We can then write the aggregate labor supply to agriculture as

$$H^a = \int_i \sum_{j=1}^{J} s_{ij} n_{ij} D_{ij}^a di, \tag{1}$$

which is simply the total labor supply in efficiency units among all villagers who choose to work in agriculture. Labor supply to the rural non-agricultural sector is given by

$$H^r = \int_i \sum_{j=1}^{J} h_{ij} n_{ij} D_{ij}^r di + \bar{h} n_r N_r, \tag{2}$$

which is the sum of labor supply from villagers who choose to work in the rural non-agricultural sector and from township households. Similarly, labor supply to the urban

non-agricultural sector is given by

$$H^u = \int_i \sum_{j=1}^{J} h_{ij} n_{ij} D_{ij}^u di + \bar{h} n_u N_u. \tag{3}$$

With these equilibrium conditions, we define the competitive equilibrium of this economy.

Definition. *A competitive equilibrium is a set of prices* (w^a, w^r, w^u, p, q, r)*, village family income* (y_i)*, occupation allocations* $(D_{ij}^a, D_{ij}^r, D_{ij}^u)$*, labor supply* (n_{ij})*, and consumption* (c_i^a, c_i^n)*, and consumption and labor supply for the township and urban households* (n_r, c_r^a, c_r^n) *and* (n_u, c_u^a, c_u^n)*, such that:*

1. *Given prices, village families choose labor supply* (n_{ij})*, occupations* $(D_{ij}^a, D_{ij}^r, D_{ij}^u)$*, and consumption* (c_i^a, c_i^n) *to maximize utility.*

2. *Given prices, township and urban households choose labor supply and consumption* (n_r, c_r^a, c_r^n) *and* (n_u, c_u^a, c_u^n) *to maximize utility.*

3. *Given prices, agricultural and non-agricultural firms maximize profits.*

4. *All markets clear:*

   (a) *Goods markets clearing:*

$$Y^a = \int_i c_i^a di + c_r^a N_r + c_u^a N_u, \quad Y^n = \int_i c_i^n di + c_r^n N_r + c_u^n N_u$$

   (b) *Labor market clearing requires that labor demands from representative firms equal to labor supply given by Equations* (1)*,* (2)*, and* (3)*.*

   (c) *Capital and land markets clearing:*

$$K^a + K^r + K^u = K, \quad L = \int_i l_i di,$$

where K is the total capital endowment in the economy, and l_i is land endowment held by village household i.

(d) Revenue from labor mobility barriers is rebated to villagers:

$$\int_i T_i di = \int_i \sum_{j=1}^{J} (D_{ij}^r w^r \xi^r + D_{ij}^u w^u \xi^u) n_{ij} h_{ij} di.$$

3.5 Intuition on the Decline in Labor Force Participation

We briefly explain the mechanisms through which the model generates a decline in labor force participation over time. Three ingredients are central: nonhomothetic preferences, barriers to labor mobility across sectors, and productivity growth.

With our non-homothetic preferences, the income elasticity of demand for the agricultural good is less than one, while agricultural and non-agricultural goods are complements. As agricultural productivity rises, demand for the agricultural good grows less than proportionally with income. Consequently, its relative price falls sufficiently that the decline in the agricultural price more than offsets the direct increase in agricultural productivity. In the calibrated economy, the decline in relative price of agricultural goods more than offsets the direct productivity effect, reducing the value of the marginal product of agricultural labor, and hence the agricultural wages. This mechanism would be absent under homothetic preferences with a unit elasticity of substitution between the two goods–for example, if agricultural and non-agricultural goods were aggregated using a Cobb–Douglas specification. In that case, the decline in the agricultural relative price would exactly offset the increase in agricultural productivity, leaving the agricultural wage unchanged.

If labor were freely mobile across sectors, individuals would respond to the decline in the agricultural wage by moving from agriculture into non-agricultural employment. This reallocation would limit the effect of agricultural productivity growth on labor force participation. Barriers to labor mobility dampen this adjustment. In an extreme case of complete immobility, villagers can work only in agriculture. A decline in the agricultural wage then reduces

the return to market work relative to home production, leading households to reduce market labor supply and increase time devoted to home production. In standard labor-supply terminology, the substitution effect of the lower wage dominates the income effect.

Importantly, this mechanism does not require labor mobility barriers to become more severe over time. Even constant barriers can generate a decline in labor force participation by preventing workers from fully reallocating toward non-agricultural employment as agricultural productivity rises and the agricultural wage falls.

4 Calibration

We calibrate our baseline framework to data moments from China in 2004, explicitly matching the observed labor force participation rate and sectoral employment share. We then re-calibrate key parameters to match moments in 2019, and assess our model's implication for labor force participation rate over time.

4.1 Parameterization

We need to make parametric assumptions on the ability distribution and the labor mobility frictions.

Ability distributions. We follow Adamopoulos et al. (2024) and Cao et al. (2026) closely on the parameterization of ability. Each individual j in family i draws an agricultural ability s_{ij} and a non-agricultural ability h_{ij}. We allow for individual abilities to be correlated across members of the same family. In addition, we allow for abilities to be correlated across sectors. In particular, the non-agricultural ability of individual j in family i is given by

$$\log(h_{ij}) = \log(h_i^H) + \log(h_{ij}^I),$$

where h_i^H is a common component for all individuals within family i and h_{ij}^I is individual j's idiosyncratic component. The common component can capture, for instance, the correlation of innate ability or accumulable skills across family members. The agricultural ability of individual j in family i is given by

$$\log(s_{ij}) = \log(s_i^H) + \log(s_{ij}^I) + \lambda \log(h_{ij}),$$

where s_i^H is the common family component, s_{ij}^I the individual component, and $\lambda \log(h_{ij})$ governs the correlation between agricultural and non-agricultural abilities of the same individual. We assume that the logarithms of the ability components s_i^H, h_i^H, s_{ij}^I, and h_{ij}^I are all drawn independently from mean-zero normal distributions. The standard deviations of the family components are σ_s, σ_h, respectively, and those of the individual components are $\psi\sigma_s$, $\psi\sigma_h$, respectively, where ψ governs the relative dispersion of the individual components compared with the family components.

Fixed utility costs of entering the non-agricultural sectors. Recall that villagers working in the non-agricultural sectors are subject to fixed utility costs (κ's). We allow for these costs varying at the household level, rather than at the individual level, for two reasons. First, the utility function is defined at the household level as our model of households is unitary. Second, this choice is also motivated by the high correlation of sectoral choices among household members that we explain in detail later. We assume that the logarithms of the fixed utility costs of entering the rural and the urban non-agricultural sectors follow normal distributions with means μ_κ^r and μ_κ^u and a standard deviation σ_κ.

4.2 Calibration: 2004 Baseline Economy

We calibrate the baseline economy to the data moments in China for the year 2004. There are in total 29 parameters to be determined: 3 parameters on productivity $\{A^a, A^r, A^u\}$, 6 parameters on technologies $\{\alpha, \alpha_a, \gamma_a, \varphi, \rho, \theta\}$, 5 parameters on endowments $\{J, N_r, N_u, K, L\}$,

5 parameters on ability distribution $\{\psi, \sigma_s, \sigma_h, \lambda, \bar{h}\}$, 5 parameters on the labor mobility barriers $\{\xi^r, \xi^u, \mu_\kappa^r, \mu_\kappa^u, \sigma_\kappa\}$, and 5 parameters on preferences $\{\phi, \varepsilon, \mu_a, \mu_n, \omega\}$.

