Home Production and Gender Gap in Structural Change

Cao, Huoqing and Chen, Chaoran and Xi, Xican

Fudan University, York University, Fudan University

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Huoqing Cao
Fudan University

Chaoran Chen
York University

Xican Xi
Fudan University

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Abstract

We document that the gender gap in non-agricultural employment in developing countries is concentrated among rural married workers. Within-family specialization is central: married women devote more time to home production, supply fewer market hours, and are less likely to pay fixed costs to enter non-agriculture. We build a general equilibrium Roy model with joint family decisions, sector-neutral gender labor wedges, and entry barriers to non-agriculture. Calibrated to China in 2010, the model successfully reproduces the observed gender gap among married workers. Gender labor wedges account for about 80 percent of this gap, amplified significantly by within-family specialization. Changes in entry barriers explain the widening gap from 2000 to 2010, consistent with institutional changes in China.

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 is central to understanding cross-country income differences, as developing countries typically employ a larger share of workers in the less productive agricultural sector.[1] A key feature of this allocation is that women in developing countries are disproportionately represented in agriculture.[2] Given the large productivity and wage gaps between the two sectors, gender differences in sectoral choices are consequential for aggregate gender gaps in income.

This paper argues that home production and *within-family specialization* are key to understanding gender gaps in structural transformation. Using Chinese micro data, we document that the gender gap in non-agricultural employment is driven almost entirely by married workers. Specifically, married women are much less likely to work in non-agriculture than married men, whereas this gender gap is negligible among single workers. We also document that home production demands are tightly linked to sectoral choices: rural households with young children exhibit lower non-agricultural employment among married women, and access to childcare facilities (kindergartens) is associated with a smaller gender gap. Similar patterns appear in other developing countries.

Motivated by these facts, we extend a general equilibrium Roy model à la Lagakos and Waugh (2013) by introducing joint family decision-making. Rural married couples jointly choose consumption, home production, and sectoral employment, allowing within-family specialization to arise endogenously. Rural workers choose between agriculture and non-agriculture but face fixed utility costs to enter the non-agricultural sector. These barriers capture commuting and migration costs, employment inflexibility, and institutional constraints (such as China's *hukou* system). Crucially, these costs differ depending on whether a single spouse or both spouses make the sectoral transition. The economy also features

[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), Lee (2024), Chiplunkar and Kleineberg (2025), and Gottlieb et al. (2025).

gender-specific (but sector-neutral) labor market wedges.

The core mechanism of our model relies on the interaction between these fixed entry barriers and within-household specialization, which transforms sector-neutral frictions into *de facto* sector-biased outcomes. Because entering the non-agricultural sector imposes a fixed cost, this transition is only optimal for individuals supplying a sufficiently large number of market hours.[3] Given that married women are more efficient in home production and face larger labor market wedges, comparative advantage leads households to allocate husbands to market work while wives absorb the bulk of home production. With a smaller residual time endowment available for the market, married women are less likely to overcome the fixed entry cost, generating a substantial gender gap in non-agricultural employment.

We calibrate the baseline economy to China in 2010 using micro data on rural household labor supply. The calibration separately identifies the gender asymmetries in home production efficiency and labor market wedges, yielding implications consistent with independent reduced-form evidence. Importantly, the model reproduces the sectoral gender gap without explicitly targeting it: it implies a 12.6 percentage point gap among rural married workers, closely matching the 12.4 percentage points observed in the data. Counterfactual experiments reveal that equalizing home production efficiency reduces this gap from 12.6 to 10.4 percentage points, while eliminating gender-specific labor wedges compresses it to 2.9 percentage points.

A subsequent quantitative exercise isolates the amplification role of *within-family specialization.* When we shut down joint decision-making—treating all workers as independent singles in an otherwise identical environment—the model fails to generate the observed sectoral gender gaps. This "singles-only" economy yields a gap of merely 4.8 percentage points. Forcing the model to match the observed gap without within-family specialization would require counterfactually large gender wage distortions.

[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). Bick et al. (2022) emphasize that fixed costs associated with formal wage jobs are crucial for explaining cross-country differences in employment.

Finally, we use our framework to understand why China's sectoral gender gap widened significantly between 2000 and 2010. We demonstrate that this divergence is driven primarily by an asymmetric decline in entry barriers. While it became easier for an individual rural worker to access non-agricultural employment, joint entry remained costly over time. As a result, marginal households increasingly adopted a split-sector arrangement, sending the husband into non-agriculture while keeping the wife in agriculture. This structural mechanism mirrors China's institutional evolution during this decade: although *hukou* reforms removed many direct occupational restrictions for individual migrants, rural families continued to face severe barriers in accessing urban public services, such as childcare and education, heavily penalizing joint migration (Song, 2014; Chan, 2019).[4]

Our paper contributes to three strands of literature.

First, we contribute to the structural transformation literature that studies the allocation of labor between agriculture and non-agriculture.[5] Recent work emphasizes selection among heterogeneous workers in sectoral choice (Lagakos and Waugh, 2013; Chen, 2017; Hamory et al., 2021; Lagakos et al., 2020; Adamopoulos et al., 2022; Chiplunkar and Kleineberg, 2025). We build on this framework but shift the unit of decision-making from the individual to the household, showing how joint decisions by married couples shape sectoral allocation and generate large gender gaps in non-agricultural employment even if driving forces in our framework are sector-neutral.[6]

Second, we connect home production to sectoral reallocation. Existing studies highlight how home production and market services interact over the course of development (Rogerson,

[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.

[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), Alvarez-Cuadrado et al. (2017), Herrendorf and Schoellman (2018), Chen (2020), Bick et al. (2022), Cao et al. (2024), Chen et al. (2025), Gai et al. (2025), and many others.

[6] A notable exception is Adamopoulos et al. (2024), who also incorporates family structure in structural transformation. Their focus is on land insecurity and family occupational choices, whereas we focus on joint consumption, home production, and sectoral employment decisions of married couples.

2008; Ngai and Petrongolo, 2017; Moro et al., 2017; Bridgman et al., 2018; Dinkelman and Ngai, 2021). We complement this work by emphasizing a different margin—agriculture versus non-agriculture—and by showing that within-household specialization, combined with fixed entry barriers, links home production demands to non-agricultural employment for married women.

Third, we contribute to the macro-family literature that studies labor supply and household decisions in equilibrium (Doepke and Tertilt, 2016; Greenwood et al., 2017, 2023). Our mechanism is closely related to multi-member household models of labor supply (Guner et al., 2012; Bick and Fuchs-Schündeln, 2018; Rogerson and Wallenius, 2019; Erosa et al., 2022; Feng et al., 2024; Bento et al., 2024; Gottlieb et al., 2025). We extend this framework to analyze gendered structural change in a developing-economy context, highlighting how home production and within-family specialization shape the transition out of agriculture.

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. Section 6 contains sensitivity analysis. Section 7 concludes the paper.

2 Facts

This section presents motivating facts on the gender gap in non-agricultural employment among rural workers. Using micro data from China, we first show that the overall gap is concentrated among married workers rather than singles. We then link this pattern to home production: households with higher home production demands (proxied by young children) exhibit lower non-agricultural employment among women, while access to local childcare (kindergartens) is associated with a smaller gender gap. Appendix F.1 documents similar patterns in other developing countries.

Fact 1: The gender gap in non-agricultural employment is concentrated among

married rural workers.

We use the 2010 China Population Census (National Bureau of Statistics of China, 2010), which contains rich information on individuals' *hukou* status, employment, and household relationships, to document the gender gap in non-agricultural employment among rural residents.[7] The first two rows of Table 1 show that, among labor force participants, men are more likely than women to work in non-agriculture, consistent with Lee (2024).[8] The non-agricultural employment share differs by 9.9 percentage points between rural men and women. The next four rows decompose this gap by marital status: the overall difference is driven by married workers. Rural married women are 12.4 percentage points less likely to work in non-agriculture than married men, while single women are *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

Categories	Share of Non-agricultural Employment (%)	Number of Observations
All rural individuals		
Men	53.1	1,014,268
Women	43.2	810,043
Rural individuals by marriage status		
Married men	49.6	758,798
Married women	37.1	652,078
Single men	63.6	255,470
Single women	68.3	157,965

Notes: The first column lists the percentage of non-agricultural employment among rural individuals (measured as rural *hukou* holders) in the labor force by category and the second column lists the number of observations of each category. Data from the 2010 Chinese Population Census.

The gap among married workers implies substantial within-household differences in sec-

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

[8] We focus on sectoral choice conditional on labor force participation. Labor force participation is high in rural China during our sample period (typically above 80 percent), and it is well understood that participation is lower for women.

toral allocation. We therefore tabulate rural married households by spouses' sectoral choices. Table 2 shows that, among households where spouses work in different sectors, it is much more common for the husband to be in non-agriculture and the wife in agriculture than the reverse. In 2010, 21.6 percent of rural households had a husband in non-agriculture and a wife in agriculture, compared to 9.1 percent with the wife in non-agriculture and the husband in agriculture.[9] The difference implies a 12.4 percentage point gender gap in non-agricultural employment among married individuals.

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

Family Structure	Percentages
Both agriculture	41.3
Both non-agriculture	28.0
Husband non-agriculture, wife agriculture	21.6
Wife non-agriculture, husband agriculture	9.1
Total	100

Notes: This table shows the fractions of four types of rural families. Data from the 2010 Chinese Population Census.

Fact 2: Home production and childcare access are associated with the gender gap in non-agricultural employment.

Married women spend substantially more time on home production than married men (Gousse et al., 2017; Bridgman et al., 2018). In the 2008 Chinese Time Use Survey (National Bureau of Statistics of China, 2008), married women devote 251 minutes per day to housework on average, compared to 97 minutes for married men (and 40 and 75 minutes for single men and single women, respectively).

To connect home production demands to sectoral outcomes, we use panel data from the National Fixed Point Survey (NFPS, Research Center for Rural Economy, Ministry of Agriculture (China), 2016), which reports individual employment and village characteristics such

[9]Technically, the 21.6 percent households refer to those split households with a husband in non-agriculture and a wife in the rural areas who can be working in agriculture or out of the labor force. Similar definition is applied to the 9.1 percent.

as kindergarten availability. We regress an indicator for non-agricultural employment on gender, child status, kindergarten availability, and their interactions, controlling for household and village×year fixed effects. Table 3 summarizes the results; Appendix B provides details.

