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Abstract

We document that the gender gap in non-agricultural work in developing countries exists primarily among rural married workers, not singles. Married women spend more time on home production, making them less likely to pursue non-agricultural employment. We extend a general equilibrium Roy model to incorporate the joint labor supply decisions of rural married couples, accounting for gender-specific labor distortions and entry barriers to non-agriculture. Calibrating the model to China, we find that the gender gap in non-agricultural employment can be largely explained by gender differences in home production and labor market distortions. Furthermore, within-household specialization among married couples greatly amplifies the effects of gender-specific labor distortions, and changes in entry barriers to non-agriculture widened the gender gap in China between 2000 and 2010. Enhancing public services such as childcare facilities can effectively induce more married women to work in non-agriculture. Extrapolating our model globally, it explains a quarter of the variation in the gender gap across countries.

Keywords: structural transformation, gender gap, home production, within-family specialization, occupational choice.
JEL Classification: E13, J11, J16, J22, J24, O11, O13, O41.

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1 Introduction

The allocation of labor between agriculture and non-agriculture plays a critical role in cross-country income disparities, particularly as developing countries tend to allocate a larger share of labor to the less productive agricultural sector.[1] Further, the female-to-male labor ratio in non-agriculture increases with per capita income, and female workers in developing countries are disproportionately represented in agriculture.[2] Given there are usually large productivity and wage gaps between the two sectors, understanding this gender gap in sectoral choices is crucial for understanding the gender income gap in developing countries.

In this paper, we argue that home production and within-family specialization are key to explaining why more men than women work in non-agriculture in developing countries. We begin by highlighting that this gap mainly exists among married workers, not singles. Specifically, we use micro data from China and document that married women, who dedicate a larger portion of their time to home production than other groups, are also far less likely to pursue non-agricultural work. In contrast, single women are slightly more likely to work in non-agriculture than single men. We then use panel data to show that variation in demand for home production across rural families affects the gender gap in non-agricultural employment. Specifically, having children at home decreases the likelihood of married women working outside agriculture, while access to childcare facilities helps mitigate this effect. These patterns are also present in other developing countries.

Motivated by these facts, we incorporate the joint decisions of married couples into a general equilibrium Roy model à la Lagakos and Waugh (2013). At the core of our model are a set of rural married couples, each consisting of two spouses with heterogeneous agricultural and non-agricultural abilities. Men and women also differ in their home production skill, likely shaped by both natural advantages and social norms. Married households make consumption, home production and occupation decisions jointly to maximize household

[1] Caselli (2005), Restuccia et al. (2008), Vollrath (2009), Herrendorf and Valentinyi (2012), and Gollin et al. (2014b), among others.

[2] See, for instance, Lagakos and Waugh (2013), Doss et al. (2024), Lee (2024).

utility. Rural workers can choose to work in agriculture or non-agriculture, but face non-agricultural entry barriers. These barriers differ depending on whether one or two spouses work in non-agriculture. Rural workers also face gender-specific (but sector-neutral) labor market distortions, modeled as labor income taxes.

We calibrate our baseline model to the Chinese economy in 2010 given the availability of micro data on rural household labor supply. Although not targeted in calibration, our model matches the observed gender gap in non-agricultural employment: 12.6 percentage points more men in the model work outside agriculture compared to 12.4 percentage points in the data. Both within-household specialization and the entry barriers to non-agriculture are essential in driving this result. Specifically, the fixed-cost barriers to non-agricultural employment imply that only individuals desiring to work substantial market hours will choose non-agriculture.[3] In our calibration, females are more efficient in home production but face higher labor market distortions. Within-household specialization then implies that married females work more at home and less on the market, hence are less likely to choose non-agricultural employment compared to married men. In contrast, the model predicts a much smaller gender gap in non-agricultural employment among single men and women, highlighting the role of within-household specialization. A canonical model without couples but otherwise identical will fail to replicate the gender disparity in home production hours and non-agricultural employment with observed labor market distortions.

Using our calibrated model, we examine the impact of gender disparities in home production productivity and labor market frictions on gender differences in non-agricultural employment. By eliminating the gender gap in home production productivity, we find that the gender gap in non-agricultural employment among rural married households decreases from 12.6 to 10.4 percentage points. Conversely, if we eliminate the gender gap in labor market frictions, the gender gap in non-agricultural employment shrinks from 12.6 to 2.9 percentage points.

[3] This non-linearity of labor supply has been well noted in the macro-labor literature (Rogerson, 1988; Rogerson and Wallenius, 2009; Erosa et al., 2022).

We further use our calibrated model to evaluate the influence of public services on the gender gap in non-agricultural employment. We extend the model to allow for public services to substitute for home production. We choose the amount of public services such that married women reduce home production hours by 8 percent compared to single women, mirroring the change we find in the data when a kindergarten, the key childcare facility in rural China, becomes available in a village. Such public services increase non-agricultural employment by 3.0 percentage points for married women in partial equilibrium and 3.8 percentage points in general equilibrium, compared to 3.7 percentage points in the data. Therefore, this result also serves as an external validation of our model.

We also use our model to understand why the gender gap in non-agricultural employment has widened in China between 2000 and 2010. We find that the widened gap can be largely explained by changes in entry costs to non-agriculture. While the cost for individual rural workers to enter the urban labor market was significantly reduced, it is still costly for the entire family to relocate to urban areas. Consequently, more married households send the husband to non-agriculture, who typically works longer hours on the market than the wife. This shift reflects changes in China's labor and migration policies. Despite reforms of the household registration (*hukou*) system and the removal of many direct occupational restrictions, rural households still face restricted access to urban public services such as childcare and education (Song, 2014; Chan, 2019).[4]

Finally, we use our model to understand the gender gap in non-agricultural employment across countries. As documented in Lee (2024), the gender gap in non-agricultural employment tends to decline along with economic development. We vary the two dimensions of gender differences in our model, i.e., home production productivity and gender-specific labor market distortions, to match the cross-country variations in wages and home production hours across genders. Our model then implies a variation of the gender gap in

[4] Tian (2024) finds that while migrant workers in China saw improvements in workplace conditions (such as wages and unemployment benefits) after 2001, the situation for their children didn't change much. Local governments welcomed the migrant labor but were hesitant to support family settlement.

non-agricultural employment that is roughly one quarter of the cross-country variation observed in the data. The remaining variations in the data may be explained by factors such as social norms or home production technologies.

Our paper contributes to the large and still growing literature on structural transformation from agriculture to non-agriculture.[5] In particular, our study builds upon recent research that highlights the role of selection among heterogeneous individuals in structural transformation, such as Lagakos and Waugh (2013), Chen (2017), Hamory et al. (2021), Lagakos et al. (2020), Gai et al. (2021), and Adamopoulos et al. (2022), among others. What sets our paper apart is that we explicitly investigate the influence of family structure, specifically the interdependent choices made by married couples regarding consumption, home production, and occupational choice.[6]

Our work is also related to recent studies that underscore the role of home production in structural transformation. These studies include Rogerson (2008), Ngai and Petrongolo (2017), Moro et al. (2017), Bridgman et al. (2018), and Dinkelman and Ngai (2021). While previous studies generally emphasize the substitution between home production and market services, our paper focuses on the allocation between agriculture and non-agriculture, and illustrates how home production affects the sectoral allocation of labor through interdependent choices and specialization within the family unit.

Our paper also connects to the growing literature that examines the role of family in the macroeconomy, summarized in Doepke and Tertilt (2016), Greenwood et al. (2017), and Greenwood et al. (2022). In particular, our paper is related to recent studies that use multi-member household models to study labor supply in macroeconomic settings, such as Guner et al. (2012), Bick and Fuchs-Schündeln (2018), Rogerson and Wallenius (2019), Erosa et al.

[5] See, for instance, Kongsamut et al. (2001), Gollin et al. (2004), Ngai and Pissarides (2007), Restuccia et al. (2008), Alvarez-Cuadrado and Poschke (2011), Yang and Zhu (2013), Gollin et al. (2014a), Adamopoulos and Restuccia (2014), Bustos et al. (2016), Herrendorf and Schoellman (2018), Chen (2020), Bick et al. (2022), Cao et al. (2024), and many others.

[6] A notable exception is Adamopoulos et al. (2024), who similarly incorporates a family structure in their analysis of structural transformation. However, their research primarily examines the role of land insecurity in occupational choices of family members, whereas our paper specifically examines the joint consumption, home production, and occupation decisions of married couples.

(2022), Doss et al. (2024), Feng et al. (2024), and Bento et al. (2024). We contribute to this literature by highlighting the interplay of family and structural transformation in developing economies.

The rest of the paper proceeds as follows. We present facts on the gender gap in non-agricultural employment in Section 2. In Section 3 we describe our model. Section 4 explains our data and calibration strategy. We perform our main quantitative analysis in Section 5. We use our model to assess the changes in the gender gap in non-agricultural employment over time in Section 6 and across countries in Section 7. Section 8 concludes the paper.

2 Facts

This section presents motivating facts on gender gaps in non-agricultural employment and home production among rural workers. Using data from China, we find that, among rural individuals, women are generally less likely to work in non-agriculture compared to men, but the difference is particularly among the married. In addition, the presence of a kindergarten in a village, which reduces home production for women with young children, facilitates them working in non-agriculture. In Section 7, we document the presence of similar patterns in other developing countries.

Fact 1: Married women are less likely to work in non-agriculture.

We use the 2000 and 2010 China Population Census (National Bureau of Statistics of China, 2010), which contains rich information on individual characteristics, including *hukou* status, employment status, and information on household relations, to document the large gender gap in non-agricultural employment among rural individuals.[7] The first two rows of Table 1 show that, among those who participate in the labor market, the non-agricultural employment share is much higher among men than women, a fact that is consistent with

[7]In China, the household registration (hukou) system divides the population into two categories: rural and urban. This classification is primarily determined by an individual's birthplace and inherited from their parents (Song, 2014; Chan, 2019).

findings in for instance Lee (2024).[8] Between rural men and women, non-agricultural employment share differs by 7.4 and 10.1 percentage points for the year 2000 and 2010, respectively. The next four rows further investigate into this gender gap in non-agricultural employment by marriage status. We find that this gap can be largely attributed to married workers. For instance, in the year 2010, rural married women are 12.4 percentage points less likely to work in non-agriculture than married men, while single women are, in fact, *more* likely to work in non-agriculture than single men by 4.7 percentage points.

Table 1: Share of Non-agricultural Employment Among Rural Individuals

Variable	2000	2010
All rural individuals		
Men	24.4	51.1
Women	17.0	41.0
Rural individuals by marriage status		
Married men	26.8	49.6
Married women	19.9	37.1
Single men	28.6	63.6
Single women	39.8	68.3

Notes: The first two rows show the share of non-agricultural employment among rural individuals (measured as rural *hukou* holders). The next four rows further show these statistics separately for married and single individuals. Numbers are in percentages. Data from the Chinese Population Census.

The disparity in non-agricultural employment between married men and women implies that in many families wives and husbands are engaged in different sectors. We calculate the share of four types of rural married families by the sectoral choice of wives and husbands. Results in Table 2 show that, among families where wives and husbands work in different sectors, husbands are more likely to be employed in the non-agricultural sector than wives. In 2010, 21.6 percent of rural families had a husband engaged in non-agricultural activity and a wife in agriculture, compared to only 9.1 percent of families consisting of wives employed in non-agriculture and husbands in agriculture. The difference between these two numbers im-

[8] We do not separately assess the margins of labor force participation here since the labor force participation rate is very high (typically higher than 90 percent) among working age individuals in rural China.

plies a gender gap in non-agricultural employment of 12.4 percentage points among married individuals.

