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Gender Gaps in Entrepreneurship in India: Entry Barriers and Growth Constraints§

ABSTRACT This paper examines gender gaps in entrepreneurship in India. Using nationally representative data, we show that female labor force participation explains much of the gender gap in self-employment, but not in entrepreneurship, where women remain under-represented and report facing disproportionate barriers in access to finance, infrastructure, and in navigating regulatory environments. Interpreted through the lens of model of occupational choice with both labor supply and demand distortions, we find large, persistent barriers to firm growth for women, even in richer states—highlighting the need for multi-dimensional, state-specific policy solutions.

Keywords: Female Entrepreneurship, Labor Supply, Occupational Sorting, India

JEL Classification: J16, O12, L26

1. Introduction

Across countries, economic development is strongly associated with increase in entrepreneurship. Figure 1 uses data from the World Bank, covering 186 countries in 2022 and shows that this relationship holds for both men and women (see Figures 1a and 1b). India aligns with this pattern for men—around 3 percent of working-age men (15–64 years) in India are entrepreneurs, which is in line with expectations, given its income level (Figure 1a). For women, however, the story is different. Less than 1 percent of Indian women are entrepreneurs, placing India far below the global trendline

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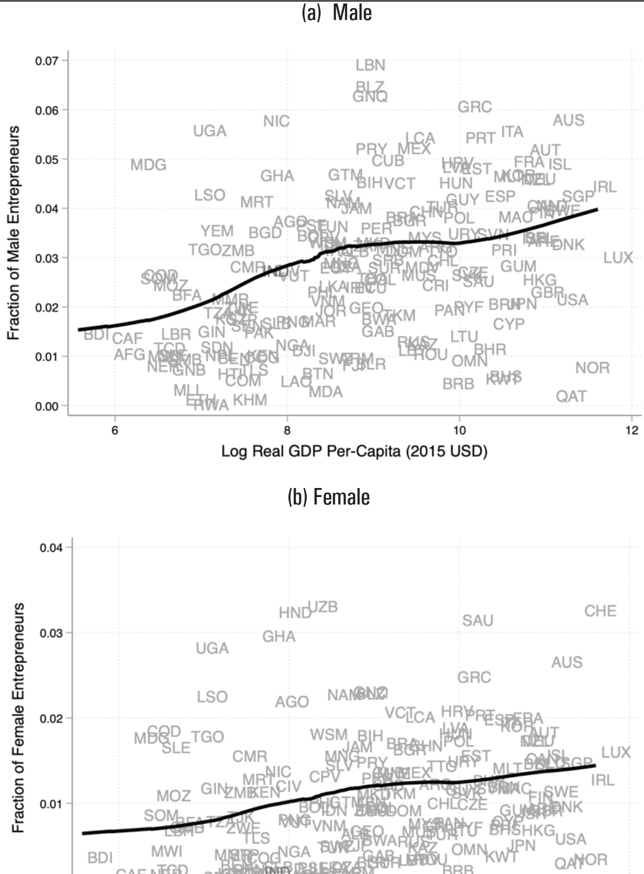
(Figure 1b). It is one of the most significant outliers in terms of low female entrepreneurship, given its stage of economic development.

FIGURE 1. Fraction of Male and Female Entrepreneurs across Countries



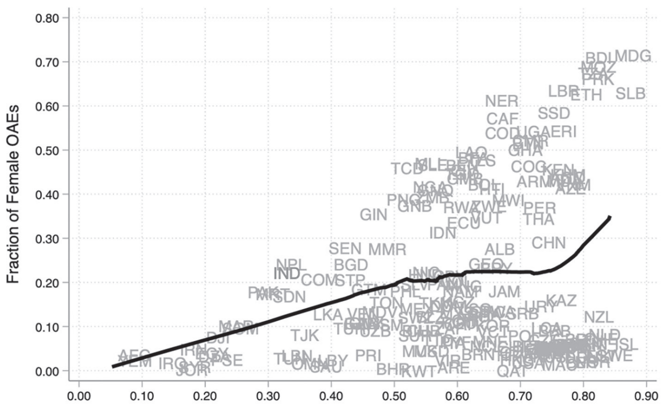
Source: The figure uses data from the World Bank across 186 countries in 2022.
Note: It The figure plots a non-parametric correlation between the 15–64-year-old male (Figure a) and female (Figure b) fraction of the population who are entrepreneurs and log real GDP per-capita. India (IND) is highlighted in red.