Table 3: Children, Kindergarten, and 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)
*KG*Child*			−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; Child is an indicator of having children younger than 6 in the household; KG is an indicator of kindergarten availability in the village in a certain year. Standard errors in parentheses: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Column (1) confirms a gender gap in non-agricultural employment in the NFPS data even after controlling for fixed effects. Column (2) links this gap to home production demands: having a child under age six in the household is associated with 3.9 percentage points lower non-agricultural employment for women relative to men.

Column (3) then assesses whether local public goods mitigate this relationship. Using a triple-difference specification, we find that kindergarten availability is associated with a 3.7 percentage point increase in non-agricultural employment for rural women with young children, relative to rural women without young children.

Overall, these results suggest that higher home production demands are associated with lower non-agricultural employment among women, and that childcare-related public services can facilitate women's entry into non-agricultural work.

3 Model

The economy consists of an agricultural sector (a) and a non-agricultural sector (n), each producing a consumption good. We treat the non-agricultural good as the numeraire (price normalized to one) and denote the price of the agricultural good by p. Households are either born to urban or rural areas. Urban households of measure N_{urban} can only work in non-agriculture. Rural households, the focus of the paper, are either married households of measure N_{married} (a male m and a female f) or single households of measure N_{single} (one individual, male or female). Each rural individual chooses between agriculture and non-agriculture as in Lagakos and Waugh (2013). In addition, all individuals can allocate time to home production.

3.1 Preferences and Endowments

3.1.1 Rural Married Households

We begin with rural married households, which 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) that represent the efficiency of one unit of labor supplied to agriculture and non-agriculture, respectively. A married household is 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 correspond to the male member and the last two correspond to the female member. The joint distribution of households is denoted by $F(\mathbf{z})$.

Each individual has one unit of time per period, allocated between market work, l^g, and home production, h^g. Market work can be supplied to either agriculture or non-agriculture.

Time allocation satisfies

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

Post-tax labor income is $w_s z_s^g l^g (1 - \tau^g)$, where $s \in \{a, n\}$ denotes the sector of employment. Here τ^g is an implicit income tax capturing gender-specific labor market frictions as in Hsieh et al. (2019). We restrict this implicit tax to be sector-neutral; we will show later that it nevertheless generates a sector-biased effect on labor supply in the model. Household income, y, is the sum of the two spouses' labor incomes. If $l^g = 0$, an individual devotes all time to home production; if $l^g = 1$, home production is fully delegated to one spouse.

Consumption decisions are made at the household level. Households derive utility from market consumption and home production. The household utility is

$$U = u(c_a, c_n) + \omega \frac{c_h^{1+\chi} - 1}{1 + \chi},$$

where $u(c_a, c_n)$ captures utility from agricultural and non-agricultural consumption and $(c_h^{1+\chi} - 1)/(1 + \chi)$ captures utility from home production; ω governs the relative weight on home production. Denote demands by $c_a(\mathbf{z})$ and $c_n(\mathbf{z})$. Following Boppart (2014), we discipline $u(c_a, c_n)$ so that the expenditure share on the agricultural good is $B(1/y)^\eta p^\gamma$, where y is household income, η is the income elasticity, γ is the price elasticity, and B is a shifter. Boppart (2014) uses an indirect utility representation since this expenditure share does not admit a convenient closed-form direct utility.[10] In addition, 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).

[10] In Appendix D.1, we verify that our main quantitative results are robust to an alternative Stone-Geary preferences setting.

3.1.2 Rural Single Households

Each rural single household consists of one individual, who can be either male or female. An 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 $F^{\text{single}}(g, \mathbf{z}^s)$. Singles choose market labor supply l^s (in either agriculture or non-agriculture) and home production h^s. Preferences are summarized by the same utility function:

$$U = u(c_a, c_n) + \omega \frac{c_h^{1+\chi} - 1}{1+\chi},$$

where

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

with $z_h = z_h^m$ if the individual is male and $z_h = z_h^f$ if the individual is female. Denote the resulting demands for agricultural and non-agricultural goods 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 consisting of a male and a female. Urban households can only work in non-agriculture; their ability is denoted by $\bar{z}$ and their labor supplies are l_{urban}^m and l_{urban}^f.[11] Preferences and home production technologies are identical to those of rural households. Denote their agricultural and non-agricultural goods demands as c_a^{urban} and c_n^{urban}.

3.2 Occupational Choices

Rural working individuals choose between agriculture (a) and non-agriculture (n). For rural married households, this sectoral (occupational) choice is made jointly by the couple, taking into account within-household time allocation.

[11]The urban households play little role in the model. We need the urban households to get the national account right in the calibration.

Married households. Let $D^g(\mathbf{z}) \in \{0,1\}$ denote the sectoral choice of spouse $g \in \{m, f\}$ in a rural married household with ability vector $\mathbf{z}$, where $D^g(\mathbf{z}) = 1$ indicates working in non-agriculture and $D^g(\mathbf{z}) = 0$ indicates working in agriculture. Conditional on (D^m, D^f), the household chooses market hours (l^m, l^f) and home production time (h^m, h^f) to maximize utility.

Working in non-agriculture entails a fixed entry cost that depends on whether one or both spouses enter. If exactly one spouse works in non-agriculture (i.e., $D^m \neq D^f$), the household incurs a utility cost κ_{one}. If both spouses work in non-agriculture (i.e., $D^m = D^f = 1$), the household incurs a utility cost κ_{both}.[12] These costs capture barriers to accessing non-agricultural jobs (e.g., search and migration costs, work inflexibility). In addition, κ_{one} may also reflect the utility loss associated with family separation, commuting, or temporary migration, while κ_{both} may reflect the difficulty of relocating and settling the entire family (e.g., housing and childcare constraints). Particularly, in the context of China, κ_{both} also proxies for institutional barriers to family migration, such as restricted access of rural migrants to urban public services under the *hukou* system (Song, 2014; Chan, 2019). When $\chi = -1$ (log utility from home production), these utility costs can alternatively be interpreted as multiplicative declines in effective home production associated with non-agricultural work.

Single households. A rural single individual of gender g with ability vector $\mathbf{z}^s$ chooses $D^s(g, \mathbf{z}^s) \in \{0,1\}$, where $D^s(g, \mathbf{z}^s) = 1$ denotes working in non-agriculture and $D^s(g, \mathbf{z}^s) = 0$ denotes working in agriculture. Choosing non-agriculture entails a utility cost of κ_{single}.

Appendix C provides the formal characterization of optimal time allocation and the resulting sectoral choice rules.

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

3.3 Technologies

A representative firm in each sector produces output according to

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

where A_a and A_n denote sectoral productivities and L_a and L_n denote efficiency units of labor in each sector. Wages per unit of efficiency labor are therefore $w_a = pA_a$ and $w_n = A_n$.

3.4 Competitive Equilibrium

Aggregate labor input in agriculture is given by

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

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

$$\begin{aligned} L_n = & N_{\text{married}} \int \left[z_n^m l^m(\mathbf{z}) D^m(\mathbf{z}) + z_n^f l^f(\mathbf{z}) D^f(\mathbf{z}) \right] \mathrm{d}F(\mathbf{z}) + \\ & N_{\text{single}} \int z_n^s l^s(g, \mathbf{z}^s) D^s(g, \mathbf{z}^s) \mathrm{d}F^{\text{single}}(g, \mathbf{z}^s) + N_{\text{urban}}(l_{\text{urban}}^m + l_{\text{urban}}^f)\bar{z}. \end{aligned} \tag{2}$$

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.

The aggregate revenue from gender-specific taxes is given by

$$
\begin{aligned}
T = \sum_g \tau^g \Bigg[& N_{\text{married}} \int \left(w_n z_n^g l^g(\mathbf{z}) D^g(\mathbf{z}) + w_a z_a^g l^g(\mathbf{z})(1 - D^g(\mathbf{z})) \right) \mathrm{d}F(\mathbf{z}) \\
& + N_{\text{single}} \int \left(w_n z_n^s l^s(g, \mathbf{z}^s) D^s(g, \mathbf{z}^s) + w_a z_a^s l^s(g, \mathbf{z}^s)(1 - D^s(g, \mathbf{z}^s)) \right) \mathrm{d}F^{\text{single}}(g, \mathbf{z}^s) \\
& + N_{\text{urban}} w_n \bar{z} l^g_{\text{urban}} \Bigg].
\end{aligned}
\tag{3}
$$

We assume for simplicity that this aggregate tax revenue is spent on the non-agricultural good.