Table 2: Shares of Different Types of Rural Families in China (%)

Family Structure	2000	2010
Both agriculture	70.4	41.3
Both non-agriculture	17.1	28.0
Husband non-agr., wife agr.	9.7	21.6
Wife non-agr., husband agr.	2.8	9.1
Total	100	100

Notes: This table shows the fractions of four types of rural families. Numbers in percentages. Data from the Chinese Population Census.

We hence conclude that married women are less likely to work in non-agriculture than other demographic groups, while single women are not necessarily so. Note that this pattern is not unique in China. In Section 7, we use data from IPUMS-International (Ruggles et al., 2024) to document this pattern for a large set of low and middle income countries.

Fact 2: Home production and public services affect the gender gap in non-agricultural employment.

It is well established that women, especially married women, spend more time on home production (Gousse et al., 2017; Bridgman et al., 2018). In the 2008 Chinese Time Use Survey, for instance, married women on average devote 251 minutes to house work, compared to 97 minutes for married men and notably 40 and 75 minutes for single men and single women. To explore the relationship between home production and non-agricultural labor supply from rural residents, we draw on the National Fixed Point Survey (NFPS, Research Center for Rural Economy, Ministry of Agriculture (China), 2016) which provides labor supply information for individuals whose *hukou* registration is in rural areas. We observe individual labor supply measured in days in the agricultural and non-agricultural sectors. The data also provide village level information such as the availability of kindergartens at the village. We define a rural resident as a non-agricultural worker if their self-reported sector is non-agriculture and as a farmer otherwise.[9] We focus on individuals aged between 20 and 40 to explore the variations in home production demand arising from children.

To confirm the gender gap in non-agricultural employment in the NFPS data, we first consider the following regression:

$$Nonag_{vit} = \beta \cdot Female_{vi} + \rho \cdot Controls + \varepsilon_{vit}, \tag{1}$$

where the binary variable $Nonag_{vit}$ refers to the employment status of individual i from village v in year t and is valued as 1 if the worker is employed in the non-agricultural sector and 0 if they work in agriculture. $Female_{vit}$ refers to gender and is valued as 1 if female and 0 if male. We control for household (dwelling unit) fixed effects and village×year fixed effects. The baseline result in column (1) of Table 3 is consistent with Fact 1 that, conditional on participating in the labor market, rural women are 14.2 percentage points less likely to work in the non-agricultural sector than rural men.

Next, we investigate how home production influences the gender disparity in non-agricultural employment. We begin by examining the variation in home production demands among rural households, focusing on the impact of young children. Since caring for young children substantially increases the burden of home production, we define a binary variable, $Child_{vit}$, which takes a value of 1 if the household has children under six, and 0 otherwise. We then interact this variable with the gender dummy and estimate the following specification

$$Nonag_{vit} = \beta \cdot Child_{vit} \cdot Female_{vi} + \gamma_f \cdot Female_{vi} + \gamma_c \cdot Child_{vit} + \rho \cdot Controls + \varepsilon_{vit}, \tag{2}$$

explicitly controlling for household fixed effects and village×year fixed effects. The results are in column (2) of Table 3. The presence of a child under the age of six in the household—and hence higher demand for home production—is associated with significantly less non-

[9] As a robustness check, we alternatively define non-agricultural employment only if a worker engaged in non-agricultural production activities for more than 30 days in the last year. Results remain similar.

agricultural employment for women compared to men by a magnitude of 3.9 percentage points.

The variation in public services provides another piece of evidence connecting home production and non-agricultural employment. Public services such as childcare could substitute for home production and hence reduce home production demand. Kindergartens are the key childcare facilities in rural China, most of which are public and admit kids ranging from age 3 to 5 (inclusive). However, the access to kindergarten varies across regions and over time.[10] In our data, kindergarten is available among 51.0 percent of village-year observations. There is also variations over time: Among villages with kindergartens, 74.4 percent continue to have at least one in the subsequent year, while among villages without kindergartens, 20.0 percent see a kindergarten becomes available in the subsequent year.

We then explore how the variation in kindergarten availability in a village is associated with non-agricultural employment. Our conjecture is that the availability of kindergarten reduces home production demand and hence facilitates non-agricultural employment for females with children. One apparent concern is that kindergarten availability may be correlated to non-agricultural employment through factors other than home production. For instance, kindergartens in village need educators which provides non-agricultural employment opportunities. To assess the correlation between kindergarten availability and non-agricultural employment through home production only, we compare females with children to those without children, with the intuition that home production demand for females without children is not affected by the kindergarten availability, while other factors, such as non-agricultural employment opportunities in villages, affect females with and without children. We hence

[10] According to the Executive Report of the 3rd Survey on the Status of Chinese Women, conducted by the All-China Women's Federation and National Bureau of Statistics, 35.9 percent of rural children aged from 3 to 10 have never been to kindergarten, a fact which is mainly attributed to the lack of kindergarten access.

estimate the following triple-difference specification:

$$
\begin{aligned}
Nonag_{vit} = & \beta \cdot KG_{vt} \cdot Female_{vi} \cdot Child_{vit} + \gamma_f Female_{vi} + \gamma_c Child_{vit} + \\
& \theta_{f,KG} \cdot Female_{vi} \cdot KG_{vt} + \theta_{f,c} \cdot Female_{vi} \cdot Child_{vit} + \theta_{KG,f} \cdot KG_{vt} \cdot Female_{vi} \\
& \rho \cdot Controls + \varepsilon_{vit},
\end{aligned} \tag{3}
$$

where KG_{vt} is a binary variable valued as 1 if there is a kindergarten in village v in year t and 0 otherwise. We control for household fixed effects, village×year fixed effects. The coefficient of interest is that of the interaction term β, which measures the effect of a nearby kindergarten on the gender gap in non-agricultural employment among local females with children compared to local females without children. The results are presented in column (3) of Table 3. A local kindergarten generally decreases the gender gap in non-agricultural employment but the effect is larger for households with children younger than 6 years old by 3.7 percentage points. This finding suggests that public services could potentially substitute for home production and facilitate more women working in the non-agricultural sector.

To summarize, we find evidence suggesting that home production is associated with non-agricultural employment especially for women, while the availability of kindergarten, which substitutes home production, facilitates non-agricultural employment among women with children compared to those without children. Again, this pattern is not unique in China. In Section 7, we summarize evidence from existing studies on this fact across a large set of countries.

3 Model

The economy consists of an agricultural sector (a) and a non-agricultural sector (n). These two sectors produce different goods that are for consumption only. The non-agricultural good is treated as the numeraire whose price is normalized to unity, while the agricultural good price is denoted as p. Households can live in an urban or rural area. Urban households of

Table 3: Effects of Children and Kindergarten on Non-agricultural Employment

	(1)	(2)	(3)
Female	-0.142***	-0.123***	-0.171***
	(0.004)	(0.005)	(0.007)
Child		-0.007	-0.005
		(0.007)	(0.010)
*Female*Child*		-0.039***	-0.063***
		(0.007)	(0.011)
*Child*KG*			-0.003
			(0.012)
*Female*KG*			0.087***
			(0.009)
*Female*Child*KG*			0.037**
			(0.015)
Controls	Yes	Yes	Yes
R^2	0.637	0.638	0.640
N	34,703	34,703	34,703

Notes: Dependent variable is an indicator that equals one if a rural individual works in the non-agricultural sector and zero if they work in agriculture. Female is an indicator of gender and Child is an indicator of having children younger than 6 in the household. KG is an indicator of whether there is any kindergarten service in the village. Standard deviations in parentheses: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

measure N_{urban} can only work in non-agriculture. Rural households, the focus of this paper, can be married households of measure N_{married}, each of which consists of two individuals, denoted as male (m) and female (f); or singles, of measure N_{single}, each of which consists of one individual who can be either male or female. Each rural individual can work in the agricultural sector or the non-agricultural sector as in Lagakos and Waugh (2013). In addition, all individuals can participate in home production.

3.1 Preferences and Endowments

3.1.1 Rural Married Households

We start with the rural married households who are the focus of our analysis. Each individual in a rural married household with gender $g \in \{m, f\}$ is endowed with a pair of abilities (z_a^g, z_n^g) which represent the efficiency of one unit of labor supplied to the agricultural or the non-agricultural sector, respectively. A married household is then described by an ability vector $\mathbf{z} \equiv (z_a^m, z_n^m, z_a^f, z_n^f)$, where the first two elements are abilities for the male member while the last two are for the female member. Denote the joint distribution of households as $F(\mathbf{z})$.

Each individual has one unit of time in each period, which can be used to provide market hours denoted as l^g in either the agricultural sector or the non-agricultural sector, to conduct home production denoted as h^g, or both. The time allocation is hence summarized by

$$h^g + l^g = 1, \quad h^g, l^g \geqslant 0.$$

Post-tax labor income is then given by $w_s z_s^g l^g (1 - \tau^g)$, where $s \in \{a, n\}$ denotes the sector in which an individual works. τ^g is an implicit income tax capturing gender-specific labor market frictions as in Hsieh et al. (2019). Note that we restrict this implicit tax to be sector-neutral; we will show later that it has a sector-biased effect on gender employment in our model. Household income, y, is then the sum of the labor income of the two members. Note that if $l^g = 0$, an individual engages strictly in home production. It is also possible that $l^g = 1$ for one of the two individuals, with home production completely delegated to the spouse.

Consumption decisions are made at the household level. We follow Boppart (2014) and assume that preferences over agricultural and non-agricultural goods are summarized by

$$v(y, p) = \frac{1}{\eta} y^{\eta} - \frac{B}{\gamma} p^{\gamma},$$

where η governs the income elasticity of agricultural goods and γ governs their price elasticity. Denote the demands for agricultural and non-agricultural goods as $c_a(\mathbf{z})$ and $c_n(\mathbf{z})$. In addition, households also value home production, and the household's utility function is then given by

$$u = v(y, p) + \omega \frac{c_h^{1+\chi} - 1}{1 + \chi},$$

where $(c_h^{1+\chi} - 1)/(1 + \chi)$ represents utility arising from home production and ω governs the utility weight between consumption and home production. Home production is described by

$$c_h = \left(z_h^m (h^m)^{\frac{\theta-1}{\theta}} + z_h^f (h^f)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}},$$

where z_h^m and z_h^f govern the efficiency of home production by gender and are common among households. θ determines the elasticity of substitution between male and female labor supply to home production (h^m and h^f).

3.1.2 Rural Single Households

Each rural single household consists of one individual who can be either male or female. Each individual of gender g is endowed with a pair of abilities $\mathbf{z}^s = (z_a^s, z_n^s)$, with the joint distribution of gender and abilities given by $F^{\text{single}}(g, \mathbf{z}^s)$. They choose the amount of labor supplied to the agricultural or non-agricultural sector l^s and home production h^s. Their preferences are also summarized by the same utility function:

$$u = v(y,p) + \omega \frac{c_h^{1+\chi} - 1}{1+\chi},$$

where

$$c_h = (z_h)^{\frac{\theta}{\theta-1}} h^s,$$

with $z_h = z_h^m$ if this individual is male and $z_h = z_h^f$ if female. Denote their agricultural and non-agricultural goods demands as $c_a^{\text{single}}(g, \mathbf{z}^s)$ and $c_n^{\text{single}}(g, \mathbf{z}^s)$.

3.1.3 Urban Households

There is a measure N_{urban} of representative urban households, each of which consists of two members, a male and a female. They can only work in non-agriculture, with their ability denoted as $\bar{z}$ and labor supply denoted as l_{urban}^m and l_{urban}^f. Urban households' preferences and home production technologies are identical to those of the rural households. Denote their agricultural and non-agricultural goods demands as c_a^{urban} and c_n^{urban}.