Among these 29 parameters, 15 are determined outside the equilibrium, either by normalization or using values from the literature. For productivity and technology parameters, we normalize the productivities (A^a, A^r, A^u) to one in our baseline calibration without loss of generality. Technically, these productivities reflect the units of measurements. We choose $\alpha = 0.33$ to match the capital share in the non-agricultural sectors (Gollin, 2002). We choose $\alpha_a = 0.18$ and $\gamma_a = 0.36$ to match the capital and land share in agriculture in China (Adamopoulos et al., 2022). We choose $\rho = 3$ such that the output from the two non-agricultural sectors are highly substitutable. We follow Cao et al. (2026) and set $\theta = 4$ which implies that home production labor from household members is highly substitutable. For endowment parameters, we choose $J = 2$ such that each rural household consists of two individuals, namely a husband and a wife. We choose $N_r = 0.209$ and $N_u = 0.683$ to match the shares of township and urban households following Adamopoulos et al. (2024). We normalize land input L to one. For preferences, we set the income elasticities to be $\mu_a = 1$ and $\mu_n = 3.678$ and the elasticity of substitution between two goods $\varepsilon = 0.197$ following Yao and Zhu (2021), who estimate the same preference specification using data from China. Note that the agricultural good has a lower income elasticity ($\mu_a < \mu_n$). The preferences are hence non-homothetic and imply structural transformation from agriculture to non-agriculture along with productivity growth.

The remaining 14 parameters are determined jointly by matching equilibrium model moments with data moments. While they are jointly determined, some moments are particularly relevant for certain parameters. We hence introduce our identification strategy for each group of parameters.

We choose the relative utility between consumption and home production (ω), the relative utility between agricultural and non-agricultural consumption (ϕ), and the weight between rural and urban non-agricultural goods (φ) to match three moments: the labor force partici-

pation rate of 0.891, and the sectoral employment shares of agriculture, rural non-agriculture, and urban non-agriculture, conditional on participating in the labor force, of 0.535, 0.278, and 0.188, respectively, among villagers. We note the three employment shares sum up to one and hence they provide two informative moments.

We choose the dispersion parameters of ability (σ_s and σ_h) to match the observed dispersion of agricultural and non-agricultural wage rates of 0.579 and 0.611, respectively. ψ governs the correlation of ability between household members. Cao et al. (2026) document that the rank correlation of years of schooling between rural couples is around 0.6. We hence choose ψ such that the rank correlation of abilities between couples is 0.6. λ governs the correlation of agricultural and non-agricultural ability for each individual. We choose λ such that the rank correlation is 0.35 following Lagakos and Waugh (2013). We choose the average productivity of township and urban households ($\bar{h}$) to match the agricultural value-added share of GDP of 15.2 percent. Note that the sectoral value-added share does not coincide with the employment share, the gap of which is exactly the nominal agricultural productivity gap (Gollin et al., 2014).

Recall that we allow for both fixed utility costs and proportional income costs for labor mobility barriers. We now describe how we separately identify their levels. Take the rural non-agricultural sector as an example. If the fixed cost μ_κ^r is high, then only those who supply sufficient amounts of labor will choose rural non-agricultural employment. We hence use the moment that the average worker in rural non-agriculture works 30.5 percent more labor days per year than farmers in agriculture do to discipline μ_κ^r. If the proportional income cost ξ^r is high, then the wage gap between agriculture and rural non-agriculture will widen. We hence choose the sectoral wage gap of 0.706 log points to discipline ξ^r. Similarly, we choose μ_κ^u and ξ^u to match the two moments that the average worker in urban non-agriculture works 34.6 percent more labor days per year than farmers in agriculture, and that the sectoral wage gap is 0.548 log points between agriculture and urban non-agriculture. In Appendix C, we discuss in detail the identification of these two types of costs separately, and how the model

performs quantitatively if only one type of cost is allowed.[8]

We now discuss how we determine the heterogeneity of the fixed utility costs (σ_κ). To start, this heterogeneity affects the correlation of occupational choices between household members. Intuitively, if the variation is at the household level, then it is more likely that both household members choose the same sector to work. The larger the variation, the higher the correlation. On the contrary, if the variation is at the individual level, then the two household members have different draws of labor mobility barriers and hence they may choose different sectors. The larger the variation, the lower the correlation of their sectoral choice. In the data, conditional on working, the correlation of both members choosing to work in the rural non-agricultural sector is 0.462. The model without heterogeneity of the labor mobility barriers generates a lower correlation. We hence allow the heterogeneity to be at the household level (as we mentioned in Section 4.1), and choose σ_κ to match exactly this correlation. Finally, we note that σ_κ has a relatively small effect on the results of our counterfactual experiments.

Finally, we choose the endowment of capital (K) such that the capital-output ratio is 3 in the non-agricultural sector following Chen et al. (2023).

To summarize, 15 parameters are determined exogenously outside the equilibrium $\{A^a,\ A^r,\ A^u,\ \alpha,\ \alpha_a,\ \gamma_a,\ \rho,\ \theta,\ J,\ N_r,\ N_u,\ L,\ \mu_a,\ \mu_n,\ \varepsilon\}$, while 14 parameters are calibrated by matching equilibrium model moments with data moments $\{\omega,\ \phi,\ \varphi,\ \sigma_s,\ \sigma_h,\ \psi,\ \lambda,\ \bar{h},\ \mu_\kappa^r,\ \mu_\kappa^u,\ \sigma_\kappa,\ \xi^r,\ \xi^u,\ K\}$. Parameters are listed in Table 2, and the first two columns of Table 3 compare the model and data moments.

4.3 Re-Calibration to 2019 Economy

A goal of our quantitative analysis is to understand the change in the labor force participation rate over time. We hence re-calibrate a set of key parameters to match the corresponding

[8]The calibrated value of ξ^u is negative in 2004. We interpret this not as a literal subsidy, but as a reduced-form wedge that captures the net return to urban non-agricultural work after accounting for observed wage gaps and other model forces. By 2019, this wedge becomes positive, indicating that effective barriers to urban non-agricultural work rise substantially for villagers.

Table 2: Model Parameters and Values, 2004 Baseline Economy

(a) Normalized or Set to Exogenous Values		
Parameter	Value	Description
A^a	1	TFP of the agricultural sector (normalization)
A^r	1	TFP of the rural non-agricultural sector (normalization)
A^u	1	TFP of the urban non-agricultural sector (normalization)
α	0.33	Capital share of the urban non-agricultural sector (Gollin, 2002)
α_a	0.18	Capital share of the agricultural sector (Adamopoulos et al., 2022)
γ_a	0.36	Land share of the agricultural sector (Adamopoulos et al., 2022)
ρ	3	Elasticity of substitution (EOS), rural and urban non-agricultural output
θ	4	EOS, home production labor among household members (Cao et al., 2026)
J	2	Two working-age members per household
N_r	0.209	Measure of township households (Adamopoulos et al., 2024)
N_u	0.683	Measure of urban households (Adamopoulos et al., 2024)
L	1	Land endowment (normalization)
μ_a	1	Income elasticity of agricultural good (Yao and Zhu, 2021)
μ_n	3.678	Income elasticity of non-agricultural good (Yao and Zhu, 2021)
ε	0.197	EOS, agricultural and non-agricultural goods (Yao and Zhu, 2021)
(b) Jointly Calibrated		
ω	0.038	Utility weight on home production
ϕ	0.251	Level shifter of agricultural good demand
φ	0.492	Weight on rural versus urban non-agricultural output
σ_s	0.481	Household component of agricultural ability
σ_h	0.690	Household component of non-agricultural ability
ψ	0.786	Relative importance of individual versus family components
λ	0.273	Correlation between two-dimensional abilities
$\bar{h}$	5.147	Relative productivity of township and urban households
ξ^r	0.066	Level of proportional tax of rural non-agriculture
ξ^u	-0.277	Level of proportional tax of urban non-agriculture
μ_κ^r	-4.616	Level of utility cost of working in rural non-agriculture
μ_κ^u	-4.476	Level of utility cost of working in urban non-agriculture
σ_κ	0.160	Dispersion of labor mobility barriers
K	10.21	Capital endowment

Notes: List of parameters and calibrated values. Parameters in Panel (a) are either normalized or directly assigned values from outside evidence, while parameters in Panel (b) are jointly determined by comparing model moments and targeted data moments.