Agricultural goods market clearing is given by

$$
N_{\text{married}} \int c_a(\mathbf{z}) \mathrm{d}F(\mathbf{z}) + N_{\text{single}} \int c_a^s(g, \mathbf{z}^s) \mathrm{d}F^{\text{single}}(g, \mathbf{z}^s) + N_{\text{urban}} c_a^{\text{urban}} = Y_a = A_a L_a \tag{4}
$$

and non-agricultural goods market clearing is given by

$$
N_{\text{married}} \int c_n(\mathbf{z}) \mathrm{d}F(\mathbf{z}) + N_{\text{single}} \int c_n^s(g, \mathbf{z}^s) \mathrm{d}F^{\text{single}}(g, \mathbf{z}^s) + N_{\text{urban}} c_n^{\text{urban}} + T = Y_n = A_n L_n. \tag{5}
$$

The competitive equilibrium of this economy is defined as follows:

Definition 1. *A competitive equilibrium consists 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^m_{urban}, h^m_{urban}, l^f_{urban}, $h^f_{urban}\}$ *for urban households; firm quantities* Y_a, Y_n, L_a, *and* L_n; *tax revenue* T; *and prices* p, w_a, *and* 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 (1), (2), (4), and (5).*

3.5 The Mechanism: Entry Barriers and Within-Household Specialization

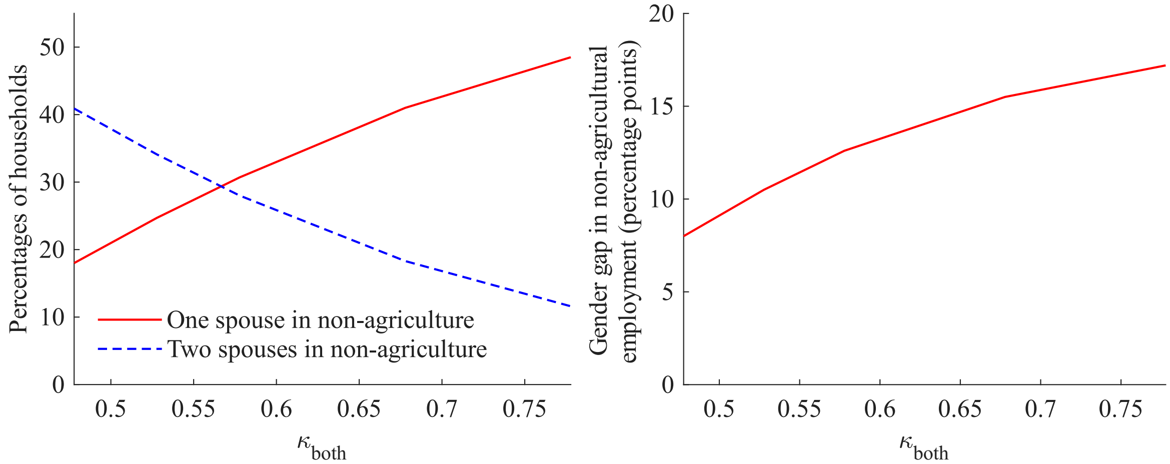
Our framework features only two sources of gender asymmetry: differences in home production efficiency and implicit labor market wedges. Importantly, both are modeled as strictly sector-neutral. Yet, as our quantitative analysis demonstrates, the model endogenously generates a substantial gender gap in non-agricultural employment. The core mechanism is driven by the fixed utility costs of entering the non-agricultural sector. These entry barriers interact with within-household specialization to transform sector-neutral frictions into *de facto* sector-biased outcomes.

Because entering the non-agricultural sector carries a fixed utility cost, making this sectoral shift is only optimal if an individual intends to supply a sufficiently large number of market hours.[13] Within-household specialization heavily amplifies this non-convexity. Given that married women are more efficient in home production and face larger labor market wedges, comparative advantage leads the household to allocate the husband to market work while the wife handles most of the home production. As a result, married women have a smaller residual time endowment available for the market, making them far less likely to overcome the fixed cost required to work in the non-agricultural sector.

Comparing the comparative statics of the two entry costs illustrates this mechanism. Consider an increase in the joint entry cost, κ_{both}, which penalizes joint non-agricultural participation. As κ_{both} rises, it breaks the arrangements of joint non-agricultural participation, forcing marginal households to divide their labor across sectors. As shown in the left panel of Figure 1, households increasingly opt to send only one spouse into the non-agricultural sector. Because comparative advantage keeps the wife in the agricultural sector (where she can more flexibly accommodate home production), this non-agricultural worker

[13] In our quantitative analysis, we provide external validation for our estimated entry barriers by analyzing regional variations in public services and *hukou* restrictions. Also, our results remain quantitatively similar under alternative mechanisms that generate labor supply non-linearities, such as increasing returns to market hours as in Erosa et al. (2022).

Figure 1: The Effects of Entry Costs on Sectoral Choices and the Gender Gap



Note: The left panel shows the percentages of households with one and two members working in the non-agricultural sector when varying the cost associated with joint non-agricultural participation (κ_{both}). The right panel shows the resulting gender gap in non-agricultural employment. All parameters, except for κ_{both}, are set to their baseline calibration values as explained in Section 4.

is more likely the husband. Therefore, a higher joint entry cost disproportionately forces women out of non-agriculture, significantly widening the gender gap in non-agricultural employment (right panel of Figure 1).

This feature is particularly relevant in the Chinese context. The *hukou* system severely restricts rural migrant households' access to urban public services, creating a high κ_{both} that makes it difficult for both spouses to relocate and work in the non-agricultural sector together. By contrast, an increase in the individual entry cost (κ_{one}) heavily penalizes split-sector households. A higher κ_{one} pushes marginal households to abandon this split-sector arrangement—either by reverting completely to agriculture or by paying the joint cost to move both members into non-agriculture. Both margins operate to compress the gender gap. In Section 5.3, we further quantify the role of these specific entry barriers in driving the evolution of China's sectoral gender gap between 2000 and 2010.

4 Calibration

We calibrate the model to China in the baseline year 2010, when we observe rich micro data on rural household labor supply. We draw on four datasets: the China Migrants Dynamic Survey (CMDS, National Health Commission of China, 2018), the Urban Household Survey (UHS, National Bureau of Statistics of China, 2015), the China Population Census (CPS, National Bureau of Statistics of China, 2010), and the National Fixed Point Survey (NFPS, Research Center for Rural Economy, Ministry of Agriculture (China), 2016). Appendix A provides detailed descriptions and the construction of the empirical moments. We later use the calibrated economy to quantify the gender gap in non-agricultural employment and to study its evolution over time.

4.1 Parameterization

We begin by specifying the ability distribution of married rural households, $F(\mathbf{z})$. Following Adamopoulos et al. (2024), we model individual non-agricultural ability (omitting the gender superscript g for brevity) as the sum of a household component and an idiosyncratic component:

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

where z_n^H is common to both spouses and z_n^I is individual-specific. The common component induces correlation in spouses' non-agricultural abilities, capturing forces such as assortative matching, shared human-capital accumulation, or correlated endowments.

Agricultural ability is given by

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

where z_a^H and z_a^I are household and individual components, and λ governs within-individual correlation between agricultural and non-agricultural abilities. We assume z_n^H, z_a^H, z_n^I, and

z_a^I are log-normal with mean zero and standard deviations σ_n, σ_a, $\psi\sigma_n$, and $\psi\sigma_a$, respectively, where ψ controls the relative importance of individual versus household components.

For single rural households, we use the same parameterization but simulate one individual per household.

This specification implies identical ability distributions for married men and women, and it also imposes that single rural individuals draw from the same distributions as married individuals. We assess the validity of these assumptions in Sections 6.1, 6.2, and 6.3, as well as Appendices D.6 and D.7.

4.2 Parameters and Moments

In total, the calibration involves 23 parameters: 3 governing household measures $\{N_{\text{married}}, N_{\text{single}}, N_{\text{urban}}\}$; 6 preference parameters $\{\omega, \gamma, \eta, B, \theta, \chi\}$; 2 technology parameters $\{A_a, A_n\}$; 7 parameters governing abilities $\{\sigma_n, \sigma_a, \psi, \lambda, z_h^m, z_h^f, \bar{z}\}$; 3 entry-barrier parameters $\{\kappa_{\text{one}}, \kappa_{\text{both}}, \kappa_{\text{single}}\}$; and 2 gender-specific distortion (tax) parameters $\{\tau^m, \tau^f\}$.

4.2.1 Individually Calibrated Parameters

We determine 10 parameters outside the equilibrium. For household measures, we normalize $N_{\text{married}} = 1$ and set $N_{\text{single}} = 0.717$ so that $0.717/(0.717+2) = 26.4$ percent of rural working-age individuals are single in 2010. We set $N_{\text{urban}} = 0.537$ so that urban non-agricultural workers account for $0.537 \times 2/(2 + 0.717 + 0.537 \times 2) = 28.4$ percent of the working-age population.

For preferences, we follow Alder et al. (2022) and Hao et al. (2020) and set the income elasticity of agricultural good demand η to 0.7 and the price elasticity γ to 0.3. We also set $\chi = -1$, which implies that home production enters utility in logarithmic form.

We further normalize sectoral productivities A_a and A_n and female home-production productivity z_h^f to one.[14] Finally, we impose revenue neutrality of the gender-specific implicit

[14]In principle, the levels of agricultural and non-agricultural productivities (A_a and A_n) represent relative

taxes ($T = 0$): once τ^m is chosen, τ^f is pinned down by Equation (3).

4.2.2 Jointly Calibrated Parameters

We then have 13 parameters left to be estimated jointly so that model-generated moments for key variables match empirical counterparts. Although the parameters are jointly determined, some moments are more relevant for identifying key parameters.

Gender Differences. We discipline two key parameters governing gender differences: male home-production productivity z_h^m and the implicit tax rate on males τ^m. Following Hsieh et al. (2019) and Adamopoulos et al. (2024), we use a quantity moment (the female–male ratio of home production hours) together with a price moment (the gender wage gap in non-agriculture) to separately identify productivity (z_h^m) and distortions (τ^m). The intuition is that z_h^m and τ^m affect home production hours in the same direction but imply opposite movements in the gender wage gap. A higher τ^m reduces the after-tax return to male market work and tends to compress the gender wage gap, whereas a higher z_h^m draws men into home production, strengthens selection among male non-agricultural workers, and therefore tends to increase average male wages in Roy-type models. We choose z_h^m and τ^m to match a 3.33-fold female–male gap in home production hours among rural households and an 11.5 percent gender wage gap among rural non-agricultural workers. Appendix D.4 shows that both parameters are needed: shutting down either channel prevents the calibrated model from jointly matching these moments and the observed gender gap in non-agricultural employment.

TFP between the two sectors. They also reflect the units we use to measure the output of these two sectors. For instance, A_a differs depending on whether we measure the agricultural output by one unit or by 1000 units. It is therefore without loss of generality to normalize both A_a and A_n to one, which is also a common practice in the literature; see for instance Herrendorf et al. (2020). Technically, one can rescale, say, A_a by an arbitrary $x > 0$ units and adjust the parameters of the preferences accordingly such that the equilibrium allocations are invariant.