One natural explanation is the country's equally low rate of female labor force participation (FLFPR). As reported in Appendix Figure A1, India's FLFPR is among the lowest in the world, well below the average of countries at similar levels of economic development. If few women work at all, then few are likely to become entrepreneurs. Figure 2a supports this logic when it comes to self-employment, that is, women operating small, own-account enterprises. Across countries, the share of self-employed women increases steadily with

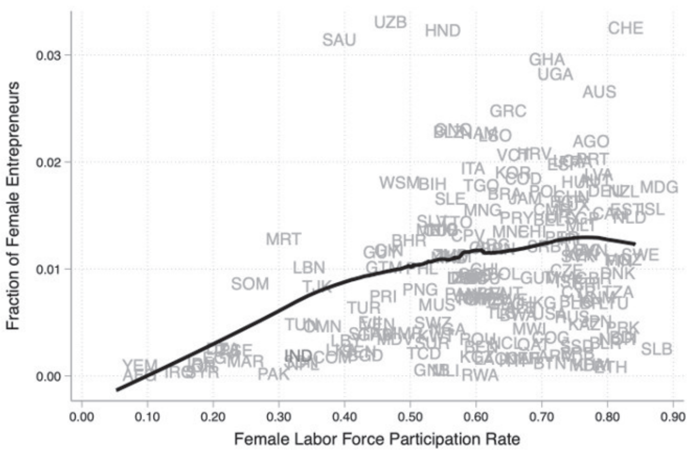
FLFPR. India (if anything) has too many self-employed women, given its level of FLFPR. However, the same logic does not extend to entrepreneurship. As Figure 2b shows, even conditional on FLFPR, India's female entrepreneurship rate is well below predicted levels. In short, while low labor force participation may explain low self-employment rates for Indian women, it cannot fully explain low levels of female entrepreneurship. The latter points to a second set of constraints–those that restrict firm growth as opposed to entry into self-employment.

FIGURE 2. Female Self-employment, Entrepreneurship and LFPR across Countries

(a) Self-employment



(b) Entrepreneurship



Source: The figure uses data from the World Bank across 186 countries in 2022.

Note: The figure plots a non-parametric correlation of the female labor force participation rate of 15-64 years old women with female self-employment, that is, operation of small, own-account enterprises (Figure 2a) and female entrepreneurship (Figure 2b). India (IND) is highlighted in the figure.

This paper investigates the structure of gender inequality in entrepreneurship in India by focusing on the interplay between labor force participation, occupational sorting, and firm growth. Throughout our analysis, we distinguish between self-employment, that is, operating small, own-account enterprises, essentially single-person firms; and employer-based entrepreneurship, which involves firms that hire workers.

Using microdata from the 2023 Periodic Labour Force Survey (PLFS), we begin by documenting some stylized facts. First, we show that the cross-country patterns discussed above hold across Indian states as well. For men, self-employment rates fall and entrepreneurship rates rise with log state GDP per capita. For women, however, this pattern breaks down. The shares of women in self-employment and entrepreneurship remain both low and are not correlated with income levels across states (Figure 3). On average, there are only 3.3 self-employed women and 0.6 women entrepreneurs for every 10 male-owned ones. However, much of the gender gap in self-employment disappears once we adjust for the low female labor force participation rates, while the gender gap in entrepreneurship remains persistent (Figure 3). For example, conditional on working, there are 8 self-employed women but only 1.4 women entrepreneurs on average, for every 10 male counterparts.

The above set of patterns highlights the central argument of this paper: while low FLFP can explain fewer women-operated establishments (in both self-employment and entrepreneurship), women are over-represented in self-employment as opposed to entrepreneurship, conditional on participating in the labor force. It highlights the need to distinguish between two sets of constraints—supply-side barriers that prevent women from entering the labor force and starting (one-person) firms, and demand-side barriers that depress the returns to entrepreneurship for women who are already working either as wage earners or self-employed.

The latter set of constraints is reflected in the qualitative experiences and perceptions of women entrepreneurs, as we document in Section 3. Using firm-level data from the World Bank Enterprise and Micro-Enterprise Surveys for India, we show that women-owned firms report significantly greater barriers in accessing capital, skilled labor, electricity, and transport, along with navigating regulatory environments related to acquiring permits, labor and trade regulations, tax administrations, and corruption (see Figure 4). These patterns represent classic 'demand-side' distortions that lower the effective returns to firm expansion for women. At the same time, data from the Global Entrepreneurship Monitor (GEM) indicate that women outside the labor force are less likely to report entrepreneurial intentions, have inferior business networks, lower self-efficacy, and are more likely to perceive entrepreneurship as socially undesirable. However, these differences disappear once we condition on labor force participation—suggesting the role of 'supply-side' barriers in shaping the selection of women who enter the labor force (and entrepreneurship). Together, these patterns suggest that women's entrepreneurial outcomes are shaped both by who enters the labor market, as well as by what they face once they are in it.

To bring these insights into a more structured framework, in Section 4, we adopt a more theoretical approach. We develop a structural model of occupational choice with gender-specific distortions, building on recent work by Goldberg et al. (2024), Chiplunkar and Goldberg (2024), and Hsieh et al. (2019). Specifically, we consider an economy with individuals of two genders (men and women), who differ in their occupation-specific talent and face gender-specific labor demand and supply distortions. Labor demand distortions are modeled as wedges that reduce the returns to specific occupations, while supply distortions reflect the (dis)utility or barriers that individuals face when employed in these occupations. In this framework, a lower share of individuals of gender g working in an occupation *o* relative to *o'* is driven by three potential factors: (i) comparative (dis)advantage, that is, relative differences in human capital; (ii) a lower return to human capital, as defined by the wage-rate per unit of human capital; and (iii) demand-side distortions, that is, higher barriers (discrimination) facing individuals of gender g employed in occupation o.