3.2 Occupational Choices

For rural married households, if one spouse works in the non-agricultural sector, then the household faces a utility cost of κ_{sep}, reflecting the likely need for the couple to reside in different locations.[11] When both spouses work in the non-agricultural sector, the household incurs a utility cost of κ_{both}. This utility loss reflects the costs associated with relocating the entire family to an urban area, including limited access to urban public services. For example, in China, the *Hukou* system restricts rural migrant workers' access to essential urban services such as education, healthcare, and social insurance (Song, 2014; Chan, 2019). These restrictions disproportionately affect married couples, particularly those with children.

[11] We model these entry costs as utility costs. Alternatively, modelling them as fixed time costs or in terms of consumption goods yields similar results.

We also note that, if $\chi = -1$ and hence home production enters the utility function as a log term, then these utility costs can also be interpreted as declines in home production efficiency associated with household members working in the non-agricultural sector. Denote $D^f(\mathbf{z}) = 1$ if the female spouse with ability vector $\mathbf{z}$ chooses to work in the non-agricultural sector, and $D^f(\mathbf{z}) = 0$ if she chooses to work in agriculture or not to work at all. The indicator function for the male spouse $D^m(\mathbf{z})$ is defined similarly.

An individual in a rural single household can choose to work in either sector, with $D^s(g, \mathbf{z}^s) = 1$ denoting this individual working in the non-agricultural sector and $D^s(g, \mathbf{z}^s) = 0$ denoting working in the agricultural sector. If this individual works in the non-agricultural sector, then a utility cost of κ_{single} is incurred. We characterize the occupational choices in Appendix B.

3.3 Technologies

A representative firm in each sector produces output with the following technology:

$$Y_a = A_a L_a, \quad Y_n = A_n L_n,$$

where A_a and A_n are the productivity of the agricultural and non-agricultural sectors; L_a and L_n are the efficiency units of labor input in each sector. Wages per unit of efficiency labor in the two sectors are hence given by $w_a = pA_a$ and $w_n = A_n$.

3.4 Competitive Equilibrium

Aggregate labor input in agriculture is given by

$$\begin{aligned} L_a = & N_{\text{married}} \int \left[z_a^m l^m(\mathbf{z})(1 - D^m(\mathbf{z})) + z_a^f l^f(\mathbf{z})(1 - D^f(\mathbf{z})) \right] \mathrm{d}G(\mathbf{z}) + \\ & N_{\text{single}} \int z_a^s l^s(g, \mathbf{z}^s)(1 - D^s(g, \mathbf{z}^s)) \mathrm{d}G^s(g, \mathbf{z}^s), \end{aligned} \tag{4}$$

where the first component of the right-hand-side represents labor supply of rural married households to agriculture and the second component is labor supply from rural single households. Similarly, aggregate labor input in the non-agricultural sector is given by

$$\begin{aligned} L_n =& N_{\text{married}} \int \left[z_n^m l^m(\mathbf{z}) D^m(\mathbf{z}) + z_n^f l^f(\mathbf{z}) D^f(\mathbf{z}) \right] \mathrm{d}G(\mathbf{z}) + \\ & N_{\text{single}} \int z_n^s l^s(g, \mathbf{z}^s) D^s(g, \mathbf{z}^s) \mathrm{d}G^s(g, \mathbf{z}^s) + N_{\text{urban}} (l_{\text{urban}}^m + l_{\text{urban}}^f) \bar{z}. \end{aligned} \tag{5}$$

The first and second components are labor supply of rural married and single households to the non-agricultural sector, respectively, while the last component is labor supply of urban households.

Agricultural goods market clearing is given by

$$N_{\text{married}} \int c_a(\mathbf{z}) \mathrm{d}G(\mathbf{z}) + N_{\text{single}} \int c_a^s(g, \mathbf{z}^s) \mathrm{d}G^s(g, \mathbf{z}^s) + N_{\text{urban}} c_a^{\text{urban}} = Y_a = A_a L_a \tag{6}$$

and non-agricultural goods market clearing is given by

$$N_{\text{married}} \int c_n(\mathbf{z}) \mathrm{d}G(\mathbf{z}) + N_{\text{single}} \int c_n^s(g, \mathbf{z}^s) \mathrm{d}G^s(g, \mathbf{z}^s) + N_{\text{urban}} c_n^{\text{urban}} = Y_n = A_n L_n. \tag{7}$$

Finally, we require the gender-specific implicit tax to be revenue neutral. In other words, the revenue of taxing gender g is then rebated as a proportional transfer to individuals of the other gender.

The competitive equilibrium of this economy is defined as follows:

Definition 1. *A competitive equilibrium consists of a list of allocations and indicator functions* $\{c_a(\mathbf{z}), c_n(\mathbf{z}), l^m(\mathbf{z}), l^f(\mathbf{z}), h^m(\mathbf{z}), h^f(\mathbf{z}), D^m(\mathbf{z}), D^f(\mathbf{z})\}$ *for rural married households,* $\{c_a^s(g, \mathbf{z}^s), c_n^s(g, \mathbf{z}^s), l^s(g, \mathbf{z}^s), h^s(g, \mathbf{z}^s), D^s(g, \mathbf{z}^s)\}$ *for rural single households, and* $\{c_a^{urban}, c_n^{urban}, l_{urban}^m, h_{urban}^m, l_{urban}^f, h_{urban}^f\}$ *for urban households, quantities for the representative firms* Y_a*,* Y_n*,* L_a*, and* L_n*, and prices* p*,* w_a*,* w_n*, such that*

1. *Given prices, the allocations and indicator functions solve the utility maximization*

problems of all three types of households;

2. *Given prices, Y_a, Y_n, L_a, and L_n solve each firm's problem;*

3. *All markets clear as defined in Equations (4), (5) (6), and (7).*

4 Calibration

We calibrate our model to the Chinese economy in the base year 2010, for which we have detailed micro data on labor supplied by rural households. We combine four different data sets: the National Fixed Point Survey (NFPS, Research Center for Rural Economy, Ministry of Agriculture (China), 2016), the China Migrants Dynamic Survey (CMDS, National Health Commission of China, 2018), the Urban Household Survey (UHS, National Bureau of Statistics of China, 2015), and the China Population Census (CPS, National Bureau of Statistics of China, 2010). Detailed descriptions of these datasets can be found in Appendix A. Later, we will also use the calibrated model to understand the gender gap in non-agricultural employment and its changes over time.

Parameterization. First, we need to specify the functional form for the ability distribution of married rural households, $F(\mathbf{z})$. Following Adamopoulos et al. (2024), the non-agricultural ability of an individual is given by the following (omitting the superscript g to simplify notation):

$$\log(z_n) = \log(z_n^H) + \log(z_n^I),$$

where z_n^H is a common component for both spouses of a household and z_n^I is each individual's idiosyncratic component. The common component allows individual abilities to be correlated across spouses within the household, which can capture, for example, the correlation of innate ability, accumulation of skills across spouses, or positive assortative matching in marriage.

Agricultural ability is given by

$$\log(z_a) = \log(z_a^H) + \log(z_a^I) + \lambda \log(z_n),$$

where z_a^H is the common component, z_a^I the individual component, and $\lambda \log(z_n)$ is the component that is correlated with non-agricultural ability, with λ governing the correlation between the agricultural and non-agricultural abilities of the same individual. We assume that all the ability components, z_n^H, z_a^H, z_n^I, z_a^I, follow log-normal distributions with mean zero and standard deviations σ_n, σ_a, $\psi\sigma_n$, $\psi\sigma_a$, where ψ governs the relative importance of individual components versus family components.

For single rural households, we parameterize their ability distribution in the same way but we only simulate one individual per household.

Parameters and Moments. There are in total 23 parameters to be calibrated: 3 for the measures of households $\{N_{\text{married}}, N_{\text{single}}, N_{\text{urban}}\}$, 6 for preferences $\{\omega, \gamma, \eta, B, \theta, \chi\}$, 2 for technologies $\{A_a, A_n\}$, 7 for abilities $\{\sigma_n, \sigma_a, \psi, \lambda, z_h^m, z_h^f, \bar{z}\}$, 3 for the sectoral barriers $\{\kappa_{\text{sep}}, \kappa_{\text{both}}, \kappa_{\text{single}}\}$, and 2 for gender-specific taxes $\{\tau^m, \tau^f\}$.

10 parameters are determined outside the equilibrium. For the measures of households, we normalize $N_{\text{married}} = 1$ and set $N_{\text{single}} = 0.717$ such that $0.717/(0.717 + 2) = 26.4$ percent of rural working-age individuals are single, as in the year 2010. We set $N_{\text{urban}} = 0.537$ so the non-agricultural urban working-age population accounts for $0.537\times2/(2+0.717+0.537\times2) = 28.4$ percent of the total working-age population. For the utility function, we follow Alder et al. (2022) and Hao et al. (2020) and set the income elasticity of the agricultural good, η, to be 0.7, and the price elasticity, γ, to be 0.3. We also set $\chi = -1$ so that home production is incorporated as a log term into the utility function. In addition, we normalize the sectoral productivities, A_a and A_n, and the female productivity in home production z_h^f to be 1. Lastly, we restrict the implicit taxes to be revenue neutral, and therefore τ^f is uniquely determined once we choose τ^m.

We then have 13 parameters left to be determined by matching equilibrium model moments to the data.[12] First, we need to pin down two key parameters on gender differences, namely the male productivity in home production, z_h^m, and the implicit tax rate on males, τ^m. Motivated by Hsieh et al. (2019) and Adamopoulos et al. (2024), we use both quantities (gender gap in home production hours) and prices (gender wage gap in non-agriculture) to separately identify the productivity (z_h^m) and distortion (τ^m) parameters. Intuitively, while z_h^m and τ^m shift home production hours in the same direction, they move the gender wage gap in opposite directions. A higher τ^m implies a higher tax rate on male wages and a reduced gender wage gap. Conversely, a higher z_h^m implies that males allocate more time to home production and less to market work, increasing average male wages through the standard selection mechanism in Roy-type models. As a result, a higher z_h^m tends to widen the gender wage gap. Therefore, we choose the two parameters to match a 3.33-fold gender gap in home production hours among rural households, and a 11.5 percent gender wage gap among rural individuals in non-agriculture.

Next, we need to determine 4 parameters capturing the ability distribution of rural married households: $\{\sigma_n, \sigma_a, \psi, \lambda\}$. The household and individual components of non-agricultural ability, σ_n and ψ, govern the dispersion of non-agricultural ability and its correlation between spouses within households, respectively. Therefore, we choose these two parameters to target the standard deviation of log wage rates of 0.441 and the within-household Spearman's rank correlation between spouses of 0.542.[13] However, agricultural income is only observed at the household level and cannot be attributed to a specific individual. We instead use the standard deviation of agricultural working time to identify σ_a, the dispersion in agricultural ability. Lastly, we restrict the Spearman's rank correlation between the two sectoral abilities of each individual, z_a and z_n, to be 0.35 following Lagakos

[12] Appendix A describes in detail how we construct the data moments.

[13] Note that we match the model moments in the equilibrium after selection to be consistent with the data moments, i.e., we calculate model moments among those households with both members working in non-agriculture.

and Waugh (2013).[14]

We need to calibrate 3 parameters measuring the barriers faced by rural households entering the non-agricultural sector: $\{\kappa_{\text{sep}}, \kappa_{\text{both}}, \kappa_{\text{single}}\}$. We choose these three parameters to jointly match three equilibrium moments: 28.0 percent of rural married households have both members working in the non-agricultural sector, 30.7 percent of rural married households have only one member working in the non-agricultural sector, and 65.3 percent of single rural individuals work in the non-agricultural sector. These three moments effectively determine the agricultural employment share. Notice that we do not explicitly target the share of males/females that work in the non-agricultural sector.