Rural Ability Distribution. We calibrate four parameters governing the ability distribution of rural married households, $\{\sigma_n, \sigma_a, \psi, \lambda\}$. The dispersion of non-agricultural ability and the degree of within-household correlation are governed by σ_n and ψ, respectively. We therefore choose σ_n and ψ to match the standard deviation of log non-agricultural wages (0.441) and the within-household Spearman rank correlation of spouses' non-agricultural wages (0.542).[15] Because agricultural income is observed only at the household level, we use the standard deviation of log agricultural labor supply (0.312) to identify σ_a, the dispersion in agricultural ability. Finally, we discipline λ by setting the Spearman rank correlation between the two sectoral abilities, z_a and z_n, to 0.35, following Lagakos and Waugh (2013). Section 6.1 shows that our results are not sensitive to this correlation.

Entry Barriers. We calibrate three parameters of fixed entry barriers to non-agricultural work, $\{\kappa_{\text{one}}, \kappa_{\text{both}}, \kappa_{\text{single}}\}$. These parameters are chosen to match three equilibrium moments: (i) 28.0 percent of rural married households have both members in non-agriculture; (ii) 30.7 percent have exactly one member in non-agriculture; and (iii) 65.3 percent of single rural individuals work in non-agriculture. Together, these targets pin down the overall extent of rural labor reallocation away from agriculture. Importantly, we do not directly target the gender difference in non-agricultural employment.

Preferences and Urban Ability. We finally calibrate the remaining four parameters, $\{\omega, B, \bar{z}, \theta\}$. The weight on home production, ω, is chosen to match the time allocation between market work and home production (market work accounts for 71.8 percent of the time endowment). We choose B, the shifter in agricultural good demand, to match the agricultural value-added share of 10.1 percent in 2010.[16] We discipline urban relative ability,

[15] 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.

[16] 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).

$\bar{z}$, so that the average wage of urban households is 29.3 percent higher than that of rural non-agricultural households (Xing, 2008). The substitution parameter θ governs how easily male and female hours substitute in home production and thereby shapes within-household specialization; we set it to match a Hicksian labor supply elasticity of 0.46 for rural married men (Prescott, 2004).[17]

To summarize, 10 parameters are either normalized or set to exogenous values, while the remaining 13 parameters are jointly calibrated by matching equilibrium model moments with data moments. Table 4 summarizes the values of parameters, and Table 5 compares model and data moments.

4.3 Interpretation and Validation of Calibration Results

Interpreting the Calibration Results. Our calibration implies that women are more efficient in home production than men ($z_h^m < z_h^f$). This difference may reflect comparative advantage in home activities and/or the influence of traditional social norms. We also find that women face larger labor market distortions than men ($\tau^f > \tau^m$), consistent with discrimination in the labor market. These distortions are sector-neutral. Appendix D.2 shows that if the distortions were sector-specific (e.g., applying only in non-agriculture), the model would predict a large gender gap in non-agricultural employment among single workers, counterfactually.

We also find a positive correlation of abilities between spouses, suggesting positive assortative matching in marriage. As shown in Section 6.2, this within-household correlation is quantitatively important for equilibrium allocations, and our calibrated value is plausible. In particular, the model-implied correlation is close to the correlation of spouses' educational

[17] 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.

Table 4: Model Parameters and Values

Parameter	Value	Description
(a) Normalized or Set to Exogenous Values		
A_a	1	TFP of the agricultural sector (normalization)
A_n	1	TFP of the non-agricultural sector (normalization)
γ	0.3	Price elasticity of agricultural good demand (Hao et al., 2020)
η	0.7	Income elasticity of agricultural good demand (Hao et al., 2020)
χ	-1	Curvature of home production
z_h^f	1	Female productivity in home production (normalization)
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
(b) Jointly Calibrated		
B	0.333	Level 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_{one}	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
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
$\bar{z}$	1.757	Ability of urban households
τ^m	-0.096	Implicit tax rate on males
τ^f	0.117	Implicit tax rate on females

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

Table 5: Targeted Moments, Data and Model

Moments	Data	Model
Agricultural employment share	0.367	0.364
Agricultural value-added share	0.101	0.104
% of rural married households with		
one member working in non-agr.	0.307	0.307
two members working in non-agr.	0.280	0.280
% of singles working in non-agr.	0.653	0.654
Wage dispersion, agr.	0.312	0.313
Wage dispersion, non-agr.	0.441	0.442
Within-household correlation of non-agr. wage	0.542	0.542
Correlation of agr. and non-agr. ability	0.350	0.350
Time spent on market production	0.718	0.717
Home production time, female/male	3.333	3.333
Wage gap, urban versus rural non-agr. workers	0.293	0.293
Gender wage gap in non-agr.	0.115	0.114
Root Mean Square Error	0.001	

Note: Reporting the 13 moments targeted in the data and the corresponding model moments.

attainment in the data.

Fixed costs of entering non-agriculture ($\kappa_{\text{one}}, \kappa_{\text{both}}, \kappa_{\text{single}}$) play a central role in the model, so it is useful to interpret their magnitudes. Because these costs are expressed in utility units, we translate them into consumption-equivalent income losses: We compute the income needed to purchase market consumption such that a household is indifferent between forgoing that consumption and paying the entry cost.

Under this metric, the cost for both spouses to work in non-agriculture is $\kappa_{\text{both}} = 0.578$, equivalent to 23.0 percent of median household income. The cost for exactly one spouse to work in non-agriculture is $\kappa_{\text{one}} = 0.393$, equivalent to 13.2 percent of median household income. For singles, $\kappa_{\text{single}} = 0.142$ is equivalent to 6.5 percent of median single income.

As expected, these cost estimates are inversely related to the corresponding entry patterns in the data. We further provide evidence supporting the plausibility of our estimate for κ_{both}—a key parameter for married couples that is naturally linked to access to public services—by exploiting regional variation within China. As described in Appendix E, we estimate entry costs separately by province and regress the province-level κ_{both} estimates on observed characteristics capturing public service provision. Consistent with our interpretation, κ_{both} is lower in provinces with greater public service provision (e.g., higher kindergarten enrollment, more school teachers, and more medical visits per capita), lower transportation costs, or less restrictive *hukou* policies.

Untargeted Moments. Although not explicitly targeted, the calibrated model implies a reasonable decomposition of labor supply elasticity: the substitution elasticity is 0.32 and the income elasticity is -0.14, close to estimates in the literature (McClelland and Mok, 2012). The model also reproduces the well-known pattern that labor supply is more elastic for married women than for married men (Hicksian elasticities of 1.11 versus 0.46), consistent with Blundell et al. (2016). In the model, this difference emerges endogenously from within-family specialization; we do not impose gender differences in the disutility of work.

The model also matches labor force participation reasonably well. In the data, 88.3 percent of rural married households have both members working, while 11.7 percent have only one member working.[18] In the calibrated economy, the corresponding shares are 91.8 and 8.2 percent. Moreover, conditional on only one spouse working, the data show that it is typically the husband (86.5 percent versus 13.5 percent for wives); the model closely matches this pattern (85.3 versus 14.7 percent).[19]

Our model is also consistent with the data that non-agricultural workers on average work more than agricultural workers. In our model, among rural married households, those who work in the non-agricultural sector on average work 59 percent more than those in agriculture. We observe similar difference in the data (67 percent). Recall that individuals endogenously work more in the non-agricultural sector due to the fixed utility cost of working in non-

[18] 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.

[19] Alternatively, we could introduce a utility cost of labor supply and calibrate it to exactly match participation. We choose not to do so in order to keep the focus on sectoral choice, given that the implied participation in the baseline model is already close to the data and participation in agriculture can be measured noisily.

agriculture. Hence, the fact that our model replicates the sectoral difference in labor hours without explicitly targeting it suggests that our calibrated fixed costs ($\kappa_{\text{one}}, \kappa_{\text{both}}, \kappa_{\text{single}}$) are reasonable. As a side note, this labor hour difference is one of the causes of the large nominal agricultural productivity gap we observed in many developing countries, where nominal output per worker is higher in the non-agricultural sector than in agriculture (Gollin et al., 2004, 2014b). As a result, our model also helps explain some of the observed nominal agricultural productivity gap.

External Validation Using Reduced-Form Results. Public services—such as publicly provided childcare—can substitute for home production and thus affect the gender gap in sectoral choices. Recall that in Section 2 we use a triple-difference estimator and find that access to kindergartens raises non-agricultural employment by 3.7 percentage points for women with children. We assess the model's prediction along this margin as an external validation.

We extend the baseline model by allowing home production to combine private time inputs and public services. Let c_p denote public services. Home production for rural married households becomes

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

where ρ is the elasticity of substitution between private home production and public services. We set $\rho = 2$, implying that public services are less substitutable than spouses' time inputs (given $\theta = 4.0$).

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.[20] Hence, we choose c_p such that home

[20]The data set we use in Section 2, the National Fixed Point Survey, does not provide information on

production is also reduced by 8 percent for rural married women compared to single women in our model, holding prices and wages constant since the empirical results from policy variations reflect partial equilibrium outcome (Caunedo and Kala, 2021; Brooks et al., 2023). This implies $c_p = 0.033$.

We then feed c_p into our baseline economy again holding prices and wages constant. We find that such public services increase non-agricultural employment by 3.0 percentage points for married women, only half a standard error different from the 3.7 percentage points in the data. This implies that our model reasonably captures the elasticity between home production hours and non-agricultural employment.

5 Quantitative Analysis

In this section, we use our calibrated model to study the sources and mechanisms driving the gender gap in non-agricultural employment, as well as its evolution over time. We first quantify the relative contributions of gender differences in home production efficiency and labor market distortions to this observed gap. We then assess the amplifying role of within-family specialization by comparing the benchmark economy to an otherwise identical environment where workers make labor supply and sectoral choices in isolation. Finally, we re-calibrate the model to the year 2000 and investigate which changes between 2000 and 2010 drive the widening of this disparity.

5.1 Explaining the Gender Gap in Sectoral Choices

We start by accounting for the observed gender gap in non-agricultural employment in the baseline year of 2010. Table 6 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 in the non-agricultural sector, a moment our model targets in calibration. Among

home production hours.