A key advantage of this theoretical framework is that it provides analytical expressions for occupational shares and earnings for each gender that we can directly map onto the data. This allows us to parsimoniously quantify the distortions faced by women (relative to men). Our quantification exercise yields three key insights (see Section 4.4): first, women face substantial labor demand distortions, in both self-employment and entrepreneurship. Our estimates indicate that even if women had identical talent and worked under identical labor market conditions as men, the returns from self-employment and entrepreneurship, relative to men, would be 27 percent and 8 percent, respectively. This implies that for women, demand-side distortions in operating larger firms (as entrepreneurs) are around three times higher than in self-employment—an indication that demand-side distortions are particularly consequential for firm growth. Second, these distortions do not correlate with income levels across states, indicating that economic development alone is not sufficient to mitigate these barriers (Figure 5). Third, we find that supply-side distortions are also substantial: conditional on earning the same income, women derive only half the utility that men do from self-employment, and one-third from entrepreneurship. However, contrary to the demand-side, supply side distortions do decline with state income (Figure 6).

These findings call for a re-examination of our understanding of gender gaps in entrepreneurship and the policies advocated to address them. Rather than viewing women's under-representation as a single problem with a single solution, we show that it stems from both entry and firm growth constraints. These two sets of constraints interact with each other, vary across space and occupation, and need to be addressed using targeted policy tools.

Our paper contributes to a growing body of research on the causes and consequences of gender gaps in economic activity, with a particular focus on entrepreneurship. On the extensive margin, it is related to recent work on female labor force participation in India that has highlighted declining FLFPR despite rising education and income (Chatterjee et al., 2018; Afridi et al., 2018; Fletcher et al., 2019; Deshpande and Singh, 2024). We add to this work by showing that the gender gap is not only about whether women work, but also about what types of work they do and how labor supply and demand barriers interact to distort these choices. On the intensive margin, our work relates to the literature on constraints to firm growth among women (De Mel et al., 2009; Field et al., 2010; Chiplunkar and Goldberg, 2024). We provide evidence that the barriers women face in scaling their businesses are not simply a continuation of entry-level frictions, but reflect a distinct set of demand-side constraints that remain binding even after conditioning on labor force participation and firm ownership. Methodologically, our work builds on recent structural models of occupational choice with distortions (Hsieh et al., 2019; Goldberg et al., 2024). By combining rich microdata with a tractable model of sorting, we are able to transparently translate observed gender gaps in occupational choices, earnings, and human capital into estimates of economically meaningful frictions—yielding a diagnostic tool for data-driven policy design.

The rest of the paper is organized as follows: Section 2 discusses the patterns in female entrepreneurship using the PLFS; Section 3 complements this analysis with a discussion of gender differences in access to inputs, entrepreneurial motivation, and social norms. Section 4 presents the theoretical model along with the calibration results. Section 5 concludes with a discussion of policy implications.

2. Patterns of Female Entrepreneurship in India

We begin by presenting some stylized facts on female self-employment and entrepreneurship in India using data from the 2023 round of the PLFS.

The PLFS is the primary national source for statistics on labor force participation, employment, and earnings. It surveys a representative set of households to measure their labor market activity. We restrict the sample to the working age population, that is, those aged 21-65 years, which leaves us with around 2,42,000 individuals. The PLFS classifies individuals as own-account workers (code 11), employers (code 12), unpaid workers in a household enterprise (code 21), wage or salaried workers (code 31), casual workers (code 41-51), and unemployed or out of the labor force (codes above 81). Throughout the paper, we define "self-employed" individuals as those who operate own-account establishments; and "entrepreneurs" as those who are employers and operate firms that employ workers. The PLFS also reports the years of education and earnings in the month preceding the survey for wage-earners and self-employed individuals. We winsorize the earnings at the top and bottom 5 percent. For individuals in these categories where earnings are not reported, we use the state-gender-occupation-education average as an estimate of their earnings.

TABLE 1. Summary Statistics from PLFS

	All	*Male*	*Female*	*Female/Male*
	(1)	*(2)*	*(3)*	*(4)*
N	242,560	120,068	122,492	
LFP	0.64	0.91	0.39	0.42
OAE	0.23	0.35	0.12	0.33
Entrepreneur	0.02	0.04	0	0.06
OAE | LFP	0.35	0.39	0.3	0.79
Entrepreneur | LFP	0.05	0.05	0.01	0.14