Lastly, we have 4 remaining parameters on preferences and ability: $\{\omega, B, \bar{z}, \theta\}$. Recall that ω governs the utility weight on home production versus consumption. We choose ω to match the relative amount of time spent on market production versus home production—market work accounts for 71.8 percent of the time endowment. We choose B, the level shifter of agricultural goods demand in the utility function, to match the agricultural value-added share of 10.1 percent for the year 2010.[15] We choose $\bar{z}$, the average ability of urban households, such that the wage rate of urban households is on average 29.3 percent higher than that of rural households who work in the non-agricultural sector (Xing, 2008). θ governs the elasticity of substitution between male and female home production hours. This parameter is closely related to within-household specialization in home production versus market work, and is chosen to match a labor supply elasticity of married men of 0.46 (Prescott, 2004).[16]

To summarize, 10 parameters are either normalized or set to exogenous values, while

[14] In Appendix C.1, we show that our results are not sensitive to this correlation coefficient, similar to findings in previous studies such as Chen (2017) and Adamopoulos et al. (2024).

[15] Note that the agricultural employment share generally does not coincide with its value-added share. The discrepancy between these two gives rise to the (nominal) agricultural productivity gap (Gollin et al., 2014b; Herrendorf and Schoellman, 2015).

[16] While earlier work tended to find small labor supply elasticities (Pencavel, 1986), more recent studies such as Chetty (2012) argue that these elasticities may be significantly underestimated due to adjustment costs of labor supply. After correction, the intensive margin Hicksian labor supply elasticity was estimated to be between 0.28 and 0.54 in a meta analysis (Chetty, 2012). To construct labor supply elasticity in our model, we regress the log labor supply of married males on log wages and log spousal income to obtain the substitution (Marshallian) elasticity and income elasticity, while the Hicksian elasticity is net of the substitution and income elasticities.

the remaining 13 parameters are jointly calibrated by matching equilibrium model moments with data moments. Table 4 summarizes the values of moments.

Table 4: Model Parameters and Values

Parameter	Value	Description
Technologies:		
A_a	1	TFP of the agricultural sector (normalization)
A_n	1	TFP of the non-agricultural sector (normalization)
Preferences:		
B	0.333	Level of agricultural good demand
γ	0.3	Price elasticity of agricultural good demand
η	0.7	Income elasticity of agricultural good demand
ω	0.262	Utility weight on market goods versus home production
θ	4.008	Elasticity of substitution: male/female labor in home production
κ_{sep}	0.393	Utility cost of one member working in non-agriculture
κ_{both}	0.578	Utility cost of two members working in non-agriculture
κ_{single}	0.142	Utility cost of singles working in non-agriculture
χ	-1	Curvature of home production (normalized)
Ability Distribution:		
λ	0.206	Correlation between two-dimensional abilities
σ_a	0.282	Household component of agricultural ability
σ_n	0.536	Household component of non-agricultural ability
ψ	0.845	Relative importance of individual vs. family components
z_h^m	0.824	Male productivity in home production
z_h^f	1	Female productivity in home production (normalization)
$\bar{z}$	1.757	Ability of urban households
Frictions:		
τ^m	-0.096	Implicit tax rate on males
τ^f	0.117	Implicit tax rate on females
Endowments:		
N_{married}	1	Measure of rural married households (normalization)
N_{single}	0.717	Measure of rural single households
N_{urban}	0.537	Measure of urban households

Notes: List of parameters and calibrated values. A set of 13 parameters, θ, ω, B, κ_{sep}, κ_{both}, κ_{single}, σ_a, σ_n, ψ, λ, z_h^m, τ^m, and $\bar{z}$, are jointly determined by comparing model moments and targeted data moments. The remaining ones are either normalized or directly assigned values from outside evidence.

Discussion. Though not explicitly targeted, our model generates a reasonable decomposition of the labor supply elasticity: the substitution elasticity is 0.32 and the income elasticity is -0.14, close to what the literature finds (McClelland and Mok, 2012). In addition, our model reproduces the fact that labor supply elasticity is substantially larger among married females than males (the Hicksian elasticity is 1.11 for females compared to 0.46 for males), consistent with the findings in the literature (Blundell et al., 2016). This difference is driven by the within-family specialization in our model; we do not assume any gender differences in disutility from labor supply.

Our model also matches the labor force participation rate reasonably well. In the data, 88.3 percent of married rural households have both members working, while 11.7 percent have only one member working.[17] In our calibrated economy, these numbers are 91.8 percent and 8.2 percent, respectively. Returning to the data, among those households where only one spouse works, it is more often the male who works (86.5 percent) compared to the female (13.5 percent). Our model is consistent with this pattern as well, yielding 85.3 percent and 14.7 percent, respectively.[18]

Our calibration implies that females are more efficient at home production than males ($z_h^m < z_h^f$). This could reflect gender differences in natural advantages, and/or the impact of traditional social norms. In addition, females face more labor market distortions than males ($\tau^f > \tau^m$), suggesting the existence of discrimination against females in the labor market. Note that these distortions are sector-neutral. In Appendix C.3, we show that if these distortions are sector-specific, such as applying only to the non-agricultural sector, then our model would imply a large gender gap in non-agricultural employment between single workers, which contradicts the data. Finally, as we show in Appendix C.2, the correlation of abilities between spouses is a key parameter that affects the equilibrium outcomes, and our calibrated value is reasonable. Specifically, the model-implied correlation of abilities between spouses is close to the correlation of educational attainment between spouses in the data.

[17]In the data, we observe a small portion of married households where neither member works. We drop these households as in our model at least one spouse has to work to finance the consumption of the household.

[18]Alternatively, we could allow for a utility cost of labor supply and calibrate it to exactly match the observed labor force participation. We choose not to do this in order to focus on the sectoral choices of households, given that the implied labor force participation of our current model is already close to the data.

5 Quantitative Analysis

5.1 Gender Gap in Sectoral Choices

We start by assessing the model prediction regarding the gender gap in sectoral choices. Table 5 illustrates this gap for rural households in the model and in the data. Specifically, in the data, 30.7 percent of rural married households have exactly one spouse working in the non-agricultural sector, which the model targets in calibration. Among this 30.7 percent of households, 21.6 percent have the male working in the non-agricultural sector, while 9.1 percent have the female in non-agriculture, implying a gender gap of 12.4 percentage points. Without explicitly targeting this moment in calibration, our model generates a very similar gender gap of 12.6 percentage points.[19]

Recall that the only gender differences we allow for in our model are those in home production efficiency and in labor market distortions, both of which are sector-neutral. Then how does our model generate a gender gap in non-agricultural employment? The key elements are within-household specialization in home production and fixed cost entry barriers to the non-agricultural sector. The interaction between the two elements turn the sector-neutral differences into de facto sector-biased forces.

In our calibration, women are more efficient in home production and face more severe distortions in the labor market. Within-household specialization then implies that the male spouse works more in the market and the female works more at home production. In the baseline economy, married men spend on average 14 percent of their time on home production, while married women spend 43 percent of their time on home production and hence work much less in the market. In addition, working in the non-agricultural sector incurs a

[19] In Appendix C.2 and C.3, we show that the model would fail to replicate this gender gap if we do not introduce the correlation of abilities between spouses, or if we model the labor market frictions to be sector-specific. In Appendix D, we further show that a re-calibrated model replicates the observed gender gap for Sub-Saharan countries but not for Latin American countries. This suggests that the modelled gender disparities in home production productivity and labor market distortions are key to explaining the gender gap in non-agricultural employment for China and Sub-Saharan countries, while other gender-sector-specific frictions may be needed to reconcile the gap in Latin American countries.

Table 5: Gender Gap in Sectoral Choices: Baseline

	Data	Model
% of rural married households with		
one member working in non-agr. (targeted)	30.7	30.7
among which:		
male working in non-agr.	21.6	21.6
female working in non-agr.	9.1	9.0
gender gap	12.4	12.6
two members working in non-agr. (targeted)	28.0	28.0
% of rural singles in non-agr. (targeted)	65.3	65.4
% of rural single males in non-agr.	63.6	67.6
% of rural single females in non-agr.	68.3	63.1

Notes: The first four rows of this table show the percentage of rural married households with one or two members working in the non-agricultural sector. For those with one member working in the non-agricultural sector, we further calculate the percentages of male and female spouses who work in the non-agricultural sector, with the difference being the gender gap in non-agricultural employment. The last three rows show the percentage of rural singles working in the non-agricultural sector, as well as this percentage by gender.

fixed entry cost (κ_{sep}, κ_{both}, or κ_{single} depending on the occupational choice of the couple). Hence, choosing the non-agricultural sector is optimal only if the individual wants to supply sufficient hours. With less time to spend on market work, married women are hence less likely to choose non-agriculture.[20] As we can expect, if we set the utility weight of home production ω to zero to remove home production, then the gender gap in non-agriculture will disappear.

Furthermore, in our baseline calibrated model, single men and women in our model spend roughly the same amount of time on home production (27 and 32 percent, respectively), despite facing the same gender differences in home production efficiency and labor market distortions as married workers. As a result, our model predicts almost no gender gap in

[20]The literature exploring the non-linearity of labor supply dates back to at least Hansen (1985) and Rogerson (1988), with more recent examples including Prescott et al. (2009), Rogerson and Wallenius (2019), and Erosa et al. (2022). Specifically, Erosa et al. (2022) uses a multi-member household model to show that gender differences in non-market responsibilities are important for gender gaps in occupational choice in the U.S. Our results would be quantitatively similar if we model other mechanisms generating non-linearities in labor supply, such as the increasing return to labor hours in the non-agricultural sector (Erosa et al., 2022), rather than the fixed cost of working in non-agriculture.

Table 6: The Role of Entry Barriers

	Baseline	Reducing κ_{both}	Reducing κ_{sep}
% of rural married households with			
one member working in non-agr.	30.7	26.7	35.8
male working in non-agr.	21.6	19.0	24.7
female working in non-agr.	9.0	7.7	11.0
gender gap	12.6	11.3	13.7
two members working in non-agr.	28.0	32.0	27.9

Notes: This table shows the results associated with reductions in the entry barriers to non-agriculture. Specifically, we reduce κ_{both} or κ_{sep} such that the share of individuals working in the non-agricultural sector increases by one percentage point. We then calculate the percentage of rural married households with one or two spouses working in the non-agricultural sector and display the numbers in Columns 2 and 3, respectively.

non-agricultural employment between single men and women, as is clear from the last three rows of Table 5. This is exactly because the single workers do not have the within household specialization mechanism. In fact, we show in Appendix C.4 that the canonical model that is based on individual rather than household decisions falls short in replicating the observed disparity in home production hours between men and women, nor can it generate the observed gender gap in non-agricultural employment unless the gender wage gap is counterfactually large.

We can also use our model to quantitatively explore the role of entry barriers to the non-agricultural sector. First, we reduce the cost for both spouses to enter the non-agricultural sector (κ_{both}) such that the share of individuals working in non-agriculture increases by one percentage point. As we see in Table 6, the gender gap in non-agricultural employment shrinks from 12.6 percent to 11.3 percent. If we reduce the cost associated with one spouse entering the non-agricultural sector (κ_{sep}) such that the share of individuals working in the non-agricultural sector also increases by one percentage point, then the gender gap would further widen to 13.7 percent.

Intuitively, as the cost of both spouses entering non-agriculture rises, more rural households choose to send only one spouse to non-agricultural employment, with a higher likelihood of it being the male, given that married women on average dedicate more time to home production. This finding holds particular relevance in the context of China, where the *Hukou* system restricts rural migrant households' access to urban public services, making it difficult for both spouses to move to cities. Later on, we will highlight the role of these entry barriers in driving changes in the gender gap concerning sectoral choices for China from 2000 to 2010.