Table 3: Targeted Data and Model Moments

	2004		2019	
	Data	Model	Data	Model
	(1)	(2)	(3)	(4)
National account				
Agr. VA share	0.152	0.152	0.071	0.071
K-Y ratio	3.000	3.000	3.000	3.000
Labor supply				
Labor force participation	0.891	0.893	—	—
Conditional on participation				
Agriculture	0.535	0.535	0.320	0.320
Rural non-agr.	0.278	0.278	0.382	0.381
Urban non-agr.	0.188	0.187	0.299	0.299
Within-household correlation	0.462	0.462	0.582	0.579
Relative labor days				
Rural/farming	1.305	1.305	1.491	1.493
Urban/farming	1.346	1.351	1.570	1.560
Sectoral wage gap				
Rural-farming	0.706	0.706	1.506	1.504
Urban-farming	0.548	0.548	1.564	1.564
Wage dispersion				
Agriculture	0.579	0.580	—	—
Non-agriculture	0.611	0.613	—	—
Productivity growth				
Non-agriculture	—	—	2.618	2.618

Note: Columns (1) and (2) compare data and model moments for our baseline calibration of the 2004 economy. Columns (3) and (4) compare data and model moments when we re-calibrate our model to the 2019 economy.

data moments for the end of our sample period, 2019, to highlight the importance of different driving forces in labor force participation rate.

We set $N_r = 1.116$ and $N_u = 2.797$ to match the shares of township and urban families in 2019. In addition, we jointly re-calibrate 10 parameters to match 2019 moments, with five relating to relative productivity and endowment $\{A^a, A^r, A^u, \bar{h}, K\}$ and five on labor mobility barriers $\{\mu_\kappa^r, \mu_\kappa^u, \sigma_\kappa, \xi^r, \xi^u\}$, to capture the changes in productivity and potential frictions over time.

Recall that we normalize A^a, A^r, and A^u to one in our baseline calibration. We now re-calibrate these three parameters to match three data moments in 2019: non-agricultural labor productivity grows by 2.618-fold during our sample period, and among those in the labor force, the employment shares of agriculture, rural non-agriculture, and urban non-agriculture are 0.320, 0.382, 0.299, respectively. Again, the three employment shares sum up to one and hence they provide two informative moments. The parameter $\bar{h}$ is a residual relative-efficiency term for township and urban households, normalized relative to the ability of villagers. We choose it to match the agricultural value-added share of 0.071 in 2019.[9] We again choose K such that the capital-output ratio is 3 as in our baseline calibration. We note that capital deepening, reflected by a change in the capital-output ratio, has implications for labor force participation that are quantitatively similar to changes in the sectoral TFP. This is because we do not explicitly model frictions in capital market. See Appendix E for a detailed discussion.

In addition, we re-calibrate the five parameters on labor mobility barriers to match exactly the same data moments in 2019, including the sectoral wage gaps of 1.506 and 1.564 log points between the rural/urban non-agricultural sectors and agriculture, the 49.1 percent and 57.0 percent more labor days in rural/urban non-agricultural sectors than in agriculture, and the within-household correlation of choosing the rural non-agricultural sector of 0.582.

[9]Its decline between 2004 and 2019 should therefore not be read literally as a collapse in urban productivity. Rather, it reflects the joint re-calibration needed to match the agricultural value-added share and sectoral employment shares after sectoral TFPs are updated.

This re-calibration captures the changes in sectoral productivity as well as frictions over time. We note that we do not target the labor force participation rate in 2019. Table 4 lists the re-calibrated parameters, and the third and fourth columns of Table 3 compare the model and data moments of this re-calibration.

Table 4: Model Parameters and Values, 2019 Re-Calibration

Parameter	Value	Description
N_r	1.116	Measure of township households (Adamopoulos et al., 2024)
N_u	2.797	Measure of urban households (Adamopoulos et al., 2024)
A^a	3.740	TFP of the agricultural sector
A^r	8.177	TFP of the rural non-agricultural sector
A^u	7.776	TFP of the urban non-agricultural sector
$\bar{h}$	0.116	Relative productivity of township and urban households
μ_κ^r	-3.440	Level of utility cost of working in rural non-agriculture
μ_κ^u	-2.789	Level of utility cost of working in urban non-agriculture
σ_κ	0.938	Dispersion of labor mobility barriers
ξ^r	0.415	Level of proportional tax of rural non-agriculture
ξ^u	0.295	Level of proportional tax of urban non-agriculture
K	73.16	Capital endowment

Notes: List of parameters and calibrated values. N_r and N_u are directly assigned values from outside evidence, while the remaining parameters are jointly determined by comparing model moments and targeted data moments.

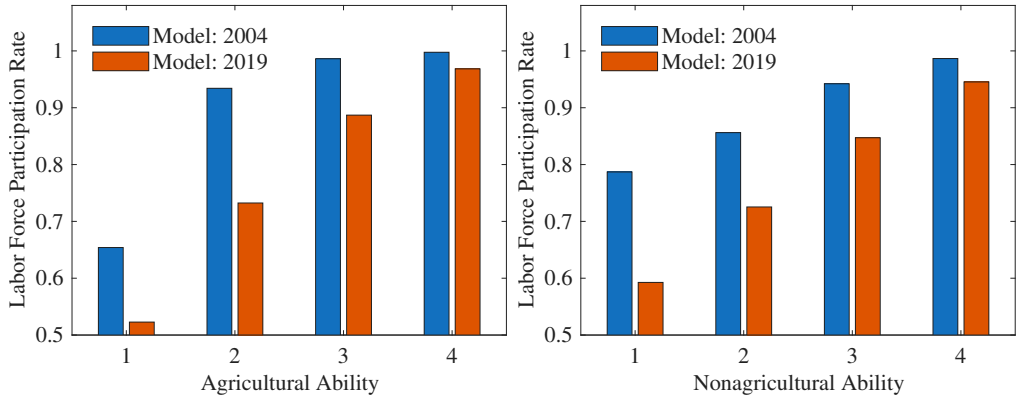
Despite not targeting the labor force participation rate in 2019, the re-calibrated model implies a labor force participation rate of 77.8 percent, very similar to the 76.3 percent participation rate in the data. This indicates that our model captures the most important features affecting the changes in labor force participation rate over time. We will now use our model to decompose the driving forces of labor force participation.[10]

4.4 Selection Patterns in the Calibrated Economies

An important question on labor force participation is who quits the labor force. In Section 2, we document that those who are female and less educated are more likely to be out of the

[10] An alternative approach is to re-calibrate ω, the utility weight on home production, to exactly match the labor force participation rate in 2019. In this way, ω serves as a residual parameter that captures all other forces affecting the labor force participation that we do not explicitly model.

Figure 5: Labor Force Participation by Ability



Note: The left (right) panel shows the labor force participation by agricultural (non-agricultural) ability quartile. The blue bars represent the baseline economy in 2004, and the red bars represent the re-calibrated 2019 economy.

labor force. We now investigate the sorting pattern in our model economy.

We start by assessing the labor force participation rate for each of the two model-simulated cross-sections, 2004 and 2019. Figure 5 shows the labor force participation rate by ability. We sort individuals into quantiles by their agricultural ability (the left panel) or non-agricultural ability (the right panel), and then plot the average labor force participation rate within each quartile, for the year 2004 (blue) and 2019 (red). We can see two patterns. First, the labor force participation rate is much lower for low-ability individuals in both 2004 and 2019. This is consistent with the empirical pattern that less educated individuals are slightly more likely to be out of the labor force. Second, the re-calibrated 2019 economy has lower labor force participation rates among all ability quartile. The model does not explicitly include gender, age, or education. Nevertheless, if education is correlated with market ability, the model's selection pattern is consistent with the larger decline observed among less educated individuals. The decline across all ability groups also echoes the broad-based decline observed across demographic groups in the data.