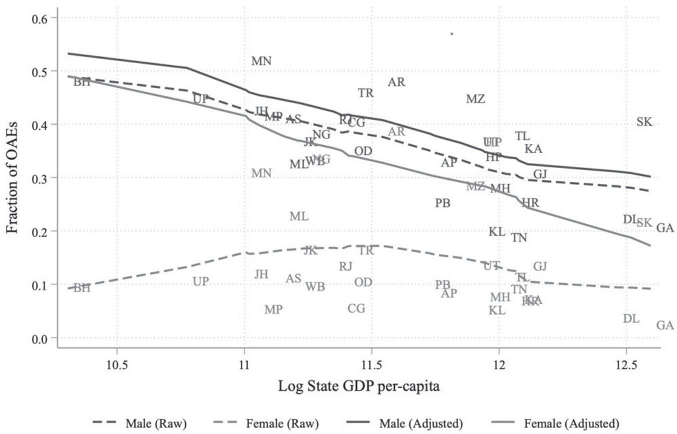
Source: The table uses data from the 2023 Periodic Labor Force Survey (PLFS).
Note: We restrict the sample to individuals aged 21-65 years. Column (1) is the mean across all individuals, while Columns (2) and (3) are for males and females, respectively. Column (4) reports the gender gap, which is the ratio of Columns (3) and (2).

Table 1 summarizes gender-specific patterns in labor force participation and self- employment. Overall, 64 percent of individuals participate in the labor force (Column 1), but this masks differences across gender: 91 percent of men participate in the labor force (Column 2), as compared to only 39 percent of women (Column 3), implying that for every 10 men, there are only 4.2 women in the labor force (Column 4). Furthermore, 35 percent of men and 12 percent of women operate own-account enterprises (OAEs), that is, they are self-employed individuals without hired labor. The gap is even more pronounced in entrepreneurship: for every 10 men, only 0.6 women operate a firm with employees.

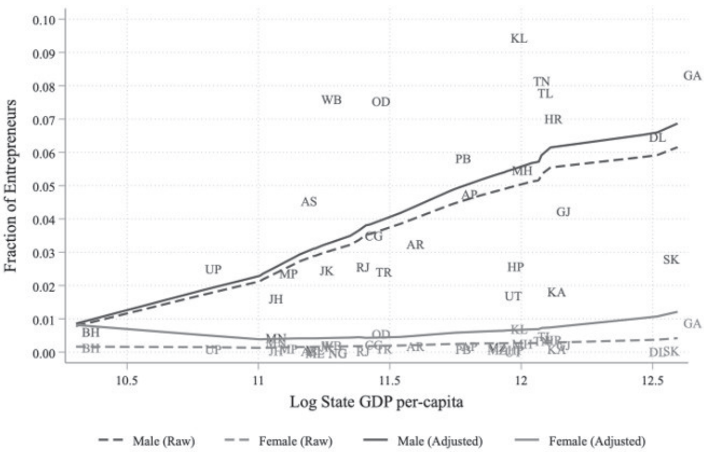
Once we condition on labor force participation, however, a more nuanced picture emerges. Among those in the labor force, there are approximately 8 women-operated OAEs for every 10 male OAEs. In contrast, there are only 1.4 female entrepreneurs for every 10 male entrepreneurs. This divergence provides our first key insight: low FLFP is an important factor in explaining the low presence of women in self-employment. However, conditional on working, the primary constraint is not in starting firms (as OAEs), but rather in expanding them as entrepreneurs.

FIGURE 3. Fraction of Self-employed and Entrepreneurs across States

(a) Self-employment



(b) Entrepreneurship



Source: The figure uses data from the 2023 PLFS.

Note: We restrict the sample to individuals aged 21-65 years. The figure shows a non-parametric correlation between the fraction of males and females in self-employment in Figure 3(a) and entrepreneurship in Figure 3(b), and log state GDP per-capita. We report the self-employed individuals and entrepreneurs as a fraction of all individuals (dotted lines) and those in the labor force (solid lines).

Next, we investigate whether these patterns vary with economic development of states. Figure A3 plots labor force participation rates across states against their log state GDP per capita. Male LFP is uniformly high across states, regardless of income levels. In contrast, female LFP exhibits substantial heterogeneity and no clear correlation with income—the Northeastern states have a high female LFP (70–75 percent), while both rich (for example, Haryana and Delhi) and poor states (for example, Bihar and Uttar Pradesh) report low female LFP (20–25 percent).

Figure 3 explores the composition of entrepreneurship across states. The share of self-employed men declines with development from 50 percent to 30 percent (Figure 3a), while the share of entrepreneurs increases from 1 percent to 7 percent (Figure 3b). Given the high male LFPR, conditioning on LFPR does not substantively change the patterns. Among women, the patterns are different. The share of self-employed women is relatively flat across the state-income distribution, hovering at around 15 percent (dotted red lines in Figure 3a). However, once we adjust for female LFPR, two distinct patterns emerge: (i) the gender-gap in self-employment almost closes across the entire income distribution; and (ii) the fraction of self-employed women declines with income (solid line), similar to men. However, unlike for men, this decline is not accompanied by a corresponding increase in the share of women entrepreneurs. Female entrepreneurship remains consistently low across states, regardless of their income or FLFPR (Figure 3b). In other words, increasing labor force participation is crucial for increasing female self-employment, but it does not seem sufficient for raising female entrepreneurship.