5.2 Home Production Efficiency Vs. Labor Market Distortions

In our model, married men and women differ in home production efficiency and in labor market distortions. We can further decompose the relative importance of these two factors in creating the gender gap in non-agricultural employment. First, we shut down the gender differences in home production efficiency by setting $z_h^m = z_h^f$ to the average of their original levels. Married men and women would then split home production time slightly more equally: men would spend 18 percent of their time on home production, compared to 14 percent in the baseline economy, while the home production time of married women would decrease from 43 to 38 percent. As a result, the gender gap in non-agricultural employment falls from 12.6 to 10.4 percentage points. Next, we eliminate labor market frictions by setting $\tau^m = \tau^f = 0$, which is also the average of their original levels. The gender employment gap shrinks from 12.6 percentage points to 2.9 percentage points. Hence, the gender differences in home production efficiency and labor market frictions contribute roughly one-fifth and four-fifths of the gender gap in non-agricultural employment, respectively. If we shut down both, the gender gap in non-agricultural employment vanishes.

The above gender differences also play a significant role in creating the gender income gap and in aggregate productivity. In our baseline economy, married women on average contribute 38.1 percent of household income. If we shut down the home production efficiency differences, then married women on average contribute 40.1 percent of household income. Real GDP per capita, measured as chain-weighted quantity index, increases by 0.4

Table 7: The Importance of Home Production Efficiency Vs. Labor Wedges

	Baseline	Same efficiency ($z_m^h = z_f^h$)	No labor wedges ($\tau_m = \tau_f = 0$)
Home production time			
male	0.14	0.18	0.21
female	0.43	0.38	0.32
Gender gap (p.p.)	12.6	10.4	2.9
Household income from female (%)	38.1	40.1	47.6
Real GDP per capita ($\Delta, \%$)	–	+0.4	+1.3
Real agr. labor productivity ($\Delta, \%$)	–	+0.6	+3.1
Agr. emp. share (%)	36.4	36.3	35.6

Notes: This table shows model moments in our baseline economy (column 2), and in the decomposition exercises where we shut down the gender differences in home production efficiency (column 3) and labor market distortions (column 4).

percent, and agricultural labor productivity increases by 0.6 percent. If we eliminate labor market wedges, then married women contribute 47.6 percent of household income, and real GDP per capita and agricultural labor productivity increase by 1.3 percent and 3.1 percent, respectively. This is consistent with findings in Lee (2024).

5.3 The Role of Public Services

In this subsection, we assess how the provision of public services that act as substitutes for home production, such as government provided child care or elder care, could affect the gender gap in sectoral choices. To do so, we modify our baseline model by allowing home production to be a composite of private home production, which depends on the time input of household members at home, and c_p which denotes public services. Home production c_h for rural married households is then determined by

$$c_h = \left[\left(z_h^m (h^m)^{\frac{\theta-1}{\theta}} + z_h^f (h^f)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}\frac{\rho-1}{\rho}} + c_p^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where ρ governs the elasticity of substitution between private home production and public services.

We assume that the government transforms 1 unit of non-agricultural goods into 1 unit of public services.[21] The government finances its expenditure on public services through a tax to the urban households, who are passive in our model.[22] In the quantitative analysis below, we choose $\rho = 2$ such that public services are less substitutable than labor inputs between spouses ($\theta = 4.0$).

Next, we need to match c_p to quantifiable public services, and here we focus on kindergarten availability. Using micro data from China Family Panel Studies (CFPS), we find that access to kindergartens on average reduces home production hours by 8 percent for married women with children compared to single women.[23] Hence, we choose c_p such that home production is also reduced by 8 percent for rural married women compared to single women in our model, holding prices and wages constant as in the reduced-form analysis. This implies $c_p = 0.033$.

To externally validate our model, recall that in Section 2, using a triple-difference estimator, we show that access to kindergartens increases non-agricultural employment by 3.7 percentage points for women with children. In our model, we also feed c_p into our baseline economy, again holding prices and wages constant, and find that it increases non-agricultural employment by 3.0 percentage points for married women, only half a standard deviation different from the 3.7 percentage points in the data. Our model hence reasonably captures the elasticity between home production hours and non-agricultural employment.

We next assess the general equilibrium effects of providing public services by allowing prices and wages to adjust. In general equilibrium, the same c_p increases non-agricultural employment by 3.8 percentage points for married women, similar to the 3.0 percentage points

[21]In general, we can consider transforming 1 unit of non-agricultural goods into υ units of public service, but in this case υ cannot be separately identified from c_p in the utility function. Technically, both c_p and υ reflect the unit of measurement for public services.

[22]We make this assumption so that the tax would not further distort the economy.

[23]The data set we use in Section 2, the National Fixed Point Survey, does not provide information on home production hours.

Table 8: Labor Supply and the Agricultural Productivity Gap

	Agriculture	Non-agriculture	Ratio: non-agr./agr.
Rural households	0.57	0.86	1.50
Rural married households	0.57	0.91	1.59
Rural single households	0.59	0.77	1.30
All households	0.57	0.87	1.51

Notes: The first row shows labor supply to market work for those who work in agriculture versus those who work in the non-agricultural sector, respectively. The next three rows show these numbers for rural married households, rural single households, and all households (including urban households).

in the partial equilibrium. This suggests that providing public services is not subject to the usual concern that its effects might be dampened in general equilibrium.[24]

In general, this experiment highlights the novel policy insights derived from our analysis. Existing studies often attribute gender gaps to labor market discrimination (e.g., Chiplunkar and Kleineberg, 2023; Lee, 2024), leading to policy recommendations focused on labor market regulations. In contrast, our experiment implies that the additional time married women dedicate to household tasks is crucial. Consequently, the provision of public services like daycare centers or eldercare facilities, which act as substitutes for home production, could prove effective in narrowing the gender gap in sectoral choices.

5.4 Agricultural Productivity Gap

A central puzzle identified by the recent macroeconomic development literature is the (nominal) agricultural productivity gap in developing countries (Gollin et al., 2014b). This gap reflects a large difference in nominal value added per worker between the agricultural and non-agricultural sectors.

This gap can be partially rationalized by the differences in working hours, with non-agricultural workers typically working longer hours compared to those in agriculture. While

[24]The differences between the general equilibrium outcomes and the causal results identified from policy variations, which are partial equilibrium in nature, have been noted in the literature (e.g. Caunedo and Kala, 2021; Brooks et al., 2023).

earlier studies have suggested that agricultural work may allow for more home production (Gollin et al., 2004), our model endogenously generates the differences in working hours across sectors. In our model, working in the non-agricultural sector incurs a fixed cost, leading only those desiring sufficiently long market hours to choose non-agricultural employment. Consequently, individuals with shorter market hours are inclined to work in agriculture.

Table 8 shows that, among rural households, those who work in the non-agricultural sector on average work 50 percent more than those in agriculture. This difference is more stark among married households: non-agricultural workers work 59 percent more than agricultural workers. Among single workers, we find a much smaller difference in hours between agricultural workers and non-agricultural workers (30 percent). The differences between the married and single workers again highlight the amplification effects of the within-household specialization mechanism in our model.

Putting all households together, including urban ones, non-agricultural workers on average work 51 percent more than agricultural workers. As a result, the nominal agricultural productivity gap is amplified by 51 percent due to hour differences. Note that the agricultural productivity gap is 4.9-fold in the baseline model (and in the data). If we take the hour differences into account, then the agricultural productivity gap based on hours (rather than worker headcounts) falls to 3.2-fold.

6 Accounting for Changes in Chinese Gender Gaps, 2000–2010

China has experienced remarkable structural change in recent decades, but the gender gaps in non-agricultural employment have in fact further widened (Cao et al., 2024). In Table 2, we show that among married rural households, the gender gap in non-agricultural employment widened from 6.9 percentage points in 2000 to 12.4 percentage points in 2010. This contrasts with the cross-country findings in Lee (2024), which shows that gender gaps tend to diminish with economic development. Following the methodology in Adamopoulos et al. (2024), we can use our model framework to investigate the factors driving these changes.

We re-calibrate a set of key parameters to match data moments from 2000, with details of the calibration provided in Appendix A.2. Our model implies a gender gap in non-agricultural employment of 7.2 percentage points in 2000, which is not targeted in the calibration, compared to the a gap of 6.9 percentage points in the data. Therefore, the gender differences in home production efficiency and labor market distortions again explain the bulk of the gender gap in non-agricultural employment.

We then modify the 2010 economy backward using parameter values from the 2000 economy to isolate the effect of specific channels influencing the gender gap in sectoral choice. We start by assessing the changes in the entry barriers to the non-agricultural sector, i.e., we change κ_{sep}, κ_{both}, and κ_{single} to their 2000 levels, and see how equilibrium outcomes change. As we show in the second column of Table 9, this experiment results in substantially more families where both members work in the non-agricultural sector rather than having only one spouse—often the male—working in non-agriculture. The gender gap in non-agricultural employment shrinks from 12.6 percentage points observed in 2010 to 6.8 percentage points with the only modification being that the entry barriers are back at their 2000 level. Hence, the changing entry barriers play a dominant role in exacerbating the gender gap in non-agricultural employment over time.

Importantly, the estimated κ_{sep} declines over time, while the estimated κ_{both} remains largely unchanged (Table 12 in Appendix C). As we discussed in Section 5.1, in response to these changes more rural households sent only one spouse to non-agricultural employment, with a higher likelihood of it being the married man, given that married women on average dedicate more time to home production. These changes are consistent with institutional changes occurring in China through this period. While the household registration (*Hukou*) system was reformed and many direct occupational restrictions were removed, rural workers still face restricted access to urban public services such as childcare and education (Song,

Table 9: Gender Gaps in Non-agricultural Employment: 2000–2010

	Baseline	2000 costs	2000 home prod. efficiency	2000 labor wedges
% of rural married households with				
one member working in non-agr.	30.7	13.5	30.7	31.0
among which:				
male working in non-agr.	21.6	9.9	21.4	22.5
female working in non-agr.	9.0	3.6	9.3	8.5
gender gap	12.6	6.3	12.1	14.0
two members working in non-agr.	28.0	42.7	28.0	27.5

Notes: Statistics for the baseline 2010 economy and three counter-factual experiments where we change the costs of working in non-agriculture (κ_{sep}, κ_{both}, and κ_{single}), home production efficiency (z_h^m), and the labor market distortions (τ^f, τ^m) to their 2000 levels, respectively. We show the percentage of rural married households with one or two spouses working in the non-agricultural sector. For those with one spouse working in the non-agricultural sector, we further calculate the fraction of households within which the male or female spouse works in the non-agricultural sector, with the difference being the gender gap in non-agricultural employment.

2014; Chan, 2019). A recent study by Tian (2024) found that changes in migration regulations post-China's WTO entry in 2001 led to better working conditions for migrant workers, such as higher wages and improved benefits. However, migrant children did not see similar positive changes. Local governments were keen on having migrant workers but were not so keen on encouraging them to bring their families along and settle down.

Next, we assess the impact of the change in the home production efficiency of men by changing z_h^m from its 2010 to 2000 level, with the home production efficiency of women remaining normalized to 1. As we can see from the third column of Table 9, this change has a rather limited impact on the gender gap in non-agricultural employment as the relative efficiency of home production between genders has remained rather stable between 2000 and 2010. Finally, we change the labor market distortions (τ^f, τ^m) to their 2000 levels. While the fraction of households with one spouse working in non-agriculture does not change much, there would be more households with the male spouse working in non-agriculture, as women faced more labor market distortions (τ^f) in 2000 than in 2010. As a result, the gender gap in non-agricultural employment would increase slightly from 12.6 to 14.0 percentage points if the labor market distortion had not shrunk over time.

In conclusion, the widening of the Chinese gender gap in non-agricultural employment between 2000 and 2010 is mainly due to the barriers to non-agricultural employment. While labor market reforms have made it easier for individual rural workers to enter the urban labor market, the lack of access to urban public services still makes it challenging for entire families to relocate to urban areas. Consequently, the fraction of married households that send only the husband to non-agricultural sectors has increased.