We next compare the participation choices of the same ability types across the two calibrated economies. Table 5 shows the average ability of each group compared to the average

Table 5: Average Ability, Stayers Versus Switchers

Types of individuals	Ability relative to population average (Δ, %)	
	Agricultural ability	Non-agricultural ability
Working ⇒ Working	+15.5	+15.5
Working ⇒ Not Working	−25.0	−42.8
Not Working ⇒ Not Working	−82.1	−64.8

Note: This table shows the average ability of each group of individuals relative to the average ability of all individuals. We show individuals for three groups: those who always work (the first row), those who work in the baseline economy but not in the 2019 re-calibration (the second row), and those who do not work in either economy (the third row).

ability of all individuals economy-wide. For illustration purposes, we show individuals for three groups: those who always work (the first row), those who work in the baseline economy but not in the 2019 re-calibration (the second row), and those who do not work in either economy (the third row). In principle there is a fourth group who do not work in the baseline economy but work in the 2019 re-calibration. There are very few of these individuals, and hence we choose not to include them in the table. Not surprisingly, those who always work tend to have higher ability than the economy-wide average for both agricultural and non-agricultural ability, and those who do not work in either sector have substantially lower ability. Importantly, those who work in the 2004 baseline economy but exit the labor market in the 2019 recalibration tend to have below-average ability in both sectors.

5 Quantitative Analysis

We now disentangle the driving forces of labor force participation over our sample period. Recall that we re-calibrate three sets of parameters over time: the share of township and urban households (i.e., the share of individuals with non-agricultural hukou), sectoral productivity, and the labor mobility frictions. We now separately investigate how these changes affect the labor force participation. We follow Adamopoulos et al. (2024) and Cao et al. (2026) and change the parameters one set at a time in the 2004 baseline economy to their

2019 levels, while keeping all other parameters constant. In other words, we ask the following question: How will a village household living in 2004 choose their labor supply if the productivity levels or mobility frictions are as the 2019 level?

5.1 Productivity Growth

We assess the effect of productivity growth on labor force participation. To start, we change agricultural productivity (A^a) in the 2004 baseline economy to its 2019 level, an increase of 3.74-fold, keeping all other parameters constant. This experiment then explores how a village household in 2004 will choose their labor supply if agricultural labor productivity is at the 2019 level. The results are in the second row of Table 6. Agricultural productivity growth substantially reduces the labor force participation rate from 89.1 percent to 74.9 percent, with the share not working more than doubling.

The intuition behind this decline is straightforward. When agricultural productivity increases, agricultural consumption does not increase proportionally due to the non-homotheticity in preferences. Specifically, the income elasticity of agricultural good is lower than that of non-agricultural good, while the elasticity of substitution between the two goods is low as well. To clear the market, agricultural prices must fall substantially, resulting in a sharp drop in agricultural wages of 56.2 percent. Working in agriculture is much less rewarding, and hence, the share of villagers working in agriculture falls from 47.8 percent to only 15.2 percent. This is the same mechanism highlighted in Ohnsorge et al. (2026). In the meantime, villagers tend to switch to working in the rural and urban non-agricultural sectors, but this is costly due to labor mobility barriers, even though the barriers are held constant in this experiment. As a result, the increase in non-agricultural employment cannot offset the decline in agricultural employment, and thus, labor force participation falls. In this case, the labor mobility barriers further amplify the effect of agricultural productivity growth on labor force participation, an amplification mechanism absent in Ohnsorge et al. (2026).

China's agricultural sector also experienced substantial capital deepening over this pe-

Table 6: The Effects of Productivity Growth

	Not in labor force (%)	Employment Share (%)			
		Total	Agr	Rural Nonagr	Urban Nonagr
	(1)	(2)	(3)	(4)	(5)
2004					
baseline	10.9	89.1	47.8	24.8	16.7
2019 productivity—agr	25.1	74.9	15.2	34.2	25.5
2019 productivity—nonagr	2.6	97.4	33.1	26.7	37.6
2019 productivity—all	6.5	93.5	11.2	34.8	47.5

Notes: This table shows the shares of villagers who are not in the labor force (column 1), in the labor force (column 2), working in agriculture (column 3), rural non-agriculture (column 4), and urban non-agriculture (column 5). Note that the shares in columns 1 and 2 sum up to 100 percent, and those in columns 3–5 sum up to that of column 2. We show the baseline economy on the first row, the baseline economy modified with 2019 agricultural productivity in the second row, with 2019 non-agricultural productivity in the third row, and with 2019 agricultural and non-agricultural productivity in the fourth row.

riod, with its capital–output ratio increasing from 1.8 to approximately 2.5 (Wang et al., 2020). This process partly reflected policies that encouraged mechanization and larger-scale farming, including central-government subsidies for agricultural machinery purchases introduced in 2004 and subsequently expanded.[11] In the model, agricultural capital deepening has effects on labor force participation that are quantitatively similar to Hicks-neutral agricultural productivity growth because both reduce the amount of labor required to produce a given quantity of agricultural output. This quantitative similarity, however, does not imply the same economic interpretation. Unlike exogenous productivity growth, capital deepening can be influenced by policies that change the effective cost of capital relative to labor. When combined with barriers that limit movement into non-agricultural employment, policies that encourage labor-saving agricultural technologies may accelerate the release of labor from agriculture without ensuring that this labor is absorbed into off-farm work. Appendix E shows that explicitly incorporating agricultural capital deepening leaves the main quantitative conclusion unchanged, but it also clarifies that policy-induced capital deepening and

[11]The Ministry of Finance of China reports that the central government established the agricultural machinery purchase subsidy program in 2004 and subsequently expanded its funding and coverage. See Ministry of Finance of China, March 2, 2012.

Hicks-neutral productivity growth need not have the same interpretation.

We next change the non-agricultural productivity in the 2004 baseline economy to the 2019 level. Three parameters jointly govern non-agricultural productivity: TFP of the rural non-agricultural sector (A^r), TFP of the urban non-agricultural sector (A^u), and the relative productivity of the township and urban household ($\bar{h}$).[12] The results are displayed in the third row of Table 6. Non-agricultural productivity growth has exactly the opposite effects compared to agricultural productivity growth: Labor force participation increases substantially from 89.1 percent to 97.4 percent, with the share not working falling by three quarters. With higher non-agricultural productivity, more villagers work in the non-agricultural sectors.

We also change both agricultural and non-agricultural productivity to the 2019 level, with the results displayed on the fourth row of Table 6. Recall that agricultural productivity growth tends to reduce labor force participation, while non-agricultural productivity growth tends to increase labor force participation. When both forces are present, the effects partially offset each other, with the net effect on labor force participation small—labor force participation increases slightly from 89.1 percent to 93.5 percent. Thus, structural transformation, if driven by economy-wide labor productivity growth, does not have to reduce labor force participation rate. In the model, labor force participation is more likely to fall when agricultural productivity growth is strong relative to non-agricultural productivity growth, and more likely to rise when non-agricultural productivity growth is sufficiently strong (Duarte and Restuccia, 2010). In addition, we note that capital deepening in agriculture, as highlighted in Chen (2020b) and Caunedo and Keller (2020), has similar effects as an increase in the sectoral productivity A^a.

As additional support for the mechanism, Appendix D reports village-level regressions relating labor force participation to agricultural productivity and non-agricultural employment

[12]Recall that the non-agricultural ability of the villagers is given by their h with a mean of one, while that of the township and urban household is simply $\bar{h}$. Hence, $\bar{h}$ can be viewed as the relative productivity between the villagers and the township and urban households.

opportunities. Consistent with the model, increases in agricultural productivity are associated with lower village labor force participation in areas where non-agricultural employment opportunities are limited. This negative association is attenuated, and in some specifications reversed, in provinces with larger non-agricultural sectors. These patterns suggest that agricultural productivity growth reduces participation primarily when labor released from agriculture is not readily absorbed into non-agricultural employment.