Taken together, these results highlight the central message of this paper: female under-representation in entrepreneurship reflects both extensive-margin barriers that limit participation and intensive-margin constraints that restrict firm growth. While low FLFP explains a significant share of the gap in self-employment, it cannot account for the persistent gender gap in entrepreneurship. To close this gap, it is essential to look beyond labor supply and investigate the demand-side frictions that women face once they are in the workforce and have started their own firms.

3. What Constrains Women's Entrepreneurship? Evidence from Firms and Individuals

The previous section showed that while differences in labor force participation can explain much of the gender gap in own-account self-employment, they do little to account for the persistent under-representation of women in entrepreneurship. In this section, we investigate the underlying barriers that may prevent women from growing firms, drawing on complementary microdata from firm-level and individual-level surveys. We group these barriers into four categories: (i) frictions that limit access to inputs and infrastructure; (ii) challenges in navigating regulatory environments; (iii) gender differences in entrepreneurial motivation, networks, and perceived capabilities; and (iv) social attitudes and norms that shape expectations about female entrepreneurship.

3.1. Access to Inputs, Infrastructure, and Regulatory Environment

We begin by documenting gender-specific barriers reported by entrepreneurs using data from the World Bank's Enterprise and Micro-Enterprise Surveys (WBES) for India in 2022. The enterprise survey includes registered firms with at least five employees, while the micro-enterprise survey focuses on smaller, informal firms with fewer than five workers, operating primarily in urban areas.[1]

What is of relevance to our analysis is that both surveys ask firms to rate the severity of various obstacles to doing business, including finance, infrastructure, labor, and regulation, on a scale of 1 ('No obstacle') to 5 ('Very severe obstacle'). We use the responses to create a binary variable that takes the value 1 if a firm i reports that a variable x is either a moderate or severe obstacle for their operations, that is, $D_i^x = 1(X \geq 3)$. We classify a firm as "female-owned" (F_i) if at least half of the owners of the firm are females. To measure the gender gap in perceived barriers, we estimate a regression of D_i^x on F_i with state fixed effects and cluster standard errors at the industry level. These fixed effects allow us to control for observable and unobservable differences across states that could impact access to inputs and the policy environment.

Figure 4 presents the estimated gender gaps (the coefficient on F_i) across a range of inputs and policy-related variables. Figure 4a shows that women-owned firms face significantly higher barriers in accessing key inputs: they are 11 percentage points (p.p.) (20 percent) more likely to report skilled labor as an obstacle; 13 p.p. (23 percent) more likely to report access to finance; and 12–15 p.p. (30-45 percent) more likely to report issues with electricity and transport.

In Figure 4b, we find that female entrepreneurs also report greater frictions in navigating the regulatory and policy environment. They are 9 p.p. (29 percent), 12 p.p. (44 percent), and 9 p.p. (16 percent) more likely to report difficulties in obtaining business permits, or citing labor and trade regulations, respectively, as an obstacle to their firm's production. Similarly, they are 10-18 p.p. (25-35 percent) more likely to mention tax agencies, the judiciary and courts, and corruption as barriers to production as well. These results suggest that women face systematically higher barriers in accessing production inputs, infrastructure, and interacting with state institutions—barriers that lower the returns to firm growth.

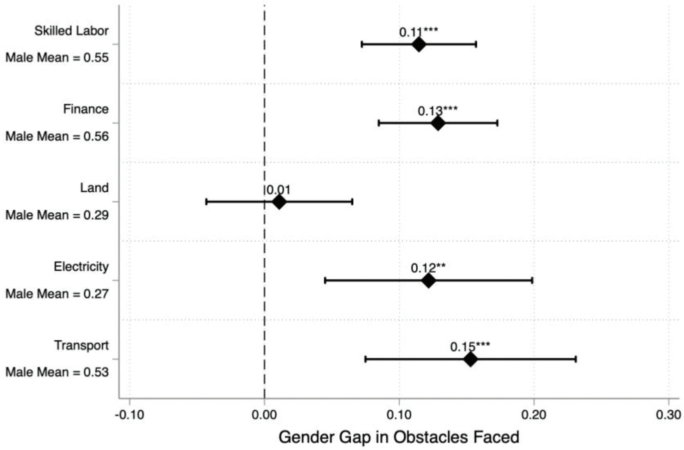
3.2. Entrepreneurial Motivation, Networks, and Capabilities

Beyond external frictions, women may differ from men in their internal drive for entrepreneurship. To investigate this hypothesis, we leverage data from the Adult Population Surveys (APS) implemented by GEM. The APS asks questions not only on business characteristics, but also on individuals'