Table 6: 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.

these 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 gap of 12.4 percentage points. Without explicitly targeting this moment in calibration, our model generates a gender gap of 12.6 percentage points, close to the data.[21]

In our model, married men and women differ in home production efficiency and in labor market distortions. We can further quantify the relative importance of these two factors in explaining 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 baseline 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 (up from 14 percent in the baseline economy), while women would spend 38 percent (down from 43 percent). As a

[21] In Appendix F.2, we show that a re-calibrated model successfully explains the observed gender gap for Sub-Saharan countries but not for Latin American countries. This suggests that the modeled 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 7: The Importance of Home Production Efficiency Vs. Labor Wedges

	Baseline (1)	Same efficiency ($z^h_m = z^h_f$) (2)	No labor wedges ($\tau_m = \tau_f = 0$) (3)	(2) + (3) (4)
Home production time				
male	0.14	0.18	0.21	0.27
female	0.43	0.38	0.32	0.27
Gender gap (p.p.)	12.6	10.4	2.9	0.0
Household income from female (%)	38.1	40.1	47.6	50.0
Real GDP per capita ($\Delta, \%$)	–	+0.4	+1.3	+1.4

Notes: This table shows model moments in our baseline economy (column 1), and in the decomposition exercises where we shut down the gender differences in home production efficiency (column 2), labor market distortions (column 3), and both (column 4).

result, the gender gap in non-agricultural employment falls from 12.6 to 10.4 percentage points, see Column (2) of Table 7.

Next, we eliminate labor market frictions by setting $\tau^m = \tau^f = 0$, which is also the average of their baseline levels. The gender employment gap shrinks from 12.6 percentage points to 2.9 percentage points, as in Column (3) of Table 7. Hence, the gender differences in home production efficiency and labor market frictions account for 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, as displayed in the last column of Table 7.[22]

The above gender differences also play a significant role in explaining the gender income gap. In our baseline economy, married women contribute an average of 38.1 percent to household income. If we eliminate labor market wedges, this share rises to 47.6 percent. Real GDP per capita, measured as a chain-weighted quantity index, increases by 1.3 percent. We obtain smaller changes if we shut down the gender differences in home production efficiency.

[22]While the above decomposition holds the baseline parameters constant, one might ask whether both frictions are strictly required if the model is allowed to re-calibrate. As we detail in Appendix D.4, either of these two ingredients alone can qualitatively generate a gender gap in non-agricultural employment. Both are necessary, however, for the model to perform quantitatively well and to jointly match key moments such as the gender wage gap and the large gender differences in home production time.

Given that gender-specific labor wedges explain about 80 percent of the non-agricultural employment gap, mitigating these frictions is paramount for fostering structural transformation and narrowing the gender income gap. In our framework, these sector-neutral wedges broadly capture implicit barriers such as wage discrimination, unequal hiring practices, or a lack of family-friendly workplace accommodations. While expanding public services like kindergartens effectively reduces the home production burden, our model predicts that policies directly targeting the labor market—such as enforcing anti-discrimination laws and ensuring equal pay—would yield substantially larger reductions in both the gender employment gap and the broader gender income gap.

5.2 The Role of Within-Household Specialization

Our framework allows married individuals to make joint decisions over consumption and labor supply, which endogenously generates within-household specialization. To isolate the role of specialization, we conduct an experiment in which we break up all married couples so that all workers are "single": They choose consumption, labor supply, and sectoral employment to maximize individual utility. We then re-calibrate this alternative model and evaluate how its key predictions differ from those of the benchmark economy.[23]

This alternative model falls short of generating the observed gender gap in non-agricultural employment. Note that here we compute the gender difference between men and women in the aggregate, rather than among married, since all individuals are "single." In the data, pooling married and single rural individuals, 53.6 percent of men and 45.3 percent of women work in the non-agricultural sector, implying an overall gap of 8.4 percentage points. This alternative model predicts a gap of only 4.7 percentage points. Matching the observed gap in this environment would require a counterfactually large gender wage gap (about 70% larger than in the data). Moreover, this alternative model also generates counterfactually small gender differences in home production hours: women spend only 1.21 times as much time

[23]In particular, we modify the parameterization of the ability distribution by removing the component common to both spouses. Details are provided in Appendix D.3.

on home production as men, compared to a 3.33-fold difference in the data.

Importantly, the two frameworks imply different determinants of occupational choice, especially for women. In the alternative model, a woman primarily chooses her sector based on whether she has a comparative advantage in non-agriculture, i.e., whether her (after-tax) wage is higher in non-agriculture: $w_n z_n^f (1 - \tau^f) > w_a z_a^f$. Everything else being equal, such women are more likely to work in non-agriculture. In the alternative model, 55.7 percent of women with a comparative advantage in non-agriculture pay the entry cost and work in the non-agricultural sector.

In the benchmark model with within-family specialization, the sectoral choice of a married woman depends not only on her own abilities but also on her husband's abilities (in particular, her non-agricultural ability relative to his). As a result, only 45.4 percent of women with a comparative advantage in non-agriculture end up working in non-agriculture. Put differently, a sizable fraction of married women optimally remain in agriculture (or out of the labor force) to maximize household utility despite having a comparative advantage in non-agriculture.

5.3 Gender Gap Changes Over Time, 2000–2010

Section 5.1 shows that the calibrated model can account for the observed gender gap in non-agricultural employment in China in 2010, the baseline year of our calibration. Despite China's rapid structural transformation, the gender gap in non-agricultural employment widened over time (Cao et al., 2024). Among rural married households, the gap increased from 6.9 percentage points in 2000 to 12.4 percentage points in 2010. This pattern contrasts with the cross-country evidence in Lee (2024), which finds that gender gaps tend to decline with economic development. Following the methodology of Adamopoulos et al. (2024), we use our framework to investigate the drivers of this change.

We begin by re-calibrating a subset of key parameters to match data moments from 2000, including population measures, sectoral productivity levels, fixed entry costs of working in non-agriculture, and the two gender differences in our model (home production efficiency and labor market distortions). Details are provided in Appendix A.2. Without targeting the married gender gap in non-agricultural employment, the re-calibrated model implies a gap of 7.2 percentage points in 2000, close to 6.9 percentage points in the data. Thus, the gender differences in home production efficiency and labor market distortions again explain almost the entire gender gap in non-agricultural employment in the 2000 economy.

Next, we decompose the changes in the gender gap by reverting 2010 parameters to their 2000 levels one group at a time. This allows us to isolate the individual channels influencing sectoral choice. We begin by assessing the role of fixed entry costs, setting κ_{one}, κ_{both}, and κ_{single} to their 2000 levels. As shown in the second column of Table 8, this leads to a substantial increase in households where both members work in the non-agricultural sector relative to those where only one spouse—typically the husband—works in the non-agricultural sector. Under this counterfactual, the gender gap in non-agricultural employment shrinks from 12.6 to 6.8 percentage points. This indicates that fixed entry costs are a primary driver of the exacerbating gender gap in non-agricultural employment in China.

Importantly, the estimated κ_{one} declines over time, while the estimated κ_{both} remains largely unchanged (details in Appendix A.2). 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, 2014; Chan, 2019).[24] Local governments were keen on having migrant workers but were not so keen on encouraging them to bring their families along and settle down.

[24] Tian (2024) also 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.

Table 8: 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_{one}, 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.

We also assess the role of relative home production efficiency by setting z_h^m to its 2000 level while holding female efficiency constant. As shown in Table 8 (column 3), this has a limited effect on the gender gap, reflecting the fact that the relative efficiency between genders remained stable over the decade. Finally, we revert labor market distortions (τ^f, τ^m) to their 2000 levels. While the share of households with exactly one spouse in non-agriculture stays nearly constant, the composition shifts toward the male-only pattern, as women faced substantially higher distortions (τ^f) in 2000. Consequently, the gender gap would have been 1.4 percentage points wider (14.0% vs. 12.6%) had these distortions not diminished over time.

In conclusion, the widening of the Chinese gender gap in non-agricultural employment between 2000 and 2010 is mainly due to the fixed entry costs 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.

6 Sensitivity Analysis

This section examines how sensitive our quantitative results are to alternative parameter choices and modeling assumptions, with a focus on the model-implied gender gap in non-agricultural employment. We consider three exercises that vary how we parameterize the joint distribution of abilities within rural married households (across sectors and across spouses). We then discuss the empirical relevance of rural non-agricultural job opportunities in China and why fixed entry costs remain a plausible friction in our setting.[25]

6.1 Correlation of Abilities between Sectors

In the baseline calibration, we set the rank correlation between agricultural and non-agricultural abilities (z_a and z_n) to 0.35 (implying $\lambda = 0.21$), consistent with estimates in the structural-transformation literature (Lagakos and Waugh, 2013; Adamopoulos et al., 2024).[26] To assess the quantitative role of this parameter, we vary λ around the baseline by setting it to 0.15 and 0.42, which imply correlations of 0.25 and 0.65, respectively. For each value, we recalibrate the remaining parameters to match the same set of moments; Appendix Table 12 reports the resulting parameters. The implied gender gaps in non-agricultural employment are 12.7 and 13.0 percentage points, close to the 12.6 percentage points in the baseline. We conclude that our main quantitative results are not sensitive to the assumed correlation between z_a and z_n.

[25] Appendix D contains additional sensitivity analysis.

[26] Recent work identifies this correlation using individuals who switch between sectors (e.g. Hamory et al., 2021; Lagakos et al., 2020; Schoellman, 2020). For example, Alvarez-Cuadrado et al. (2025) find that high-ability farmers are more likely to move to non-agriculture, suggesting a strong positive association between the two ability dimensions and a larger dispersion of non-agricultural ability, or a negative correlation between comparative and absolute advantages in agriculture, as in our high correlation case here.

6.2 Correlation of Abilities between Spouses

In the baseline calibration, the within-couple correlation in abilities (disciplined by ψ) is positive, implying positive assortative matching (PAM) in marriage (Greenwood et al., 2014; Siow, 2015). The calibrated ψ implies a Spearman rank correlation of 0.56 for spouses' non-agricultural abilities (z_n^m and z_n^f) among rural married households. This magnitude is broadly consistent with the data: Using the China Health and Nutrition Survey (CHNS), we compute the rank correlation of years of schooling between rural couples (Chinese Center for Disease Control and Prevention, 2010). The correlation is 0.54 in 2000 and 0.60 in 2010, and the model-implied value (0.56) lies perfectly within this range if education is a reasonable proxy for non-agricultural ability.