7 Cross-Country Analysis

Thus far, our analysis has concentrated on China. In this section, we extend our analysis to other countries. We start by documenting evidence across countries on the gender gap in non-agricultural employment and its relation with home production. We then extend the quantitative analysis to other countries, aiming to evaluate how the gender gap in non-agricultural employment in other countries could be understood by differences in home production efficiency and (sector-neutral) labor market distortions between genders.

7.1 Evidence across Countries

In Section 2, we document empirical patterns on gender gaps in non-agricultural employment and home production among rural workers in China. These patterns are, however, not unique to China. In this section, we explore available data and findings in the literature to provide evidence of these patterns in other countries.

Married females are less likely to work in non-agriculture. We explore cross-country patterns of non-agricultural employment by gender and marital status using data from the Integrated Public Use Microdata Series-International (IPUMS-International, Ruggles et al., 2024), which harmonizes census data collected from over 100 countries with basic demographic information. We restrict the sample to rural individuals in low or middle income countries and use all data since the 1960s, ending up with 50 countries and 133 country-year observations.[25]

To assess the role of gender and marital status in employment patterns across countries, we regress the outcome variables on an indicator of an individual's gender, an indicator of marriage status, and an indicator representing the interaction of gender and marriage, controlling for age, years of schooling, and country×year fixed effects. We construct four outcome variables: *Laborforce* as 1 if a person participates in the labor force and 0 otherwise; *Housework* as 1 if a person is not in labor force for doing housework and 0 otherwise;[26] *Non-agri* as 1 if a person is employed in the non-agricultural sector and 0 if employed in agriculture or not in the labor force; *Non-agri-EMP* as 1 if a person is employed in the non-agricultural sector and 0 if employed in the agricultural sector while we restrict the sample to individuals in the labor force.

The regression results are presented in Table 10. We focus on the coefficient of the interaction between marriage and gender. The first two columns show that married females are less likely to participate in the labor force but more inclined to do housework. Importantly, married females are substantially less likely to work in the non-agricultural sector (the third column), and this fact holds even conditional on participating in the labor force (the last column).

Home production and public services affect the gender gap in non-agricultural employment. In Section 2, we draw on Chinese data to document that home production affects non-agricultural labor supply for rural residents, exploring variations in kindergarten availability across villages and comparing the effect on women with children to that on

[25]The World Bank classifies countries into four income groups according to GNI per capita in 2000: low income, lower middle income, upper middle income, and high income countries. We restrict our sample to countries within the first three groups. Our findings are robust to including high income countries.

[26]The individuals are classified by IPUMS into three groups: employed, unemployed, and inactive. We define the status of "Housework" for those classified as inactive due to household duties.

Table 10: Rural Employment by Gender and Marital Status

	Laborforce = 1	Housework = 1	Non-agri = 1	Non-agri-EMP = 1
Female*Married	–0.238***	0.266***	–0.100***	–0.107***
	(0.001)	(0.001)	(0.001)	(0.002)
Female	–0.243***	0.221***	–0.006***	0.146***
	(0.001)	(0.001)	(0.001)	(0.002)
Married	0.128***	0.008***	0.038***	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
R-squared	0.343	0.414	0.124	0.141
N	2,008,439	2,016,949	1,688,301	983,630

Notes: Sub-sample of individuals living in rural areas, data from IPUMS-International (with 0.1% sample density). We exclude high income countries defined by the World Bank, those with GNI per capita higher than 9,265 US dollars in 2000. Controls include age, age-squared, years of schooling, and country-year fixed effects. See the text for the definitions of dependent variables. Standard deviations in parentheses: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

women without children. Our empirical findings align with insights from existing studies, which highlight the role that motherhood plays in widening the gender gap in employment among different countries (Browning, 1992; Bertrand et al., 2010; Kleven et al., 2019). In European countries, grandparents often invest significant time providing childcare (Zanella, 2017), which can increase employment and labor force participation among married women with young children (Compton and Pollak, 2014; Bratti et al., 2018). Public programs that provide childcare can also increase labor force participation among mothers, as found in Chile and Nicaragua (Martínez and Perticará, 2017; Hojman and López Bóo, 2019). Utilizing the Mexican household survey, Marcos (2023) documents the substitutability between grandmothers and public services. The deaths of grandmothers can reduce the employment rate of mothers by 12 percentage points through their impact on childcare availability, while public daycare or affordable private schools can reduce the negative effects by substituting for grandmother-provided childcare.

Table 11: Gender Gaps in Non-Agricultural Employment Across Countries

Level of development (log GDP per capita)	Gender gap in non-agricultural employment (p.p.) Data	Model
7	6.40	6.56
8	2.70	4.92
9	−1.00	4.34
10.5	−6.56	2.43

Note: This table displays the cross-country variation in the gender gap in sectoral employment as the agricultural employment share among females minus the share for males, by level of economic development. Data are from Lee (2024).

7.2 Quantitative Analysis across Countries

The gender gap in non-agricultural employment varies systematically across countries. To illustrate this pattern, we calculate the cross-country variation in the gender gap in non-agricultural employment—the agricultural employment share among females (in percentages) minus that among males—with agricultural employment shares by gender obtained from Lee (2024). We then regress this gap against log GDP per capita obtained from the Penn World Table 8.1 (Feenstra et al., 2015), and the fitted values are displayed in Table 11. This linear fit implies that the gender gap changes from 6.4 percentage points for countries with a log GDP per capita of 7 to −6.6 percentage points at a log GDP per capita of 10.5, or a difference of 13.0 percentage points.

We then assess how well our model accounts for this cross-country variation by varying the two dimensions of gender differences in our model, i.e., τ^f and z_m^h, to match the observed cross-country differences in the gender wage gap and the gender disparity in home production hours. Specifically, we obtain data on home production hour differences between men and women from Bridgman et al. (2018), and gender wage gap data from the International Labour Organization (2024). We again fit these moments against log GDP per capita, and find that both the gender disparity in home production hours and the gender wage gap decline with economic development. We then choose our model parameters τ^f and z_m^h to match the fitted data moments of the gender disparity in home production hours and the gender wage gap associated with log GDP per capita from 7 to 10.5.[27] The model implied gap—the agricultural employment share among women minus that among men—varies from 5.6 percentage points for a country with log GDP per capita of 7 to 2.4 percentage points for log GDP per capita of 10.5, or a difference of 3.2 percentage points. This is illustrated in the third column of Table 11. Recall that this gap varies by 13.0 percentage points in the data while our model explains 3.2 percentage points. We hence conclude that our model explains around a quarter of the observed gender gap across countries.

The remaining of the observed gender gap could be explained by other factors. For instance, non-agricultural labor demand could differ systematically across countries due to the structural transformation process, while this is not accounted for in this experiment. Furthermore, social norms or the technology of home production can differ across countries as well. For instance, electronic appliances may be less prevalent in poor countries, reducing home production productivity levels for both mem and women (Greenwood et al., 2005). Recall that in our cross-country comparison we only re-calibrate the relative productivity of home production between genders, not their absolute levels. Lower home production productivity levels imply that individuals in poor countries spend more time on home production (Bridgman et al., 2018), and hence the gender gap in non-agricultural employment may be larger. Additionally, there may be country-specific factors in play. For instance, we show in Appendix D that our model accounts for the majority of the observed gender gap in non-agricultural employment in Sub-Saharan countries after re-calibrating to data moments from Sub-Saharan countries. On the contrary, our model explains a relative small portion of the observed gender gap in Latin American countries despite re-calibration, which suggests that the two gender differences in the model—home production efficiency and labor market distortions—may not be the primary drivers of the gender employment gap in Latin American countries.

[27] Note that we project data moments from various data sets onto log GDP per capita rather than directly merging these data sets. This is mainly to avoid losing observations.

8 Conclusion

In this paper, we study the role of home production and within-family specialization in explaining why more men than women work in non-agriculture in developing countries. Our analysis of micro data reveals that married women, who dedicate a larger portion of their time to home production, are far less likely to pursue non-agricultural work compared to other groups. In contrast, the difference between single men and women is less pronounced and is even reversed in certain countries. Moreover, having children at home decreases the likelihood of married women working in the non-agricultural sector, while access to childcare facilities like kindergartens helps mitigate this effect.

Motivated by these facts, we extend a general equilibrium Roy model to incorporate the joint labor supply decisions of rural married couples, accounting for gender-specific labor distortions and entry barriers to non-agriculture. Calibrating the model to China, we find that within-household specialization greatly amplifies the effects of gender-specific labor distortions, and the changes in entry barriers play a significant role in the widened gender gap in China between 2000 and 2010. In addition, enhancing public services such as increased childcare facilities can effectively induce more married women to work in non-agriculture. Extrapolating our model to a global scale, it explains a quarter of the differences in the gender gap across countries.

Our findings underscore the importance of home production, within-family specialization, and relevant public policies for understanding gender disparities and structural change in developing countries. While our model successfully explains the level and evolution of gendered employment choice in China, the model forces seem to play a smaller role in some other developing countries. This indicates the relevance of additional factors such as culture and social norms. We leave the investigation of these crucial factors to future studies.

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Appendix

A Data

A.1 Moments Used in Baseline Calibration

Moments on Income and Labor Supply Heterogeneity. In our calibration, we use the dispersion (standard deviation) of non-agricultural hourly wage rates among migrant workers. This moment is calculated from the China Migrants Dynamic Survey (CMDS, National Health Commission of China, 2018). Specifically, among migrant workers, we calculate individual wages as reported total annual income divided by the number of hours an individual reports working in the previous month and by 12 months. We drop individuals with zero reported income or labor hours and further trim observations by one percent on each tail of the wage rate distribution. We then use this distribution of wage rates to calculate the standard deviation of log wage rate, 0.441, pooling observations from 2011 to 2013 as per our data availability. We also use the CMDS data to calculate the gender wage gap by comparing the average wage of males to that of females. We find that men earn 11.5% more per hour.

We also need the correlation of non-agricultural wage rates within households. The CMDS data, unfortunately, do not explicitly record incomes of spouses. We hence use information from the Urban Household Survey (UHS, National Bureau of Statistics of China, 2015) to calculate the correlation. We calculate wage rates in the same way as we did in the CMDS data, and then calculate the Spearman's rank correlation of income for husbands and wives to be 0.542, pooling observations from 2002 to 2006. Note that a caveat of the UHS data is that this data source includes all urban residents, rather than just migrants.

We use the 2010 National Fixed Point Survey (Research Center for Rural Economy, Ministry of Agriculture (China), 2016) to calculate the dispersion of labor supply among individuals. Specifically, we observe individual labor supply measured in days to agriculture or non-agriculture. We restrict our calculation to individuals who work less than half of their labor days in non-agricultural jobs, and then normalize their labor days by 365 to make it consistent with the model variable (where labor endowment is normalized to one). We calculate the standard deviation of log labor supply to be 0.312.

Moments on Home Production. Time spent on home production is calculated using the 2008 Time Use Survey (National Bureau of Statistics of China, 2008). This survey explicitly characterizes individual time spent on market production as employment or self employment versus on home production. We classify time spent on work, searching for jobs, other income-generating activities, and commuting to work as "market work", while time spent on household work, in-home care for children or senior household members, shopping, seeking medical services, and commuting for household work as "house work". On average, rural individuals spend 150 minutes per day in home production and 381 minutes in market production, while their remaining time is spent on activities such as recreation, learning, dining, or sleeping. We hence calculate that market production accounts for 71.8% of time endowments ($381/(150+381)$). Among rural households, female members on average spend 230 minutes on home production while male members spend 69 minutes. Female members hence on average work 3.33-fold more than male members in home production.