5.2 Changes in Endowments: The Share of Villagers

In our model, the share of villagers maps to individuals with agricultural *hukou*, while the share of township and urban households maps to individuals with non-agricultural *hukou*. The key distinction between these two is that villagers, or agricultural *hukou* holders, have access to farmland and hence can choose to farm or to work in the non-agricultural sectors, while the township and urban households only work in the non-agricultural sectors. Over time, the share of village households declines, while that of township and urban households increases. This could be due to three reasons. It could reflect natural fertility/mortality differences among different households; it could be due to the urbanization of the peri-urban localities with agricultural *hukou* individuals obtaining non-agricultural *hukou*; or it could be due to rural migrants receiving non-agricultural *hukou*. We do not explicitly model the process of these changes in this paper. Rather, in the re-calibration, we change N_r and N_u to reflect the fact that the shares of township and urban households increase, without taking a stand on the sources. We investigate how this change in household composition affects the labor force participation.

We now consider the following experiment: in the 2004 baseline economy, if the share of individuals with non-agricultural *hukou* is the same as in 2019, what happens to labor force participation? The results are listed in the second row of Table 7: Labor force participation rate increases drastically from 89.1 percent to 96.9 percent among remaining villagers. This experiment should be interpreted as a partial decomposition within the model. We change

Table 7: The Effects of Hukou Changes

	Not in labor force (%)	Employment Share (%)			
		Total	Agr	Rural Nonagr	Urban Nonagr
	(1)	(2)	(3)	(4)	(5)
2004					
baseline	10.9	89.1	47.8	24.8	16.7
2019 hukou	3.1	96.9	93.6	2.9	0.3

Notes: This table shows the shares of villagers who are not in the labor force (column 1), in the labor force (column 2), working in agriculture (column 3), rural non-agriculture (column 4), and urban non-agriculture (column 5). Note that the shares in columns 1 and 2 sum up to 100 percent, and those in columns 3–5 sum up to that of column 2. We show the baseline economy in the first row and the baseline economy modified with 2019 *hukou* composition in the second row.

the measure of village, township, and urban households to their 2019 values while holding productivity and mobility barriers at their 2004 levels. As a result, the remaining village population is much smaller relative to aggregate demand for agricultural goods. To clear the agricultural market, the agricultural wage rises sharply by 4.95-fold, making agricultural work more attractive and raising participation among remaining villagers. Indeed, in this scenario, 93.6 percent of villagers in the labor force choose to work in agriculture.

5.3 Changes in Labor Mobility Barriers

The calibrated labor mobility barriers increase over time. We interpret this increase as an increase in the effective barriers faced by the remaining rural population, not necessarily as direct evidence that formal policy restrictions became more severe. These effective barriers may reflect policy, selection, changes in the composition of rural residents, or other unmodeled costs of accessing non-agricultural employment. With this interpretation in mind, comparing Table 2 and Table 4 shows that the barriers faced by remaining rural population, especially the implicit income tax rates, increase substantially.

In light of this increase in labor mobility barriers, we now perform the following experiment: In the 2004 baseline economy, if we change the labor mobility barrier parameters

Table 8: The Effects of Changes in Labor Mobility Barriers

	Not in labor force (%)	Employment Share (%)			
		Total	Agr	Rural Nonagr	Urban Nonagr
	(1)	(2)	(3)	(4)	(5)
2004					
baseline	10.9	89.1	47.8	24.8	16.7
2019 frictions—fixed	13.7	86.3	50.4	23.5	12.4
2019 frictions—proportional	19.5	80.5	53.7	24.8	1.9
2019 frictions—both	21.2	78.8	55.3	18.9	4.6

Notes: This table shows the shares of villagers who are not in the labor force (column 1), in the labor force (column 2), working in agriculture (column 3), rural non-agriculture (column 4), and urban non-agriculture (column 5). Note that the shares in columns 1 and 2 sum up to 100 percent, and those in columns 3–5 sum up to that of column 2. We show the baseline economy on the first row, the baseline economy modified with 2019 fixed utility cost of labor mobility in the second row, the 2019 implicit income tax of labor mobility in the third row, and the 2019 labor mobility barriers (both utility cost and implicit income tax) in the fourth row.

$\{\xi^r, \xi^u, \mu^r_\kappa, \mu^u_\kappa, \sigma_\kappa\}$ to their 2019 levels, how will the labor force participation change? The results are displayed in Table 8. Labor mobility barriers, both fixed utility costs and implicit income tax associated with non-agricultural employment, tend to reduce labor force participation. The reason is also straightforward: Over time the labor mobility barriers are higher, especially the ones associated with urban non-agriculture. As a result, fewer villagers choose to work in the urban non-agricultural sector, many of whom switch to agricultural employment. The agricultural wage falls by 27.6 percent. With agricultural employment less rewarding and non-agricultural employment impeded by the barriers, more villagers choose not to work. Comparing the fixed-cost and proportional-tax experiments shows that the proportional wedge is quantitatively more important. In other words, the widening sectoral wage gaps play a large role in discouraging labor force participation.

5.4 Explaining the Decline in Labor Force Participation

Having examined each force separately, we now combine them to assess how the model accounts for the observed decline in labor force participation in China. Note that the in-

Table 9: Decomposing the Decline in Labor Force Participation

	Not in labor force (%)	Employment Share (%)			
		Total	Agr	Rural Nonagr	Urban Nonagr
	(1)	(2)	(3)	(4)	(5)
2004					
baseline	10.9	89.1	47.8	24.8	16.7
+ 2019 productivity	6.5	93.5	11.2	34.8	47.5
+ 2019 barriers	32.2	67.8	14.8	28.8	24.1
+ 2019 *hukou*	22.2	77.8	24.9	29.6	23.3
2019 (data)	23.7	76.3	24.4	29.1	22.8

Notes: This table shows the shares of villagers who are not in the labor force (column 1), in the labor force (column 2), working in agriculture (column 3), rural non-agriculture (column 4), and urban non-agriculture (column 5). Note that the shares in columns 1 and 2 sum up to 100 percent, and those in columns 3–5 sum up to that of column 2. We show the baseline economy on the first row, the baseline economy modified with 2019 productivity in the second row, further adding the 2019 labor mobility barriers in the third row, further adding the 2019 household composition in *hukou* status in the fourth row, and then the 2019 data moments in the fifth row.

cremental contribution of each force in this sequential decomposition depends on the order in which the forces are introduced. We therefore interpret the results together with the one-at-a-time experiments in Tables 6–8.

We begin with the 2004 baseline economy, and then first introduce the 2019 levels of agricultural and nonagricultural productivity. The results are in the second row of Table 9. As discussed above, agricultural and non-agricultural productivity growth have opposing effects on labor force participation. Agricultural productivity growth pushes labor out of agriculture and tends to reduce participation, while nonagricultural productivity growth raises the return to market work and tends to increase participation. When both productivity forces operate together, these effects largely offset one another. Labor force participation rises slightly from 89.1 percent in the baseline economy to 93.5 percent.

We then introduce the 2019 level of labor mobility barriers, holding productivity at its 2019 level. This change substantially reduces labor force participation. Labor force participation falls from 93.5 percent to 67.8 percent, implying an increase in the share of villagers

out of the labor force from 6.5 percent to 32.2 percent. This result should be interpreted as applying to the effective barriers faced by villagers who continue to have rural *hukou*. It does not necessarily imply that formal migration or *hukou* restrictions became more severe over time. The increase in calibrated barriers may reflect policy, selection, changes in the composition of the remaining rural population, or other unmodeled costs of accessing nonagricultural employment. The effect of mobility barriers is larger in this sequential decomposition than in the barrier-only experiment as shown in Table 8 because productivity growth has already shifted labor away from agriculture and increased the importance of access to non-agricultural employment.