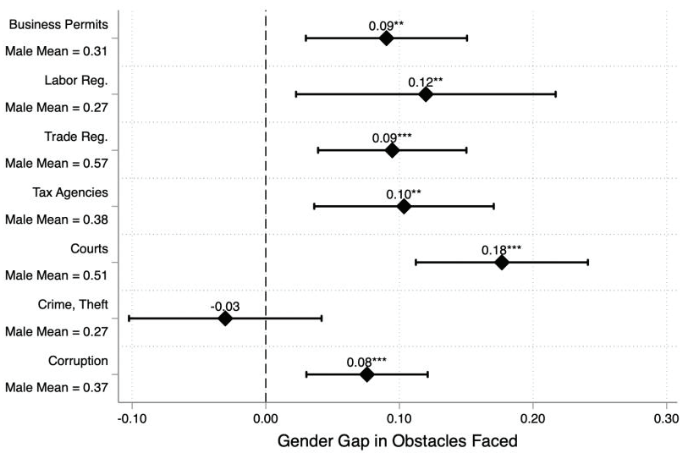
1. Details for the enterprise and micro-enterprise surveys are available at: https://microdata.worldbank.org/index.php/catalog/6500 and https://microdata.worldbank.org/index.php/catalog/6495, respectively.

FIGURE 4. Excess Barriers Faced by Female Entrepreneurs in Access to Inputs and Policy Environment

(a) Access to Inputs



(b) Policy Environment



Source: The figure uses data from the World Bank Enterprise and Micro-Enterprise Surveys for India in 2022.
Note: Figure 4(a) reports results from barriers faced by entrepreneurs in accessing inputs, while Figure 4(b) reports policy barriers. Each variable takes the value 1 if an entrepreneur reports that it is a moderate or severe obstacle to the firm's operations. Male mean reports the fraction of male entrepreneurs who report it as an obstacle. We report the average gender gap from a regression of each outcome variable on a female dummy with state fixed effects. 95% confidence intervals clustered at industry-level are reported in parentheses. * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

motivation for starting a business, the actions taken to start and run a business, as well as entrepreneurship-related personality traits. The APS is administered to a minimum of 2000 adults in each economy, ensuring that it is nationally representative. We use all rounds of the APS in India between 2015 and 2019 and similarly of the PLFS, restricting the sample to adults between the ages of 21 and 65 years.

For an individual i, surveyed in year t, we estimate the following regression:

$$Y_{it} = \alpha_t + \beta \text{Female}_i + \gamma X_i + \varepsilon_{it}$$

where, Y_{it} is the outcome of interest. α_t is a year fixed effect and X_i are individual controls that include fixed effects for age, income, and education categories of the individual. Table A1 in the Appendix provides details on the definition of each outcome variable.

TABLE 2. Perceptions and Motivations for Entrepreneurship

	Opportunities and Perceptions				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Intentions	*Networks*	*Buss. Op.*	*Skills*	*Prob. Success*
Female	-0.03***	-0.10***	-0.10***	-0.14***	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Male Mean	0.23	0.41	0.48	0.54	0.61
N	12104	12104	12104	12104	12104
Female | LFP	0.07***	0.05***	0.00	-0.02	0.03**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Male Mean | LFP	0.25	0.44	0.50	0.58	0.60
N	6926	6926	6926	6926	6926

Source: The table uses data on India from the GEM between 2015 and 2018.

Note: See Table A1 for the definition and details of all outcome variables. Female takes the value 1 if an individual is female and 0 otherwise. Female | LFP constrains the sample to individuals in the labor force. All regressions include fixed effects for household income category, age bins, education categories, and year. Robust standard errors are reported in parentheses. * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

The results in Table 2 reveal meaningful gender differences. In the full sample, women are 3 p.p. (13 percent) less likely to start a business as compared to men (Column 1 of the table). From Columns (2) and (3) of the table, we see that women are 10 p.p. less likely to report knowing another entrepreneur (a 24 percent gap), and 10 p.p. (21 percent) less likely to believe that good business opportunities would emerge in the near future. Furthermore, women are 14 p.p. (26 percent) less likely to report having the necessary knowledge, skills, and experience to start a business. These gaps suggest that women may face motivational and informational constraints, or may be internalizing societal skepticism regarding their entrepreneurial potential. Interestingly, however, women are 3 p.p. more likely than men to believe that their business would succeed — an indicator of optimism or self-efficacy conditional on entry.

However, when we restrict the sample to individuals who are already in the labor force, these gaps shrink considerably or even reverse. Among working men and women, there are no statistically significant differences in entrepreneurial opportunity perception or skills, and women are, in fact, more likely to express the intention to start a business and to report knowing other entrepreneurs. This suggests that the observed gender differences in entrepreneurial readiness are largely due to selection of women into the labor force rather than intrinsic gender differences in ambition or capability.

TABLE 3. Social Attitudes towards Entrepreneurship

	Desirable Career	*Respect*	*Media Coverage*
	(1)	*(2)*	*(3)*
Female	-0.06***	-0.05***	-0.06***
	(0.01)	(0.01)	(0.01)
Male Mean	0.55	0.58	0.51
N	11591	11591	11591
Female | LFP	-0.00	0.00	0.01
	(0.02)	(0.02)	(0.02)
Male Mean | LFP	0.57	0.62	0.53
N	6630	6630	6630

Source: The table uses data on India from the GEM between 2015 and 2018.