A.2 Moments on the 2000 Economy

We re-calibrate 9 parameters of our model ($A_a, A_n, \kappa_{\text{sep}}, \kappa_{\text{both}}, \kappa_{\text{single}}, z_h^m, \tau^f, N_{\text{single}}, N_{\text{urban}}$) to Chinese data moments for the year 2000. Specifically, we choose $N_{\text{single}} = 0.512$ such that $0.512/(0.512+2) = 20.4\%$ of rural working-age individuals are single. We choose $N_{\text{urban}} = 0.468$ such that the non-agricultural urban working-age population accounts for $0.468 \times 2/(2+0.512+0.468 \times 2) = 27.1\%$ of the total working-age population.

Sectoral productivity growth is calculated by dividing real GDP (via a Laspeyres price index) by employment for the agricultural and non-agricultural sectors. These data series are from the China Statistical Yearbook (National Bureau of Statistics of China, 2011). Real labor productivity grows by 1.43-fold and 2.77-fold between 2000 and 2010 for the agricultural and non-agricultural sectors, respectively, which requires $A_a = 0.544$ and $A_n = 0.509$ (recall that for 2010 we normalize $A_a = 1$ and $A_n = 1$).

The costs $\kappa_{\text{sep}}, \kappa_{\text{both}}, \kappa_{\text{single}}$ are chosen to jointly match three data moments: 17.1 percent of rural married households have both members working in the non-agricultural sector, 12.5 percent of rural married households have only one member working in the non-agricultural sector, and 32.2 percent of single rural individuals work in the non-agricultural sector. These moments are calculated using the 2000 China Population Census (National Bureau of Statistics of China, 2010).

The labor market wedge, τ^f, is chosen to match the gender wage gap in the non-agricultural sector among migrants. In our baseline 2010 calibration, we use the CMDS data which provides information on migrant wages for 2011 to 2013. This data source, however, is not available for 2000. A few studies have documented a non-monotone trend for the gender wage gap which is largely explained by a change in the wage structure rather than gender-specific factors such as discrimination (Liu and Zuo, 2023). Existing literature, however, offers no evidence on the trend of the gender wage gap among migrants. We hence use its 2010 value for this re-calibration.

Finally, we choose z_h^m to match the ratio of home production hours of married women versus that of married men. Recall that in the baseline 2010 calibration, we use the 2008 China Time Use Survey to calculate that married women on average spend 3.33-fold more time on home production compared to married men. We use the same number for the 2000 calibration, since there exists no time use survey prior to 2008. We believe that it is reasonable to use the 2008 number since time use patterns should change fairly slowly over time.

The parameter values are reported in Table 12 in Appendix C.

B Characterization of the Model

We now briefly describe how to choose the parameters relating to labor supply, l^m, l^f, h^m, h^f, D^m, and D^f, to maximize the utility of the married rural household. The problem is specified as

$$\max_{\{l^m,l^f,h^m,h^f,D^m,D^f\}} \frac{1}{\eta}y^\eta - \frac{B}{\gamma}p^\gamma + \omega\frac{c_h^{1+\chi}-1}{1+\chi} - \kappa,$$

where

$$c_h = \left(z_h^m(h^m)^{\frac{\theta-1}{\theta}} + z_h^f(h^f)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}},$$

subject to

$$D^m, D^f \in \{0,1\}, \quad l^m + h^m = 1, \quad l^f + h^f = 1, \quad l^m, l^f, h^m, h^f \geqslant 0,$$

while family income y is given by

$$y = (D^m z_n^m w_n + (1-D^m)z_a^m w_a)l^m(1-\tau^m) + (D^f zn^f w_n + (1-D^f)z_a^f w_a)l^f(1-\tau^f),$$

and the utility cost of working in the non-agricultural sector κ is given by

$$\kappa = \begin{cases} \kappa_{\text{sep}} & \text{if } D^m = 1, D^f = 0 \text{ or } D^m = 0, D^f = 1; \\ \kappa_{\text{both}} & \text{if } D^m = 1 \text{ and } D^f = 1; \\ 0, & \text{otherwise }. \end{cases} \tag{8}$$

The last constraint indicates that the cost κ_{sep} is incurred if one of the two members work in the non-agricultural sector and the other one works in agriculture or does not work, while the cost κ_{both} is incurred if both members work in the non-agricultural sector.

We solve this problem through backward induction. Assume that the occupational choices have been made and the incomes per unit of labor supply (taking into account abilities) are w^m and w^f for the male and female members, respectively. We can write down the first order condition of labor supply for the male member as

$$y^{\eta-1}w^m(1-\tau^m) = \omega c_h^{\chi+\frac{1}{\theta}} z_h^m (h^m)^{-\frac{1}{\theta}}.$$

Assuming we have an interior solution for h^m, we can then solve out

$$h^m w^m(1-\tau^m) = \omega y^{1-\eta} \frac{z_h^m (h^m)^{\frac{\theta-1}{\theta}}}{\left(z_h^m (h^m)^{\frac{\theta-1}{\theta}} + z_h^f (h^f)^{\frac{\theta-1}{\theta}}\right)^{-(\chi+\frac{1}{\theta})\frac{\theta}{\theta-1}}}. \tag{9}$$

The relative labor supply of male and female members of the household can be characterized by the following condition:

$$\frac{h^f}{h^m} = \frac{1-l^f}{1-l^m} = \left(\frac{w^m}{w^f}\frac{1-\tau^m}{1-\tau^f}\frac{z_h^f}{z_h^m}\right)^{\theta}.$$

The amount of labor supplied to the market is a function of the relative ability of members: the member with higher ability supplies more labor to the market and works less at home production. In addition, if, for instance, women are more productive at home production than men ($z_h^f > z_h^m$), or if women face higher labor market distortions ($\tau^f > \tau^m$), then the female member supplies more labor to home production than the male member and less labor to market production, ceteris paribus.

Note that we allow for within-household specialization, or technically corner solutions to this problem, i.e., one of the two members can choose not to participate in the labor market and spend all their time in home production. This is often optimal when the other member has high ability z_a or z_n in market production. Similarly, we also allow for the solution that one member does not participate in home production. It is never optimal, however, for both members to engage in full-time home production or full-time market work.

We now investigate the occupational choice problem. Specifically, we have solved the labor supply and home production decisions for both members given the male member's wage rate w^m and the female member's wage rate w^f, denoted as $l^m(w^m, w^f)$, $l^f(w^m, w^f)$, and $c_h(w^m, w^f)$. We further denote

$$\mathscr{U}(w^m, w^f) = \frac{1}{\eta}y^\eta - \frac{B}{\gamma}p^\gamma + \omega\frac{c_h(w^m, w^f)^{1+\chi} - 1}{1+\chi},$$

where $y = w^m(1-\tau^m)l^m(w^m, w^f) + w^f(1-\tau^f)l^f(w^m, w^f)$. The occupational choice problem is then

$$\max_{D^m, D^f} \mathscr{U}(w^m, w^f) - \kappa,$$

subject to

$$w^m = (z_a^m w_a(1 - D^m) + zn^m w_n D^m), \quad w_f = (z_a^f w_a(1 - D^f) + z_n^f w_n D^f).$$

and equation (8) which determines κ.

For single rural households, we have a similar condition for labor supply:

$$h^s w^s = \omega y^{1-\eta} c_h^\chi (z_s^h)^{\frac{\theta}{\theta-1}}, \tag{10}$$

Note that for single rural households, it is never optimal to not participate in the labor market. Then the occupational choice problem is to choose the occupation that maximizes utility.

C Robustness and Alternative Specifications

C.1 Correlation between z_a and z_n

In our baseline calibration, we choose $\lambda = 0.21$ such that the rank correlation of agricultural and non-agricultural abilities is 0.35, quantitatively in line with the literature (Lagakos and Waugh, 2013; Adamopoulos et al., 2024). To assess the importance of this parameter for the model implications, we conduct a robustness analysis by considering values of λ below and above our baseline estimate. In particular, we set λ to 0.15 and 0.29, implying correlations between the two dimensions of ability to be 0.25 and 0.45, respectively. We then re-calibrate the entire model to match the same set of data moments, with parameters reported in Table 12.

Table 12: Model Parameters and Values

Parameter	Value: Baseline	Low corr	High corr	No positive assortative matching	Sector-specific labor friction	No married households	2000 calibration	SSA calibration	Latin calibration
Technologies:									
A_a	1	1	1	1	1	1	0.556	1	1
A_n	1	1	1	1	1	1	0.514	1	1
Preferences:									
B	0.333	0.331	0.327	0.347	0.334	0.326	0.333	0.793	0.638
γ	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
η	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
ω	0.262	0.252	0.248	0.279	0.248	0.231	0.262	0.262	0.262
θ	4.008	3.791	3.884	4.872	5.082	—	4.008	4.008	4.008
κ_{sep}	0.393	0.437	0.408	0.472	0.479	—	0.475	0.610	0.316
κ_{both}	0.578	0.637	0.601	0.547	0.667	—	0.546	0.816	0.401
κ_{single}	0.142	0.157	0.158	0.100	0.182	0.343	0.229	0.391	0.266
χ	−1	−1	−1	−1	−1	−1	−1	−1	−1
Ability:									
λ	0.206	0.152	0.290	0.151	0.255	0.194	0.206	0.206	0.206
σ_a	0.282	0.301	0.291	0.269	0.340	0.338	0.282	0.282	0.282
σ_n	0.536	0.536	0.529	0.699	0.522	0.684	0.536	0.536	0.536
ψ	0.845	0.860	0.872	—	0.796	—	0.845	0.845	0.845
z_h^m	0.824	0.812	0.790	0.680	0.755	1	0.860	0.793	0.998
z_h^f	1	1	1	1	1	1	1	1	1
$\bar{z}$	1.757	1.758	1.749	1.759	1.734	1.804	1.757	1.757	1.757
Frictions:									
τ^m	−0.096	−0.096	−0.092	−0.068	−0.131	−0.079	−0.096	−0.118	−0.173
τ^f	0.117	0.116	0.111	0.085	0.178	0.084	0.134	0.149	0.209
Endowments:									
N_{married}	1	1	1	1	1	0	1	1	1
N_{single}	0.717	0.717	0.717	0.717	0.717	2.717	0.512	0.420	0.455
N_{urban}	0.537	0.537	0.537	0.537	0.537	0.537	0.468	0.579	2.391

Notes: List of parameters and calibrated values in our baseline and alternative calibrations. A set of 13 parameters, θ, ω, B, κ_{sep}, κ_{both}, κ_{single}, σ_a, σ_n, ψ, λ, z_h^m, τ^m, and $\bar{z}$, are jointly determined by comparing model moments and targeted data moments. The remaining ones are either normalized or directly assigned values from outside evidence.

Table 13: Robustness: Correlation between the Two Dimensions of Ability

	Data	Model		
		Baseline	Low corr	High corr
Percentage of rural married households with				
one member working in non-agr. (targeted)	30.7	30.7	30.4	30.7
male working in non-agr.	21.6	21.6	21.5	21.7
female working in non-agr.	9.1	9.0	8.8	9.0
two members working in non-agr. (targeted)	28.0	28.0	27.7	27.9

Notes: This table shows the percentage of rural married households with one or two members working in the non-agricultural sector. For those with one member working in the non-agricultural sector, we further calculate the percentages with just the male or the female member working in the non-agricultural sector. The first column shows the statistics in the data, while the next three columns show statistics for our baseline calibration, low-correlation calibration, and high-correlation calibration, respectively.

We now assess the model's implication on the gender gap in sectoral employment. Table 13 shows the model-predicted gender gap in our baseline calibration as well as in the calibrations with alternative correlations. Clearly, the model-implied gender gap in non-agricultural employment is barely affected by this correlation. We hence conclude that our results are not sensitive to the choice of correlation between agricultural and non-agricultural abilities.