Finally, we introduce the 2019 household composition by hukou status, reducing the measure of village households and increasing the measure of township and urban households. This change raises labor force participation among the remaining villagers. As some villagers obtain non-agricultural hukou and are no longer available for agricultural work, the remaining rural population becomes smaller relative to aggregate demand for agricultural goods. In equilibrium, this raises the return to agricultural work for those who remain rural and increases their labor force participation. With all three forces operating together, the model predicts a labor force participation rate of 77.8 percent, close to the 76.3 percent observed in the data.

We can now draw the main conclusion from the decomposition. Productivity growth by itself is not the main reason for the decline in labor force participation. Agricultural productivity growth lowers participation, while non-agricultural productivity growth raises it; taken together, their net effect is small. Changes in the hukou composition of the population also increase participation among the remaining rural population. The force that reduces participation most strongly is the rise in effective labor mobility barriers faced by those who remain in villages. Quantitatively, this negative effect dominates the positive effect of changing hukou composition, allowing the model to replicate the observed decline in rural labor force participation.

Several remarks are important for interpreting the result. First, the labor mobility barriers and the *hukou* system are highly related, but their effects are not the same. On the one hand, more villagers obtained non-agricultural *hukou* over time and can work in non-agricultural sectors without facing the same mobility barriers. On the other hand, among those villagers who continue to have agricultural *hukou*, the calibrated effective barriers to nonagricultural work rise substantially. This pattern highlights the countervailing effects of *hukou* change. It may simultaneously ease access to nonagricultural employment for some individuals while leaving behind a selected group that faces higher effective costs of moving out of agriculture.

Second, the rise in calibrated mobility barriers should not be interpreted mechanically as the direct effect of hukou reform. Selection may be important. Individuals who faced lower mobility barriers in 2004 may have been more likely to obtain nonagricultural hukou or move permanently into non-agricultural employment, leaving agricultural hukou increasingly concentrated among individuals facing higher barriers. Under this interpretation, the increase in calibrated barriers reflects the changing composition of the remaining rural population rather than a worsening of formal policy restrictions.

Third, a decline in labor force participation is not necessarily welfare-reducing. If participation falls because productivity growth allows households to maintain consumption while devoting more time to home production, lower participation may reflect an improvement in welfare. If participation falls because mobility barriers prevent workers from accessing better non-agricultural opportunities, the welfare implications are less benign. The decomposition is therefore useful because it distinguishes between productivity-driven reductions in market work and reductions associated with the frictions.

6 Conclusion

This paper studies the interaction between structural change and labor force participation in China. We document a large decline in labor force participation over recent decades. While the decline during the late 1990s was concentrated in urban areas and closely associated with state-sector restructuring, the decline after 2000 was concentrated among rural individuals. This rural decline was broad-based: participation fell among men and women, across age groups, across education groups, and across regions.

We develop a quantitative framework to interpret this pattern. The model combines three ingredients: non-homothetic demand, endogenous labor force participation, and barriers to labor mobility across sectors and locations. Agricultural productivity growth releases labor from agriculture because demand for agricultural goods is income-inelastic. Whether this released labor remains in the labor force depends on the ability of non-agricultural sectors to absorb it. When non-agricultural productivity growth is strong and mobility barriers are limited, labor can move from agriculture into non-agricultural employment. When this adjustment is impeded, some workers may instead leave market work and shift toward home production.

The calibrated model reproduces both the rapid movement of labor out of agriculture and the decline in rural labor force participation. The decomposition shows that agricultural and non-agricultural productivity growth have opposing effects on participation. Agricultural productivity growth lowers participation by pushing labor out of agriculture, while non-agricultural productivity growth raises participation by pulling labor into market work. Taken together, these productivity forces have little net effect on participation. The observed decline is instead largely accounted for by rising effective mobility barriers faced by the remaining rural population, partly offset by changes in hukou composition that reduce the size of the remaining rural population.

These results qualify a common interpretation of structural change. The movement of labor out of agriculture does not necessarily imply that workers are smoothly absorbed

into non-agricultural employment. Structural change also operates through the participation margin. In settings where mobility barriers remain important, productivity growth in agriculture can reduce agricultural employment without producing an equivalent increase in non-agricultural employment. The result may be a decline in market work, especially among individuals with weaker market opportunities.

The results also highlight how the policy environment can shape labor force participation during structural transformation. Labor-market frictions, including mobility costs, hukou-related barriers, and limited access to urban public services, can impede the absorption of workers released from agriculture. At the same time, policies that encourage mechanization and capital deepening may accelerate the release of agricultural labor. In the model, capital deepening and Hicks-neutral agricultural productivity growth have similar quantitative effects on participation, but their policy interpretations differ. When policies encouraging labor-saving agricultural technologies operate alongside barriers to non-agricultural employment, they may lower market participation rather than simply reallocate workers toward non-agricultural sectors. Thus, the effect of structural change on participation depends not only on productivity growth, but also on the policy environment governing both the release and absorption of labor.

The welfare implications of declining labor force participation are therefore ambiguous. If households reduce market work because productivity growth allows them to consume more while devoting more time to home production, lower participation may reflect improved welfare. If participation falls because frictions prevent workers from accessing better non-agricultural opportunities, the welfare implications are less benign. Distinguishing between these mechanisms is essential for interpreting labor force participation during structural transformation.

More broadly, the findings suggest that models of structural change should pay attention not only to where workers are employed, but also to whether they remain attached to market work. This distinction is likely to matter in other developing economies undergoing rapid

movement out of agriculture, especially where migration costs, sectoral barriers, or household responsibilities limit the ability of workers to move into expanding non-agricultural sectors.

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Online Appendix

A Data

We mainly use three data sources. The first one is the China Statistical Yearbook National Bureau of Statistics of China (2021). We use information from the yearbooks to calculate the aggregate moments, such as the value-added share of agriculture. Note that numbers may be revised in the yearbooks over time. We record data moments when they first appeared in the yearbooks. For instance, the agricultural value-added share in 2004 is obtained from the 2005 Yearbook.

The second data source is the China Population Census Yearbooks (National Bureau of Statistics of China, 2020). We use various rounds of the census to document the labor force participation rates over time, together with the participation rates in rural versus in urban areas, as displayed in Section 2. We use census data to construct labor force participation rates at the national level, by rural–urban residence, and by demographic group (gender and age). The census waves we used are 1982, 1990, 1995, 2000, 2005, 2010, 2015, 2020. We construct the labor force participation rate as the ratio of labor force participants to the population aged 16–64. Up until 1995, individuals only reported whether they had a job or not. Starting in 2000, individuals are defined as participating in the labor force if they worked at least one hour for pay during the previous week. We separately estimate the labor force participation based on the residence location, which includes rural areas, township areas, and urban areas. Most of the residents in rural areas have rural *hukou*. In township and urban areas, except for those local residents with urban *hukou*, a considerable share of rural migrants holds rural *hukou*.

The third data source is the Rural Fixed Point Survey (Research Center for Rural Economy, Ministry of Agriculture (China), 2020). This is the main data source that we use throughout the paper. The Rural Fixed Point Survey (RFPS) provides labor supply infor-

mation for individuals whose *hukou* registration is in rural areas. The survey is conducted annually and covers 31 provinces and more than 300 villages across China. For each year, it contains about 20,000 households and nearly 80,000 individuals. The survey was first conducted in 1986, but it was only in 2003 that individual-level labor supply data were collected. We observe individual labor supply measured in days in the agricultural and non-agricultural sectors, and the wage payments obtained in non-agricultural occupations outside of their home villages/towns. We also observe inputs and outputs of their family farms. This data set has been widely used in the literature, see for instance Chari et al. (2021), Adamopoulos et al. (2022), Adamopoulos et al. (2024), and Gai et al. (2025). We now briefly describe how we construct data moments used in the calibration.

We define an individual as being in the labor force if she works for at least 30 days per year, regardless of whether she is self-employed or hired. The labor force participation rate is constructed as the number of individuals participating in the labor force divided by the population aged 16–64. To alleviate concerns about underestimating labor force participation due to missing values, we take three steps. First, if an individual reports working location, costs of working outside the village or town, and wage payments, we classify her as participating in the labor force. Second, if a household reports positive wage income but no member reports the above information, we define the member as participating in the labor force if she reports her working sector and if household per capita wage income is reasonable relative to the village median level. Third, for the remaining households with wage income but no reported employment by any member, we impute labor force participation using information from the previous two years.