Note: See Table A1 for the definition and details of all outcome variables. Female takes the value 1 if an individual is female and 0 otherwise. Female LFP constrains the sample to individuals in the labor force. All regressions include fixed effects for household income category, age bins, education categories, and year. Robust standard errors are reported in parentheses. * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

3.3. Social Norms and Attitudes toward Entrepreneurship

We next examine whether differences in social attitudes and perceived societal support for entrepreneurship could contribute to the gender gap in firm formation and growth. Social norms, especially those surrounding the appropriateness of entrepreneurial careers for women, can influence both labor supply decisions and occupational sorting.

Using the APS, we examine gender differences in three measures of societal perception of entrepreneurship: (i) whether entrepreneurship is considered a desirable career; (ii) whether entrepreneurs receive social respect; and (iii) whether entrepreneurship is positively represented in the media. Table 3 shows that in the full sample, women were 5-6 p.p. (10-12 percent) less likely than men to agree with each of these statements on perceptions. These findings suggest that women may perceive entrepreneurship as less socially acceptable or valued—possibly discouraging their entry into business ownership.

However, as with motivational factors, these differences disappear among individuals already in the labor force. Conditional on working, women and men report similar views about the social status and desirability of entrepreneurship. This again points to a strong selection effect: women who overcome these extensive-margin barriers and participate in the workforce exhibit similar entrepreneurial attitudes as men.

3.4. Discussion

The above findings suggest that women face two sets of constraints related to entrepreneurship.

On the extensive margin, entry into the labor market and entrepreneurship is shaped by norms, self-perceptions, and confidence in perceived capability. Gender gaps in these dimensions discourage women from participating in the labor force (and hence entrepreneurship) and are reinforced by societal expectations that may discourage women from developing entrepreneurial aspirations in the first place.

On the intensive margin, business expansion and firm growth are influenced by barriers to accessing inputs, markets, and state institutions. These constraints are present even among those women who are already in the labor force, potentially discouraging them to transition from own-account work to larger-scale entrepreneurship.

This two-sided framework, where selection into entrepreneurship is governed by 'labor-supply side' factors such as social norms and perceptions, and performance within entrepreneurship is governed by 'labor-demand side' considerations, provides a more nuanced understanding of the persistent gender gap in entrepreneurial outcomes. The implication is that addressing gender gaps in entrepreneurship requires more than just removing entry barriers. It also requires tackling the frictions that suppress returns to entrepreneurship. The next section uses a theoretical framework to quantify these two sets of constraints and assess their implications across occupations and states.

4. Quantifying Gender Barriers to Self-Employment: A Theoretical Approach

We use the framework of Goldberg et al. (2024) that extends a standard Roy model of occupational choice to allow for occupation- and gender-specific distortions. We briefly review this framework below. Consider an economy with Ng individuals of two genders (g), men (m) and women (f). Each individual can choose between four occupations: (i) wage employment (W); (ii) self-employment (OAE); (iii) entrepreneurship (E); and (iv) not being in the labor force, that is, working at "home" (H). The difference between OAE and E is that self-employed individuals do not hire any external workers, whereas entrepreneurs operate firms that hire workers.

Men and women differ in three dimensions. First, they have occupation-specific human capital, denoted by h_{og}. Second, they face gender-specific labor-demand distortions, denoted by λ_{og}, which we model as an implicit tax on their labor earnings. Third, they face gender-specific labor-supply distortions, denoted by ξ_{og}. These include factors that may increase (or reduce) the utility associated with a certain occupation. Such factors include amenities in the job, and restrictive social norms, among others, which make it more (or less) attractive for individuals to work in one occupation relative to another.

4.1. Labor Supply Decisions

Each individual is endowed with occupation-specific talent, represented by h_{og}, and draws an idiosyncratic productivity shock $e \sim Frechet(\theta)$ *i.e.,* $F(e)=e^{e-\theta}$. This allows individuals to differ in their comparative and absolute advantages in different occupations. They choose an occupation $o \; \varepsilon \; \{H, W, OAE, E\}$ that maximizes their indirect utility:[2]

$$V_{og} = \frac{1}{\xi_{og}} \cdot \underbrace{\left(\frac{w_o \cdot h_{og} \cdot e}{\lambda_{og}}\right)}_{\text{Effective earnings in o}} \tag{1}$$

where w_o are the prevailing returns per unit of human capital to working in occupation *o*. ζ_{og} is a distortion in *labor supply* that indicates the fraction of (real) income that an individual of gender *g* is willing to give up (or be compensated by) in order to work in occupation *o*. Consider two occupations *o* and *k* where $\xi_{og} > \xi_{kg}$. This implies that a worker would need to earn a higher income in occupation o relative to *k* to make him/her indifferent in choosing between the two. Alternately, it implies that for the same income earned in both occupations, an individual gets lower utility from working in *o* relative to *k*.