To assess sensitivity, we consider an extreme case with no PAM, so that spouses' abilities are independent. Operationally, we eliminate the household components z_a^H and z_n^H and recalibrate the model to the same moments as in the baseline, except for the within-couple wage correlation that pins down ψ. Appendix Table 12 reports the resulting parameters. Even without PAM, the model generates a non-trivial gender gap in non-agricultural employment (7.9 percentage points), though smaller than the 12.4 percentage points in the data.

Two implications follow. First, sector-neutral forces in our model can generate a sizable gender gap even absent PAM. Second, PAM is quantitatively important for matching the full magnitude of the gap. This mechanism operates through the calibration of the fixed entry costs, κ_{one} and κ_{both}. Because PAM strongly aligns spouses' comparative advantages, a large share of households would naturally prefer both members to work in the non-agricultural sector absent any frictions. In the data, however, "split" arrangements (where only one spouse enters non-agriculture, 30.7 percent) actually outnumber "joint" arrangements (28.0 percent). To match this reality and push against the strong gravitational pull of assortative matching, the calibration strictly requires a substantially higher joint cost (κ_{both}) relative to the individual cost (κ_{one}). As we discuss in Section 3.5, this large κ_{both} effectively deters women—who already face a heavier burden of home production—from joining their husbands in the non-agricultural sector, thereby substantially widening the gender employment gap among married individuals.

6.3 Comparative Advantage between Genders

While our model allows for rich correlation patterns across sectors and across spouses, we impose one simplifying restriction in the baseline: comparative advantage in non-agriculture relative to agriculture is symmetric across genders. We cannot separately identify gender-specific comparative advantage using wage and employment data alone (as in Lee (2024)) because sectoral choices are made jointly within the household. The literature often argues that women have a comparative advantage in non-agriculture, especially in services that are more "brain"-intensive than "brawn"-intensive (Lagakos and Waugh, 2013; Ngai and Petrongolo, 2017; Autor et al., 2019; Feng et al., 2024; Rendall, 2025). In China, however, rural non-agricultural employment is heavily concentrated in manufacturing, while the service sector is relatively under-developed (Fang and Herrendorf, 2021).[27] It is therefore less clear a priori whether women have an overall comparative advantage in non-agriculture in this specific context (Cao et al., 2024).

To explore the quantitative implications of gender-specific comparative advantage, we consider a structural extension that allows women to be relatively more productive in non-agriculture. To discipline the magnitude of this parameter, we exploit differences in sectoral employment patterns between single men and women. In the data, single women are slightly more likely to work in non-agriculture than single men—an empirical pattern that our baseline model cannot fully rationalize. We adjust this data moment to explicitly purge away single individuals who migrate and work in the non-agricultural sector primarily for marriage purposes (Koh et al., 2025). After adjustment, we attribute the residual gap among singles entirely to women's comparative advantage in non-agriculture, and re-calibrate the

[27] Around 60 percent of rural individuals who work in the non-agricultural sector work in manufacturing.

remaining parameters to match the same set of data moments. This approach implies that the female-to-male mean productivity ratio in the non-agricultural sector is 1.11 times that in agriculture.[28] Reassuringly, even when incorporating this estimate, the core quantitative mechanism remains robust: the model still generates a substantial 9.9 percentage point gender gap in non-agricultural employment among married individuals, compared with 12.6 percentage points in the baseline. Further details are provided in Appendix D.5.

Finally, allowing for absolute advantage (e.g., men being more productive in both sectors in levels, as in Lee (2024)) does not affect the main quantitative conclusions once the model is re-calibrated. In our framework, absolute advantage and sector-neutral labor wedges are observationally similar in how they map into sectoral employment gaps.

6.4 Rural Non-Agricultural Employment Opportunities

A substantial amount of non-agricultural activity in developing countries takes place in rural areas (Alvarez-Cuadrado et al., 2025). China also has a significant rural non-agricultural sector, with *township and village enterprises* serving as prominent employers and key drivers of post-1978 manufacturing growth (Brandt and Zhu, 2010). Our model does not distinguish rural from urban non-agricultural jobs. A natural concern is that if rural workers can easily access local, informal non-agricultural work (e.g., small-scale trading within the village), they may avoid the fixed costs (search, inflexibility, and migration) emphasized in our framework. We argue that, in the Chinese context, most rural non-agricultural employment is highly formalized and spatially dispersed, making it unlikely to circumvent these costs.

First, most rural non-agricultural workers are employed away from home. Using NFPS data, we document that in 2010, 63.6 percent of rural individuals in the non-agricultural sector worked outside their own towns, and 53.8 percent worked outside their home counties.

[28] This identifying assumption likely provides an upper bound for married women's comparative advantage. As we document in Appendix D.7, the gender gap in educational attainment is significantly wider among married couples than among single workers, with married women being the least educated group overall. If education is associated with a comparative advantage in non-agriculture, then the true comparative advantage for married women is likely lower than what we infer from single women.

Thus, a vast majority of non-agricultural employment necessitates commuting or temporary migration, consistent with significant spatial separation and relocation costs.

Second, the informal sector in China is exceptionally small compared to other developing countries; according to the World Bank, it contributed only 10.8 percent of China's GDP in 2010, well below the 30.7 percent average across 156 countries (Elgin et al., 2021). Even for the rural non-agricultural jobs located within their hometowns, the majority of workers (58.5 percent) are employed in manufacturing through township and village enterprises, which typically entail formal wage work with rigid schedules.[29] This contrasts sharply with patterns in other developing regions where informal, highly flexible non-agricultural jobs (e.g., selling goods from home or roadside food processing) are prevalent. We view this loss of flexibility as another core component of the fixed entry costs.[30]

7 Conclusion

This paper studies how home production and within-household specialization shape gender differences during structural transformation. Using Chinese microdata, we document that the non-agricultural employment gap is overwhelmingly concentrated among rural married workers. Specifically, married women devote substantially more time to home production and are far less likely to enter the non-agricultural sector than married men. We further show that home production demands constrain sectoral choices: the presence of young children reduces married women's non-agricultural employment, while access to local childcare (kindergartens) narrows this gender gap.

Motivated by these facts, we develop a general equilibrium Roy model featuring joint

[29] Adamopoulos et al. (2024) report that 17.4 percent of rural individuals in China work in both sectors, yet these individuals do not divide their time evenly; on average, 80 percent of their labor days are dedicated to non-agriculture, a pattern consistent with other countries (Gollin et al., 2014b). This highly skewed time allocation suggests that these "mixed" workers are likely seasonal migrants who return to farming during brief planting or harvesting seasons, rather than individuals flexibly mixing daily tasks. See Appendix A for details.

[30] A similar point is made by Bick et al. (2022), who highlight higher fixed costs as the primary distinction between formal wage work and self-employment.

household decision-making, sector-neutral gender labor wedges, and fixed entry barriers to non-agriculture. In our framework, fixed entry costs make non-agricultural work viable only for individuals supplying sufficient market hours. Consequently, within-household specialization amplifies baseline gender wedges into large sectoral disparities by reducing married women's market hours, thereby discouraging their entry into non-agriculture. Calibrated to China in 2010, the model successfully reproduces the untargeted gender gap among rural married workers. Our decomposition reveals that gender-specific labor wedges account for roughly 80 percent of this gap. The model also attributes the widening of this disparity between 2000 and 2010 to changes in the relative costs of having one versus both spouses entering non-agriculture.

More broadly, our results highlight that gender-specific labor market frictions, home production burdens, and the effective costs of accessing non-agricultural jobs are central to understanding gender disparities during structural change. Given that our quantitative analysis identifies implicit labor wedges as the main driver of the sectoral employment gap, policies directly targeting labor market discrimination and unequal pay emerge as the primary levers for closing the broader gender income gap. At the household level, lowering fixed entry costs is essential to enable both spouses to enter the non-agricultural sector. These entry costs are often inflated by institutional barriers to public services—such as China's *hukou* system—making their reduction essential for an inclusive structural transformation.

At the same time, certain features prevalent in other developing countries fall outside our current framework, including widespread informal rural non-agricultural work and dual-sector employment. In addition, endogenous marriage and fertility choices may shape sectoral allocations differently for men and women (Koh et al., 2025). We view incorporating these margins, alongside richer measures of public service provision, as promising directions for future research.

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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 the log) 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 percent 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. Note that these labor days in agriculture do not include days spent on home production such as cooking or caring for household members. A piece of evidence is that, on average, rural individuals spent roughly 68 days on farms in a year. If farmers report home work as a part of their farm labor days, then the number of farm labor days should be close to 365 days a year.

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. 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.

Note that we pay special attention on distinguishing home production from agricultural production. The Time Use Survey separately records the time usage in production activities under the definition of *System of National Accounts* and non-SNA production activities. SNA production activities include formal and informal employment, self-employment, and home business, while non-SNA production activities include housework, caring household members, and community services. We classify time usage on SNA production activities as market work and that on non-SNA production activities as home production. The data set also records time usage in other categories, such as recreation and transportation. We do not include those hours as home production and hence our definition of home production differs from leisure.

Assigning Individuals to Sectors. We briefly explain how we assign an individual to a sector if an individual works in multiple sectors. In the China Population Census (National Bureau of Statistics of China, 2010), workers are classified based on their primary employment—specifically, the sector in which they spent the most labor days during the year. To understand how prevalent it is for rural individuals to engage in multiple sectors, we draw extra information from the micro data moments reported in Adamopoulos et al. (2024). For the year 2010, in total 17.4 percent of rural individuals in the labor force were engaged in both sectors, compared to 43.0 percent full-time in agriculture and 39.6 percent full-time in non-agriculture. Importantly, those individuals engaging in both sectors spend on average 80 percent of their labor days in non-agriculture, and roughly half of these individuals work in manufacturing jobs.

A.2 Moments on the 2000 Economy

We re-calibrate 9 parameters of our model ($A_a, A_n, \kappa_{\text{one}}, \kappa_{\text{both}}, \kappa_{\text{single}}, z_h^m, \tau^f, N_{\text{single}}, N_{\text{urban}}$) 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 $\kappa_{\text{one}}, \kappa_{\text{both}}, \kappa_{\text{single}}$ 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 as we do not have time use data available 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.