We construct the wage gap between agriculture and rural/urban non-agricultural sectors as the differences of median wage rate across sectors. Wage rates in the non-agricultural sector are calculated as the reported labor income divided by the reported labor days. Constructing agricultural wage rates is slightly more complicated. We construct household-farm operational profit following Adamopoulos et al. (2024) and then divide it by the average

number of labor days for farm operators as the wage rate of the farming sector. We further use the wage rate of hired labor, calculated as the cost of hiring labor divided by the days of hired labor, to approximate the wage rate of sideline agriculture, where the production is not annual in nature and hence more difficult to calculate. Agricultural wage rate is then the weighted average of farming wage rate and the wage rate of sideline agriculture. Note that the sideline agriculture accounts for around a quarter of agricultural employment in our sample period. We also use the dispersion in wage rates in our calibration. The dispersions of rural/urban non-agricultural wage rates are simply the standard deviation of log wage rates among individuals working in that sector. The dispersion of agricultural wage rate is approximated by the dispersion of wage rate of hired labor in agriculture.

B Village Household's Problem

The village household's problem can be solved in two steps. In the first step, we hold occupational choices $(D_{ij}^a, D_{ij}^r, D_{ij}^u)$ and hence κ_i constant and solve the consumption and labor supply decision. Specifically, given any income level y_i, we choose c_i^a and c_i^n to maximize c_i subject to $pc_i^a + c_i^n = y_i$. Denote the resulting optimal level of composite market consumption by $c(y_i)$. The labor supply decision is then

$$\max_{\{n_{ij}\}_{j=1}^J} \log(c(y_i)) + \omega \log(c_i^h) - \kappa_i,$$

where

$$c_i^h = \left[\sum_{j=1}^J (1 - n_{ij})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}.$$

The first order condition with respect to n_{ij} is given by

$$c(y_i)^{-1} \frac{dc(y_i)}{dy_i} w_{ij} = \omega c_{hi}^{\frac{1}{\theta}-1} (1 - n_{ij})^{-\frac{1}{\theta}}, \text{ for all } j.$$

This condition states that the marginal utility gain from working, given by the product of the marginal utility of market consumption and the wage rate, equals the marginal utility loss from the associated reduction in home production. We use the implied labor supplies to compute household income and iterate over consumption and labor supply until household income converges. Then we have solved out the consumption and labor supply decision, namely (c_i^a, c_i^n, n_{ij}). In the second step, we explore all possible combinations of $(D_{ij}^a, D_{ij}^r, D_{ij}^u)$ and choose the one that maximizes the household utility.

C Two Types of Labor Mobility Barriers

Our work differs from some of the existing studies as we allow for two types of labor mobility barriers: an implicit tax proportional to labor income in the non-agricultural sectors and a fixed utility cost associated with working in the non-agricultural sectors. The proportional one has been widely used in the structural change literature, see, for example, Restuccia et al. (2008), Hsieh et al. (2019), Lee (2024), and Adamopoulos et al. (2024). Some studies also use the fixed cost setup, see for instance Cao et al. (2026). Our framework allows for both types of costs, and in this section we briefly discuss the distinct roles played by these two types of costs, and also shed some light on how we separately identify these two types of costs.

We construct the following two alternative models to highlight the role of the labor mobility barriers. The first alternative model allows for the fixed utility costs associated with working in the non-agricultural sector, but not for the implicit tax. The model is otherwise identical to our baseline model. We then re-calibrate this alternative model by matching the same set of data moments in 2004, except for the sectoral wage gaps between agriculture and rural/urban non-agricultural sectors, which are used to determine the implicit tax rates in our baseline model. We find that this alternative model cannot match the observed sectoral wage gaps: The model generates wage gaps of 0.631 and 0.784 log points between agriculture

and the rural and the urban non-agricultural sectors, compared to 0.706 and 0.548 percent in the data.

The second alternative model allows for the implicit tax, but not the fixed utility costs. Note that in our baseline economy we assume that the implicit tax rates are the same across individuals while the fixed utility costs are heterogeneous. Without the fixed utility costs, we now allow for the implicit tax rates to be heterogeneous. Specifically, the implicit tax rates take the following functional form:

$$\xi_i^r = \frac{\varepsilon_i^{\xi,r}}{\sqrt{1+\left(\varepsilon_i^{\xi,r}\right)^2}}, \quad \xi_i^u = \frac{\varepsilon_i^{\xi,u}}{\sqrt{1+\left(\varepsilon_i^{\xi,u}\right)^2}},$$

where $\varepsilon_i^{\xi,r}$ and $\varepsilon_i^{\xi,u}$ follow normal distribution with mean μ_ξ^r and μ_ξ^u and standard deviation of σ_ξ. This functional form guarantees that the tax rates are bounded between -1 and 1. We then re-calibrate this alternative model without matching the observed differences in the intensive margin of labor supply across sectors, which are used to determine the fixed utility costs in the baseline model. We choose μ_ξ^r and μ_ξ^u to match the observed wage gaps across sectors. The dispersion parameter, σ_ξ, plays little role quantitatively. Technically, the dispersion stabilizes the solution to the model. We hence choose a minimal dispersion $\sigma_\xi = 0.005$. We find that this alternative model substantially under-estimates the observed differences in the intensive margin of labor supply across sectors. In the data, individuals working in the rural and urban non-agricultural sectors work 30.5 percent and 34.6 percent more days than individuals working in agriculture. This alternative model only generates 3.1 and 3.1 percent differences, respectively. Moreover, this alternative model also over-estimates the implicit tax rates compared to our baseline calibration: The implicit tax rates associated with rural and urban non-agricultural employment are estimated to be 46.0 and 36.2 percent, compared to 6.6 and -27.7 percent in our baseline economy.

We hence conclude that both fixed utility costs and the implicit tax are required to capture the pattern of labor supply and wage differences across sectors. We note that it is

not as clear if one type of barrier tends to be more important than the other type. In our baseline 2004 calibration, it seems that the fixed utility costs play a larger quantitative role, while the implicit tax tends to be more important in the 2019 calibration.

D Village-Level Evidence on Labor Force Participation

This appendix provides additional descriptive evidence on the mechanism emphasized in the paper. The model implies that agricultural productivity growth can reduce labor force participation when labor released from agriculture is not absorbed into non-agricultural employment. The negative participation effect should therefore be weaker in localities with greater access to off-farm opportunities.

We test this prediction using village-year data in 2004–2013 from the Rural Fixed Point Survey (Research Center for Rural Economy, Ministry of Agriculture (China), 2020). The dependent variable is the village labor force participation rate, defined as the share of non-student individuals aged 16–64 who worked at least 30 days during the year. We relate village labor force participation to alternative measures of agricultural productivity, including a value-added-weighted measure of crop TFP and crop yield. The crops include wheat, rice, corn, and soybean. The crop TFP is calculated as in Adamopoulos et al. (2024) and aggregated to the village level using value added as weights. To capture off-farm opportunities, we use the provincial non-agricultural employment share and interact it with village agricultural productivity. The provincial non-agricultural employment share is obtained from provincial Statistical Yearbooks. Overall, the share of non-agricultural employment increased from 53.2% in 2004 to 62.8% in 2013. We include year and province fixed effects and, in more demanding specifications, add village controls, village fixed effects, and province-year fixed effects.