Recent literature identifies this correlation using information from individuals who switch from agriculture to non-agriculture (e.g. Hamory et al., 2021; Alvarez-Cuadrado et al., 2023). The key empirical pattern to infer the correlation of abilities in Alvarez-Cuadrado et al. (2023) is whether we observe high-ability or low-ability farmers quit farming. For instance, if high-ability farmers quit farming first, then overall these farmers must be of higher ability in non-agricultural sectors. This implies that the two dimensions of ability are highly correlated, and the dispersion of ability is larger in the non-agricultural sector. This same identification assumption does not apply to our framework, since the occupational choice is not an individual choice, but a family decision. A high-ability farmer quitting farming does not necessarily imply they would earn more in the non-agricultural sector—it could be that their spouse is productive in the non-agricultural sector and this farmer is choosing to migrate as well to avoid the cost of separating (κ_{sep}).

C.2 Correlation of Abilities between Couples

In our baseline calibration, we allow for the abilities to be correlated between couples, governed by the parameter ψ, to capture the observed positive assortative matching in marriage that has been widely documented in the literature (Greenwood et al., 2014; Siow, 2015). We now assess how sensitive our results are to this setting. Specifically, we consider an alternative setting without positive assortative matching such that the abilities between couples are independent. We argue that our results are qualitatively robust to this extreme setting, but the correlation is quantitatively important.

We modify the parameterization of abilities as

$$\log(z_n) = \log(z_n^I), \quad \log(z_a) = \log(z_a^I) + \lambda \log(z_n),$$

where z_n^I and z_a^I follow log-normal distributions with mean zero and standard deviations σ_n and σ_a. We re-calibrate the entire model to match the same set of data moments, except for the correlation of wages between couples. The parameter values are listed in Table 12.

In this alternative specification, our model still generates a gender employment gap of 7.9 percentage points, although somewhat lower than the 12.4 percentage point gap observed in the data. This result provides two pieces of information. First, the key mechanism of our model does not rely on positive assortative matching to work qualitatively. Even without positive assortative matching, within-household specialization and non-linearity in labor supply can generate a gender employment gap with sector-neutral forces. Second, positive assortative matching is quantitatively crucial for our model to match the magnitude of the gender employment gap. Specifically, the level of positive assortative matching affects the calibrated migration costs, i.e., κ_{sep} versus κ_{both}, while these costs affect the gender employment gap as discussed in Section 5.1.

Given its quantitative importance, we argue that our chosen ψ is reasonable in our baseline calibration. Recall that we choose ψ to match the observed correlation of non-agricultural wage rates between couples after sample selection. This implies a Spearman's rank correlation of 0.56 between the underlying abilities z_n^m and z_n^f for the population of rural married households. We then follow Lagakos and Waugh (2013) and use other moments to approximate ability. It is well known that non-agricultural ability is closely related to schooling or human capital accumulation. As a robustness check, we then calculate the rank correlation of years of schooling between couples for the population of rural married households using CHNS data (Chinese Center for Disease Control and Prevention, 2010). The correlation is 0.54 for the year 2000 and 0.60 for 2010. Our implied rank correlation of 0.56 falls well within the empirical range.

C.3 Sector-Specific Labor Market Frictions

We assume that the labor market friction τ^g is sector-neutral, i.e., it applies to both sectors. Alternatively, we can consider an alternative situation where this friction only applies to the non-agricultural sector. We re-calibrate the model by matching the same set of data moments that we choose in our baseline calibration, and the parameter values are reported in Table 12.

In this alternative specification, the model substantially over-predicts the gender gap in structural transformation. Specifically, the model predicts that married males are 21.9 percentage points more likely to work in the non-agricultural sector than married females, as opposed to the 12.4 percentage points observed in the data. Importantly, this alternative specification predicts a large gender gap among singles as well: single males are 19.6 percentage points more likely to work in the non-agricultural sector compared to single females. This is inconsistent with the data, where single females are slightly more likely to work in the non-agricultural sector than single males. As a result, we conclude that a sector-specific friction in our model generates inconsistent predictions compared to the data, especially regarding the gender gap among singles. We view this as a novelty of our work: we do not need a gender-sector-specific friction to reconcile the observed gender gap in non-agricultural employment as in Doss et al. (2024) and Lee (2024). In our framework, the gender gap in non-agricultural employment is explained by the gender difference in home production and non-linearity in labor supply, rather than wedges specific to the non-agricultural sector.

C.4 A Model Without Married Households

One key novelty of our framework is that we explicitly allow for household decisions over consumption and labor supply among married individuals. To better understand the role of household decisions, we consider an alternative version of our model without married households, i.e., all agents are treated as single and hence all decisions are made by individuals. This alternative model is then closer to Lagakos and Waugh (2013) and Lee (2024) extended with home production.

Our calibration strategy is similar to that of our baseline model. To calibrate this alternative model, we restrict N_{married} to zero and set N_{single} to 2.717, which is the measure of the entire rural population. For the ability distribution, we modify the parametric assumption as

$$\log(z_n) = \log(z_n^I) \text{ and } \log(z_a) = \log(z_a^I) + \lambda \log(z_n).$$

We choose the standard deviations of $\log(z_n^I)$ and $\log(z_a^I)$, denoted as σ_n, and σ_a, to match the dispersion of wage rates in the non-agricultural sector and the dispersion of labor supply in agriculture, the same data moments used in our baseline calibration, and choose λ to match the correlation between agricultural and non-agricultural abilities of 0.35 as in Lagakos and Waugh (2013). We choose κ_{single} to match the share of rural individuals who work in the non-agricultural sector. Importantly, without within-household specialization, the home production productivities z_h^f and z_h^m barely affect home production hours. We hence set both to one. Parameters $\{\theta, \kappa_{\text{both}}, \kappa_{\text{sep}}, \psi\}$ are irrelevant in this alternative model. All other parameters are calibrated in the same way as in our baseline calibration, with their values reported in Table 12.

This alternative model falls short in generating the gender gap in non-agricultural employment. Note again that in our calibration strategy we choose κ_{sep} to match the share of rural individuals working in the non-agricultural sector, without targeting the gender composition. In the data, pooling married and single rural individuals together, 53.6 percent of men and 45.3 percent of women work in the non-agricultural sector, implying a gap of 8.4 percentage points. Our alternative model predicts a gap of only 4.7 percentage points. This further suggests the importance of within-household specialization in our baseline model. In fact, a counterfactually large gender wage gap will be needed in order for this alternative model to generate a gender gap in non-agricultural employment comparable to the data. In addition, given that z_h^f and z_h^m do not affect home production hours, our alternative model predicts that women spend 21% more time on home production than men, which is entirely generated by the gender-specific labor market distortions, compared to the 3.33-fold disparity observed in the data.

We conclude that modelling household decisions, or more specifically within-household specialization, allows us to simultaneously match the observed hour differences in home production between men and women and the gender gap in non-agricultural employment.

D Case Studies: Sub-Saharan and Latin American Countries

We perform two case studies in which we re-calibrate our model to match data moments from Sub-Saharan and Latin American countries to assess the performance of our model in different countries.

In this analysis, we utilize two datasets. The first dataset is the Demographic and Health Surveys (DHS) (ICF, 2017). This data set has been used in other studies such as Young

(2013). DHS covers a range of developing countries, including both Sub-Saharan ones and Latin American ones. Importantly, DHS provides information that allows us to link couples. We focus on individuals whose childhood location was in a rural area. We can then calculate the fraction of couples of which one member, both members, or the single member works in the non-agricultural sector. We also use DHS data to calculate the gender wage gap in the non-agricultural sector among these households. The DHS data also provide information on the fraction of rural individuals who are single and the relative measure of rural and urban individuals. The DHS data, however, do not include information on home production. Therefore, our second dataset is sourced from Bridgman et al. (2018), providing data on time spent in home production by gender across a wide range of countries. Note that the home production hours provided in Bridgman et al. (2018) are for *all* individuals, including both rural and urban dwellers. As a result, when we construct our model moments, we also calculate home production hours for all individuals, rural and urban, to be consistent. This is different from our baseline calibration where we know home production hours for *rural* households in China and the corresponding model moment can be constructed accordingly. We further need the agricultural value-added share, which can be obtained from the World Development Indicators (The World Bank, 2024). Combining these data sources, we have in total 11 countries in our sample which can be easily divided into two groups: Sub-Saharan countries (Benin, Chad, Ghana, Mali, Mozambique, Togo, Zambia, and Zimbabwe) and Latin American countries (Bolivia, Nicaragua, and Peru). We then calculate the statistics for each country and take an average within each group.

Sub-Saharan Countries. We first examine whether our model can explain the observed gender gap in non-agricultural employment in Sub-Saharan countries. To achieve this, we re-calibrate six parameters to match data moments from these countries. Specifically, we set B, representing the level of agricultural demand, to correspond with the share of agricultural

Table 14: Gender Gap in Non-agricultural Employment in Other Countries

	Data	Model
(a) Sub-Saharan Countries		
% of rural married households with		
one member working in non-agr. (targeted)	13.2	13.6
among which:		
male working in non-agr.	9.8	9.6
female working in non-agr.	3.4	3.9
gender gap	6.4	5.7
two members working in non-agr. (targeted)	13.2	13.3
(b) Latin American Countries		
% of rural married households with		
one member working in non-agr. (targeted)	16.6	16.5
among which:		
male working in non-agr.	13.8	10.2
female working in non-agr.	2.8	6.3
gender gap	11.0	3.9
two members working in non-agr. (targeted)	19.3	19.3

Notes: This table shows the percentage of rural married households with one or two members working in the non-agricultural sector. For those with one member working in the non-agricultural sector, we further calculate the percentages when the male or the female member works in the non-agricultural sector, the difference of which is the gender gap in non-agricultural employment. Panel (a) shows results for the modelled Sub-Saharan countries, while panel (b) shows results for the modelled Latin American countries.

value-added in Sub-Saharan countries.[28] In addition, we choose κ_{sep}, κ_{both}, and κ_{single} to match the proportions of households where one spouse, two spouses, or a single worker is employed in the non-agricultural sector. Furthermore, we re-calibrate the two critical parameters that determine gender differences, namely z_h^m and τ^f, to align with the data indicating that, on average, women spend 3.79 times more time on home production than men, and that the gender wage gap in the non-agricultural sector is 15%. The calibrated parameter values are provided in Table 12.

We then present our model's prediction of the gender gap in non-agricultural employment

[28]Alternatively, we could keep B unchanged and adjust A_a to match the agricultural value-added share. These two approaches are essentially equivalent in terms of outcomes. Here, we adhere to the methodology of Alder et al. (2022) by allowing B to vary across countries.

in Panel (a) of Table 14. It is evident that the re-calibrated model reasonably matches the gender gap in non-agricultural employment for the Sub-Saharan countries, without directly targeting it. The observed gender gap is 6.4 percentage points, while our model explains 5.7 percentage points through the two modeled gender differences: home production efficiency and labor market distortions. We proceed to analyze the relative significance of these factors. When we equalize home production efficiency between genders (i.e., setting $z_m^h = z_f^h$), the gender employment gap decreases slightly to 4.5 percentage points. Conversely, by eliminating labor market distortions (i.e., setting $\tau_m = \tau_f = 0$), the gender employment gap significantly shrinks to just 1.5 percentage points. Consequently, we infer that although home production efficiency plays a smaller role compared to labor market distortions, these gender differences account for most of the observed gender gap in non-agricultural employment within Sub-Saharan countries.

Latin American Countries. Turning our attention to the Latin American countries within our sample, we now re-calibrate the same six parameters of our model to match the data moments from these countries. Panel (b) of Table 14 reveals that, despite the re-calibration efforts, our model falls short in explaining the observed gender gap in non-agricultural employment for Latin American countries. Specifically, while the observed gender gap is 11 percentage points, our model only accounts for 3.9 percentage points of this gap. This discrepancy suggests that the two gender differences in the model—home production efficiency and labor market distortions—may not be the primary drivers of the gender employment gap in Latin American countries. It is plausible that gender-sector-specific labor market distortions, as explored in Lee (2024), are necessary to reconcile the observed disparities in these countries.