B Evidence on Home Production and Gender Gap

The National Fixed Point Survey (NFPS, Research Center for Rural Economy, Ministry of Agriculture (China), 2016) 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.[31] 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:

$$Nonag_{vit} = \beta \cdot Female_{vi} + \rho \cdot Controls + \varepsilon_{vit}, \tag{6}$$

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 affects the gender disparity in non-agricultural employment. We begin by examining the variation in home production demands arising from young children. 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

$$Nonag_{vit} = \beta \cdot Child_{vit} \cdot Female_{vi} + \gamma_f \cdot Female_{vi} + \gamma_c \cdot Child_{vit} + \rho \cdot Controls + \varepsilon_{vit}, \tag{7}$$

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-

[31] 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.

We also explore the variation in kindergarten availability to connect home production and non-agricultural employment. Kindergartens are the key childcare facilities in rural China, most of which are public and admit kids ranging from age 3 to 5 (inclusive). In our sample, the access to kindergarten varies across regions and over time.[32] In our data, kindergarten is available among 51.0 percent of village-year observations. There are 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

[32] 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:

$$
\begin{aligned}
Nonag_{vit} = & \beta \cdot KG_{vt} \cdot Female_{vi} \cdot Child_{vit} + \gamma_f Female_{vi} + \gamma_c Child_{vit} + \\
& \theta_{f,KG} \cdot Female_{vi} \cdot KG_{vt} + \theta_{f,c} \cdot Female_{vi} \cdot Child_{vit} + \theta_{KG,c} \cdot KG_{vt} \cdot Child_{vit} \\
& \rho \cdot Controls + \varepsilon_{vit},
\end{aligned} \tag{8}
$$

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 and 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.

C Characterization of the Model

We now briefly describe how to choose the variables related 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

$$
\max_{\{l^m, l^f, h^m, h^f, D^m, D^f\}} u(c_a, c_n) + \omega \frac{c_h^{1+\chi} - 1}{1+\chi} - \kappa,
$$

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

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

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

$$\kappa = \begin{cases} \kappa_{\text{one}} & \text{if } D^m = 1, D^f = 0 \text{ or } D^m = 0, D^f = 1; \\ \kappa_{\text{both}} & \text{if } D^m = 1 \text{ and } D^f = 1; \\ 0, & \text{otherwise .} \end{cases} \tag{9}$$

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 further assume that y is the household income. Given this income level, we solve the optimal consumption bundle (c_a, c_n) where the expenditure share on c_a is given by $B(1/y)^\eta p^\gamma$ as in Boppart (2014). Given this specification, the marginal utility associated with household income is simply $y^{\eta-1}$, and 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

$$h^m w^m (1-\tau^m) = \omega y^{1-\eta} \frac{z_h^m (h^m)^{\frac{\theta-1}{\theta}}}{\left(z_h^m (h^m)^{\frac{\theta-1}{\theta}} + z_h^f (h^f)^{\frac{\theta-1}{\theta}} \right)^{-(\chi+\frac{1}{\theta})\frac{\theta}{\theta-1}}}. \tag{10}$$

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 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 on 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

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

where $y(w^m, w^f) = w^m(1-\tau^m) l^m(w^m, w^f) + w^f(1-\tau^f) l^f(w^m, w^f)$. 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 (9) which determines κ. We then choose the combination of D^m and D^f to maximize utility.

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

$$h^s w^s = \omega y^{1-\eta} c_h^{\chi} (z_s^h)^{\frac{\theta}{\theta-1}}, \tag{11}$$

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.

D Quantitative Robustness and Model Extensions

In this section, we discuss several alternative specifications and calibration strategies to assess the sensitivity of our main results, i.e., how much our model explains for the observed gender gap in non-agricultural employment. For each specification, we discuss the re-calibration strategy, and the parameter values are reported in Table 12.

D.1 Alternative Preferences: Stone-Geary

We use the price-independent generalized linear (PIGL) preferences in our baseline specification. We highlight that our results do not depend on this specification. In this section, we show the results with the Stone-Geary preferences that has long been used in the literature (e.g. Kongsamut et al., 2001). Specifically, we require the utility from market consumption to take the Stone-Geary form:

$$u(c_a, c_n) = \phi \log(c_a - n\bar{c}) + (1 - \phi) \log(c_n),$$

where ϕ is the utility weight on agricultural consumption, $\bar{c}$ represents the subsistence level of agricultural consumption, and $n = 2$ $(n = 1)$ for married (single) households. The first order condition for labor supply, corresponding to Equation (10), is now

$$h^m w^m(1-\tau^m) = \omega(y - p\bar{c}n)\frac{z_h^m (h^m)^{\frac{\theta-1}{\theta}}}{\left(z_h^m (h^m)^{\frac{\theta-1}{\theta}} + z_h^f (h^f)^{\frac{\theta-1}{\theta}}\right)^{-(\chi+\frac{1}{\theta})\frac{\theta}{\theta-1}}}. \tag{12}$$

We set $\phi = 0.05$, and then choose $\bar{c} = 0.12$ to match the agricultural value-added share of 10.1 percent. Recall that this moment determines B of the PIGL preferences in our baseline specification. All other parameters are chosen to match the same data moments as in our baseline calibration. With this alternative specification, the gender gap in non-agricultural employment is 13.3 percentage points, similar to the 12.6 percentage points we find with our baseline PIGL specification, and to the data moment as well. We hence conclude that our quantitative results are not specific to the PIGL preferences.

D.2 Sector-Specific Labor Market Frictions

Our baseline specification assumes 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. 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. 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.

D.3 The Alternative Individual-Based Model

In Section 5.2 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. 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 $\{\theta, \kappa_{\text{both}}, \kappa_{\text{one}}, \psi\}$ are irrelevant in this alternative model. All other parameters are calibrated in the same way as in our baseline calibration. As we explain in Section 5.2, this alternative model has counterfactual implications along several lines, including the gender gap in non-agricultural employment and the gender gap in home production time. This alternative model also offers different interpretations on the pattern of sorting into non-agricultural employment among married females.

D.4 Roles of Home Production Efficiency Versus Labor Wedges

As we explain in Section 4, gender differences in home production productivity (z_h^m, z_h^f) and labor market distortions (τ^m, τ^f) can be separately identified in our framework. To further illustrate the role of these two gender differences in our model, we now consider two alternative specifications.

In the first one, we allow for gender differences in home production productivity (z_h^m, z_h^f) but we eliminate labor market distortions by setting $\tau^m = \tau^f = 0$. We then re-calibrate our model to match the same set of data moments, except for the observed gender wage gap in the non-agricultural sector which restricts the labor market distortions in our baseline calibration. In this case, to match the observed gender differences in home production time, the calibrated difference in z_h^m and z_h^f is much larger: z_h^m is roughly 58 percent of z_h^f, compared to 82 percent in the baseline calibration. Furthermore, this alternative specification generates counterfactual gender wage gap in the non-agricultural sector, as women on average earn 6.2 percent more than men, while in the data women on average earn 11.5 percent less. The model predicts women to earn more because of the selection effect: If women are substantially more productive at home, then only the most talented women with highest pay choose to work. Finally, this alternative specification under predicts the gender gap in non-agricultural employment, with a gap of 8.5 percentage points in the model compared to 12.4 percentage points in the data.

In the second specification, we allow for labor market distortions but we eliminate gender differences in home production productivity by setting $z_h^m = z_h^f = 1$. We then re-calibrate our model to match the same set of data moments, except for the observed gender difference in home production time which restricts the z_h^m in our baseline calibration. This alternative specification under predicts the home production time differences, as women on average spend 1.66-fold time on home production compared to men, compared to 3.33-fold in the data. This alternative specification also under predicts the gender gap in non-agricultural employment, with a gap of 10.8 percentage points in the model compared to 12.4 percentage points in the data.

D.5 Gender-Specific Comparative Advantage

In our baseline calibration, we assume that men and women have the same mean of abilities. Literature suggests a comparative advantage of women in the non-agricultural sector compared to men (Ngai and Petrongolo, 2017; Lee, 2024). We discuss this issue in Section 6.3, while here we elaborate on how we calculate the comparative advantage of women in the non-agricultural sector, given that we cannot identify the comparative advantage in our framework using wage and employment data only like in Lee (2024).

Specifically, we explore the difference between married and single individuals. In the data, single women are slightly more likely to work in the non-agricultural sector than single men—a pattern that our baseline model cannot fully rationalize. We then use this information to restrict the comparative advantage of women in the non-agricultural sector. Note that we adjust the unexplained gap between the singles downwards for the following reason: Koh et al. (2025) find that the incentive of single women to marry up in urban areas is quantitatively important. According to the China Population Census (National Bureau of Statistics of China, 2010), 8.4 percent of rural out-migrated women aged 16–25 list marriage motivation as their primary incentive to migrate to the urban areas, compared to only 1.1 percent of men. We hence adjust the unexplained difference between the singles accordingly to purge away individuals who work in the non-agricultural sector for marriage purposes. We then re-calibrate the model, choosing the level of the comparative advantage to match the adjusted gap among singles. This approach implies a comparative advantage of single women in the non-agricultural sector of 1.11-fold. We find that this alternative model generates a gender gap of non-agricultural employment of 9.9 percentage points among the married individuals, again similar to the 12.6 percentage points in our baseline calibration.

D.6 Asymmetric Ability Dispersions by Gender

We now discuss on the assumption that the dispersion of ability is the same for men and women. To start, the observed income dispersion is similar between genders. In the data, the dispersion (standard deviation of the log) of wage rate is 0.441 in the non-agricultural sector for all individuals. This dispersion is very similar between men and women: it is 0.430 for men and 0.410 for women. It is hence unlikely that the dispersion of ability differs substantially between genders.