The results are displayed in Table 10 and are broadly consistent with the mechanism. In the annual panel, higher agricultural productivity is generally associated with lower village

Table 10: Panel Evidence on Labor Force Participation

	Dependent Variable: Labor Force Participation Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agr. productivity	−0.043	−0.025	−0.026	−0.014	−0.047	−0.029	−0.042	−0.025
	(0.017)	(0.014)	(0.016)	(0.015)	(0.018)	(0.022)	(0.016)	(0.016)
Non-agr. emp. share	−0.582	−0.310	−0.266		−0.655	−0.498	−0.564	
	(0.165)	(0.133)	(0.180)		(0.230)	(0.268)	(0.175)	
Interaction	0.079	0.049	0.046	0.026	0.079	0.071	0.083	0.054
	(0.025)	(0.020)	(0.027)	(0.024)	(0.031)	(0.038)	(0.026)	(0.026)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Village FE	No	No	Yes	Yes	No	No	Yes	Yes
Province FE	Yes	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Prov×Year FE	No	No	No	Yes	No	No	No	Yes
No. of Obs.	3,076	2,932	2,925	2,922	3,099	2,954	2,948	2,945
R^2	0.157	0.281	0.722	0.749	0.151	0.288	0.723	0.749

Note: This table shows village-level regression results with labor force participation rate as the dependent variable. We measure agricultural productivity using value-added-weighted crop TFP in logarithm (columns 1–4) and yield in logarithm (columns 5–8). Non-agricultural employment share is a number between 0 and 1, and is measured at the provincial level. Interaction denotes the interaction between agricultural productivity and the provincial non-agricultural employment share. Control variables include distance to the nearest county, cultivated land per worker, share of working-age population in the total population, average household size, share of female labor, share of the working-age population with 7–9, 10–12, and more than 12 years of education, and share of the working-age population aged 25–34, 35–44, and 45–54, 55–64. Standard errors are clustered at the provincial level and reported in parentheses.

labor force participation when off-farm opportunities are limited. The interaction between agricultural productivity and the non-agricultural employment share is positive across specifications. This implies that the negative association between agricultural productivity and labor force participation is attenuated in provinces with larger non-agricultural sectors. The pattern is similar when agricultural productivity is measured using crop yields rather than TFP (see Columns 5–8).

We also estimate long-difference specifications comparing average outcomes in 2004–2007 with average outcomes in 2010–2013. These results, displayed in Table 11, point in the same direction. Villages with larger increases in agricultural productivity tend to experience larger declines in labor force participation. This relationship is attenuated in provinces

Table 11: Long-Difference Evidence on Labor Force Participation

Dependent Variable: Labor Force Participation Rate				
	(1)	(2)	(3)	(4)
Δ Agr. productivity	−0.081	−0.094	−0.052	−0.068
	(0.047)	(0.055)	(0.036)	(0.041)
Non-agr. emp. share (04–07)	−0.059		−0.046	
	(0.055)		(0.051)	
Interaction	0.141	0.157	0.099	0.112
	(0.067)	(0.080)	(0.049)	(0.056)
Labor force participation (04–07)	−0.272	−0.305	−0.279	−0.308
	(0.074)	(0.084)	(0.073)	(0.083)
Agr. productivity (04–07)	0.010	0.004	0.012	0.003
	(0.015)	(0.016)	(0.012)	(0.013)
Controls	Yes	Yes	Yes	Yes
Province FE	No	Yes	No	Yes
No. of Obs.	305	305	305	305
R^2	0.103	0.202	0.101	0.197

Note: This table reports village-level regressions in which the dependent variable is the change in the labor force participation rate between 2004–2007 and 2010–2013. We measure agricultural productivity using value-added-weighted crop TFP in logarithm (columns 1–2) and yield in logarithm (columns 3–4). Non-agricultural employment share is a number between 0 and 1, and is measured at the provincial level. Interaction denotes the interaction between the change in agricultural productivity and the average of the provincial non-agricultural employment share in 2004–2007. Control variables include distance to the nearest county, cultivated land per worker, share of working-age population in the total population, average household size, share of female labor, share of the working-age population with 7–9, 10–12, and more than 12 years of education, and share of the working-age population aged 25–34, 35–44, and 45–54, 55–64. All of the control variables above are measured using their average values over 2004–2007. Standard errors are clustered at the provincial level and reported in parentheses.

where the initial non-agricultural employment share is higher. The specifications also control for initial labor force participation and initial agricultural productivity, helping to separate changes over time from baseline differences across villages. The long-difference results suggest that the annual panel patterns are not driven solely by short-run fluctuations in measured productivity.

These regressions are not intended to provide a stand-alone causal test. Agricultural productivity, labor allocation, migration, and local non-agricultural development are jointly determined. The estimates should therefore be interpreted as descriptive evidence on whether

the village-level co-movement of agricultural productivity, participation, and off-farm opportunities is consistent with the model. Taken together, the results are consistent with the paper's central mechanism: Agricultural productivity growth is associated with lower labor force participation primarily where non-agricultural employment opportunities are limited, while stronger off-farm opportunities help absorb labor released from agriculture.

E The Role of Capital Deepening in Labor Supply

Economic growth is typically accompanied by capital deepening in agriculture (e.g., Chen, 2020b). For China, Wang et al. (2020) document an increase in the agricultural capital–output ratio from 1.8 in 2004 to 2.5 in 2017, the final year of their sample. To capture agricultural capital deepening in a parsimonious way, we conduct an alternative calibration for 2019 in which α_a is raised to 0.28, a value that implies an agricultural capital–output ratio of approximately 2.5. We then recalibrate the model to the same set of 2019 data moments.

Importantly, agricultural TFP in 2019, A_a, is chosen to match the agricultural employment share. With a higher value of α_a, agricultural labor productivity growth is driven by both capital deepening and Hicks-neutral TFP growth. Consequently, the calibrated growth in A_a is lower. We leave the capital share in the non-agricultural sector unchanged because it is relatively stable over time and across countries (Gollin, 2002; Chen, 2020a).

We then repeat the experiment in Section 5 by introducing the calibrated 2019 productivity levels into the 2004 economy and assessing their effect on labor force participation. Specifically, we increase the capital share in agricultural production from 0.18 to 0.28 and raise Hicks-neutral agricultural TFP to its calibrated 2019 level. As reported in the last row of Table 12, the labor force participation rate declines by 13.8 percentage points, from 89.1 percent to 75.3 percent. Recall that, in Section 5, introducing the 2019 level of agricultural productivity reduces the labor force participation rate by a similar 14.2 percentage points.

Table 12: The Effects of Productivity Growth

	Not in labor force (%)	Employment Share (%)			
		Total	Agr	Rural Nonagr	Urban Nonagr
	(1)	(2)	(3)	(4)	(5)
2004					
baseline	10.9	89.1	47.8	24.8	16.7
2019 agr capital share	14.8	85.2	39.2	27.1	19.0
2019 agr TFP	22.9	77.1	19.5	33.1	24.5
2019 both	24.7	75.3	16.6	33.7	25.1

Notes: This table shows the shares of villagers who are not in the labor force (column 1), in the labor force (column 2), working in agriculture (column 3), rural non-agriculture (column 4), and urban non-agriculture (column 5). Note that the shares in columns 1 and 2 sum up to 100 percent, and those in columns 3–5 sum up to that of column 2. We show the baseline economy on the first row, the baseline economy modified with 2019 agricultural capital share in the second row, with 2019 agricultural TFP in the third row, and with both in the fourth row.

Thus, abstracting from capital deepening in the quantitative analysis does not necessarily yield misleading conclusions about labor force participation, provided that the model is properly calibrated. In our model, capital deepening and Hicks-neutral TFP growth have quantitatively similar effects on labor force participation and are therefore partially isomorphic along this dimension.

The alternative calibration also provides additional insight into the relative contributions of capital deepening and TFP growth. Increasing only the agricultural capital share reduces the labor force participation rate by 3.9 percentage points. This captures the conventional labor-displacing effect of capital deepening in production. By contrast, increasing only agricultural TFP to its calibrated 2019 level reduces the labor force participation rate by 12.0 percentage points. Hicks-neutral agricultural productivity growth is therefore quantitatively more important than capital deepening in accounting for the decline in labor force participation.