Nevertheless, we design a robust test that explicitly allows for the dispersion parameter to differ between genders. Specifically, the dispersions of individual abilities are σ_a and σ_n for men, and $\sigma_a \nu$ and $\sigma_n \nu$ for women. We then calibrate the model to match the same set of data moments, with σ_n and ν chosen to match the income dispersions of men and women in the non-agricultural sector. Interestingly, the calibration implies that the dispersion of ability is 17.9 percent larger for women than for men ($\nu = 1.179$), despite that in the equilibrium income dispersion is smaller for women. This is due to the selection effect where fewer women choose to work in the non-agricultural sector. We find that our main results remain robust to this specification. In this alternative specification, the model implies a gender gap in non-agricultural employment of 14.1 percentage points, compared to 12.6 percentage points in the baseline calibration. We hence conclude that the assumption of identical ability dispersion is unlikely to affect our quantitative results.

D.7 Ability Distributions Across Marital Statuses

We now discuss on the assumption that the the ability distribution is the same between the single individuals and the married ones. We highlight that the focus of is paper is on the married individuals rather than on the singles, and the ability distribution in our baseline analysis is estimated using moments from the married individuals only. Hence, the analysis on the married individuals is internally consistent. Even if the singles do have different ability distributions, it is unlikely to substantially bias our findings for the married individuals.

We further use the 2010 China Population Census (National Bureau of Statistics of China, 2010) to assess the validity of this assumption. Specifically, we regress years of schooling on a gender dummy, a marriage dummy, and the interaction of these two for all rural individuals, controlling for age, age square, and prefecture fixed effects. We find that on average married women have 0.904 fewer years of schooling than married men, while single women and single men have 0.451 and 0.094 more years of schooling than married men. Note that the population average years of schooling is 8.720 years among rural individuals, and hence the differences reported above are not large.

E Spatial Variations in Entry Costs across Provinces

As we explain in Section 4, κ_{both} captures the cost associated with both members working in the non-agricultural sector, and is supposedly influenced by access to public services and other policies. In this appendix, we provide evidence how the estimated κ_{both} represents observed public services and other policies by exploring the spatial variations across Chinese provinces.

For each province, we calculate the shares of rural households with one and two members working in the non-agricultural sector, respectively, using the 2010 China Population Census (National Bureau of Statistics of China, 2010). We then treat each province as a small open economy, taken national prices and wages as given. We simulate rural married households with ability distribution being the same as in our baseline calibration. We then choose the entry costs $\{\kappa_{\text{one}}, \kappa_{\text{both}}\}$ such that the shares of households with one or two members working in the non-agricultural sector match the data moments. We repeat this process for 28 Chinese provinces and estimate a set of costs $\{\kappa_{\text{one}}, \kappa_{\text{both}}\}$ for each province.[33]

We then correlate the estimated costs to province level characteristics. We start by correlating κ_{both} with the public services provided by the government. Intuitively, a better

[33] We have data for 30 out of 34 provinces of China. We further exclude Beijing and Shanghai where the share of individuals with agricultural *hukou* is relatively small.

provision of public services facilitates rural households to work in the non-agricultural sector. We construct three measurements: the number of kindergarten enrollment per capita, the number of primary school enrollment per capita, and the number of clinic/hospital visits per capita. We then regress the estimated κ_{both} on the log of these measures. Since these measures are correlated with the level of development, we further control for the log GDP per capita of each province. The results in Panel (a) of Table 9, Columns (1), (2), and (3), confirm our conjecture that public services reduce κ_{both}. We also consider the effect of transportation cost. To approximate the efficiency of transportation, we construct a measure of road density as the ratio between the total length of roads and the land area of each province. Column (4) shows that a higher the road density, which implies a lower the transportation cost, reduces the cost κ_{both}. In addition, the *hukou* system in China imposes substantial institutional challenges for rural individuals when they work in the non-agricultural sector, especially when the entire family migrate to urban areas. We hence adopt the *hukou* index from Zhang and Lu (2019), who combine variables on the requirements to obtaining city *hukou* to construct a *hukou* index where a larger number indicates harder to obtain city *hukou*. We then regress κ_{both} on this *hukou* index, and results in Column (5) show that a higher *hukou* index indeed increases the cost κ_{both}. Note that all measurements, except for the *hukou* index, are constructed from the China Statistical Yearbook (National Bureau of Statistics of China, 2011).

We also consider the cost difference between one member and two members working in the non-agricultural sector. We regress $\kappa_{\text{both}} - \kappa_{\text{one}}$ on the constructed province level characteristics. The results are displayed in Panel (b) of Table 9. The results are overall similar: public services, transportation, and *hukou* index affect κ_{both} more compared to κ_{one}.

These correlations suggest that our estimated κ_{both} is grounded on observed characteristics of the real world policies and hence are reasonable.

Table 9: Provincial Costs and Observed Characteristics

	(a) Dependent variable: κ_{both}				
	(1)	(2)	(3)	(4)	(5)
Kindergarten enrollment per capita	−0.829***				
	(0.122)				
Primary school enrollment per capita		−0.474			
		(0.309)			
Medical treatments per capita			−0.533*		
			(0.289)		
Road density				−0.257***	
				(0.056)	
Hukou index					0.857**
					(0.342)
GDP per capita	−0.139	−0.544**	−0.088	−0.130	−0.237*
	(0.083)	(0.209)	(0.168)	(0.105)	(0.123)
R^2	0.705	0.230	0.259	0.544	0.327

	(b) Dependent variable: $\kappa_{\text{both}} - \kappa_{\text{one}}$				
	(1)	(2)	(3)	(4)	(5)
Kindergarten enrollment per capita	−0.172***				
	(0.027)				
Primary school enrollment per capita		−0.093			
		(0.066)			
Medical treatments per capita			−0.133**		
			(0.060)		
Road density				−0.053***	
				(0.012)	
Hukou index					0.158**
					(0.075)
GDP per capita	−0.029	−0.110**	−0.010	−0.027	−0.050*
	(0.018)	(0.045)	(0.035)	(0.023)	(0.027)
R^2	0.679	0.215	0.293	0.518	0.281

Notes: This table shows the regression coefficients of fixed entry costs on the left hand side and explanatory variables on the right hand side. All explanatory variables are in logs except for the *hukou* index which is ordinal in nature. Panel (a) shows results for κ_{one} as the dependent variable, while panel (b) shows results for $\kappa_{\text{both}} - \kappa_{\text{one}}$ as the dependent variable. Standard errors in parentheses: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

F Cross-Country Analysis

Our analysis in the main text concentrates 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.

F.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.[34]

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

[34]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.

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;[35] *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).

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 errors in parentheses: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

[35] 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.

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 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.

F.2 Quantitative Analysis for Other 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 use 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 value-added in Sub-Saharan countries.[36] In addition, we choose κ_{one}, 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

[36] 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.

Table 11: 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.

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 percent. The calibrated parameter values are provided in Table 12.

We then present our model's prediction of the gender gap in non-agricultural employment in Panel (a) of Table 11. 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 substantially 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 11 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.

Table 12: Model Parameters and Values

Parameters	Specifications													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Technologies:														
A_a	1	1	1	1	1	1	1	1	1	1	1	0.556	1	1
A_n	1	1	1	1	1	1	1	1	1	1	1	0.514	1	1
Preferences:														
B	0.333	—	0.342	0.311	0.347	0.334	0.326	0.325	0.352	0.330	0.333	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	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	0.7	0.7	0.7	0.7
ω	0.262	0.245	0.253	0.260	0.279	0.248	0.231	0.296	0.194	0.263	0.265	0.262	0.262	0.262
θ	4.008	6.815	3.790	4.025	4.872	5.082	—	3.900	1.484	3.483	4.017	4.008	4.008	4.008
κ_{one}	0.393	0.855	0.435	0.370	0.472	0.479	—	0.370	0.580	0.421	0.403	0.475	0.610	0.316
κ_{both}	0.578	0.993	0.635	0.545	0.547	0.667	—	0.555	0.905	0.627	0.588	0.546	0.816	0.401
κ_{single}	0.142	0.803	0.159	0.148	0.100	0.182	0.343	0.125	0.320	0.164	0.153	0.229	0.391	0.266
χ	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1
Ability:														
λ	0.206	0.171	0.091	0.417	0.151	0.255	0.194	0.182	0.435	0.210	0.210	0.206	0.206	0.206
σ_a	0.282	0.210	0.306	0.244	0.269	0.340	0.338	0.250	0.547	0.286	0.276	0.282	0.282	0.282
σ_n	0.536	0.481	0.535	0.525	0.699	0.522	0.684	0.537	0.493	0.536	0.516	0.536	0.536	0.536
ψ	0.845	0.787	0.859	0.856	—	0.796	—	0.871	0.909	0.864	0.774	0.845	0.845	0.845
z_h^m	0.824	0.822	0.815	0.820	0.680	0.755	1	0.582	1	0.831	0.896	0.860	0.793	0.998
z_h^f	1	1	1	1	1	1	1	1	1	1	1	1	1	1
$\bar{z}$	1.757	1.619	1.767	1.750	1.759	1.734	1.804	1.763	1.709	1.849	1.756	1.757	1.757	1.757
Frictions:														
τ^m	−0.096	−0.067	−0.095	−0.099	−0.068	−0.131	−0.079	0	−0.103	−0.135	−0.105	−0.096	−0.118	−0.173
τ^f	0.117	0.094	0.115	0.121	0.085	0.178	0.084	0	0.111	0.155	0.126	0.134	0.149	0.209
Endowments:														
N_{married}	1	1	1	1	1	1	0	1	1	1	1	1	1	1
N_{single}	0.717	0.717	0.717	0.717	0.717	0.717	2.717	0.717	0.717	0.717	0.717	0.512	0.420	0.455
N_{urban}	0.537	0.537	0.537	0.537	0.537	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_{one}, 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. Column (1) displays parameter values for the baseline calibration, Column (2) for the Stone-Geary preferences specification, column (3) for the specification with low correlation between abilities, column (4) for the specification with high correlation between abilities, column (5) for the specification with no positive assortative matching, column (6) for the specification with sector-specific labor frictions, column (7) for the alternative model without married households, column (8) for the specification with no labor market distortions, column (9) for the specification with no gender differences in home production productivity, column (10) for the specification allowing for comparative advantage between genders, column (11) for the specification allowing for different dispersions for abilities between genders, column (12) for the China 2000 calibration, column (13) for the Sub-Saharan Africa calibration, and column (14) for the Latin America calibration.