The term λ_{og}, on the other hand, is a *labor-demand* wedge that is an implicit tax on wage earnings of gender *g* in occupation *o*. A higher λ_{og} implies lower earnings for the same wage rate, w_o. We can, therefore, express the occupation-specific returns for each gender as:

$$\kappa_{og} = \underbrace{\lambda_{og}^{-1}}_{\text{Labor Demand Distortions}} \cdot \underbrace{w_o h_{og}}_{\text{Earnings}} \cdot \underbrace{\xi_{og}^{-1}}_{\text{Labor Supply Distortions}}$$

This implies $V_{og}\,(h)=K_{og}\,.\;e$. Individuals choose occupation o to maximize their utility *V*. Given this set-up, the occupational shares and average earnings for an individual of gender g in an occupation o are given by:

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2. This is equivalent to a utility function: $\ln U_{og} = \ln C_{og} + \ln \xi_{og}$, where C_{og} denotes consumption and ζ_{og} denotes the (dis)utility of working in occupation *o*. Consumption is, in turn, determined by the budget constraint of the individual and hence income π_{og} earned in occupation *o*.

$$p_{og} = \frac{\kappa_{og}^{\theta}}{\sum_j \kappa_{jg}^{\theta}} \tag{2}$$

$$\overline{w}_{og} = \Gamma_{\theta} \cdot \left(\sum_j \kappa_{jg}^{\theta\backslash} bigg \right)^{1/\theta} \cdot \xi_{og} \tag{3}$$

where p_{og} is the fraction of individuals of gender g who choose occupation o and w_{og} are their average earnings in that occupation. The relative occupation shares and relative average earnings for an individual of gender g in two occupations j and k are then given by:

$$\frac{p_{jg}}{p_{kg}} = \left(\frac{\lambda_{jg}}{\lambda_{kg}}\right)^{-\theta} \cdot \left(\frac{w_j h_{jg}}{w_k h_{kg}}\right)^{\theta} \cdot \left(\frac{\xi_{jg}}{\xi_{kg}}\right)^{-\theta} \tag{4}$$

$$\frac{\overline{w}_{jg}}{\overline{w}_{kg}} = \frac{\xi_{jg}}{\xi_{kg}} \tag{5}$$

The last two equations show what in the data identifies labor supply and labor demand distortions in this framework. First, note that according to Equation (5), variation in average earnings across occupations for a specific gender g is driven only by labor supply distortions ξ_{og}. Higher earnings play the role of compensating differentials in this setting. Second, according to Equation (4), individuals can be sorted into different occupations based on three considerations: their relative human-capital-adjusted earnings ($w_o h_{og}$), relative labor demand distortions (λ_{og}), and relative labor supply distortions (ξ_{og}). This implies that if we observe a high share of individuals of gender g working in an occupation o, this could be because they either: (i) earn a high wage-rate (w_o); (ii) have a comparative advantage in that occupation (h_{og}); (iii) face low demand-side distortions (λ_{og}); and (iv) face low supply-side distortion (ξ_{og}) in that occupation. Hence, Equation (5) can be used to pin down supply-side distortions. Conditional on them, and with data on occupation-specific wages and occupation-gender-specific human capital, Equation (4) can be used to pin down the demand-side distortions.[3]

4.2. Normalization and Identification Assumptions

Our objective to identify the excess distortions faced by women relative to men in an occupation o, that is, $\lambda_{of}/\lambda_{om}$ and ξ_{of}/ξ_{om}. To this end, we introduce two key assumptions.

3. The fact that relative average earnings depend only on supply-side distortions is a convenient feature of the Fréchet distribution. See Goldberg et al (2024) for a more extensive discussion. However, the logic of using two Equations ((4) and (5) in our case) to pin down two unknowns (demand-side and supply-side distortions, that is, λ_{og} and ζ_{og}) applies more generally.

First, we assume that men do not face any labor-demand distortions in any occupation, i.e., $\lambda_{om}=1$. This allows us to use men's observed outcomes to recover occupational wages w_o. The demand-side distortions λ_{of} faced by women are accordingly interpreted relative to those of men.

Second, we assume that men and women do not face differential supply-side distortions when staying at home, i.e., $\xi_{Hm}=\xi_{Hf}$. Intuitively, this assumption implies that if women do not enter the labor force and decide to stay home instead, this is not because of any underlying preference or utility they derive from staying home, but because gender-specific distortions in the labor market prevent them from entering the labor force.

These assumptions allow us to identify excess distortions faced by women on both the labor supply and labor demand side. Specifically, the occupation-specific distortions are interpreted as follows: a high value of λ_{of} implies that women face lower effective returns relative to men when working in occupation o, conditional on identical human capital and wages—reflecting potential credit constraints, regulatory frictions, or outright discrimination. Meanwhile, a high value of ξ_{of} relative to ξ_{om} implies that, for the same monetary earnings, women receive less utility from working in occupation o relative to men. This could reflect underlying social norms, household responsibilities, safety concerns, and lack of amenities, among other things, that impact labor supply decisions.

4.3. Measuring Labor-Demand and Labor-Supply Distortions

To measure the excess labor-demand and labor-supply distortions faced by women in various occupations, we make use of the empirical measures of: (i) occupational shares (p_{og}); (ii) average wage earnings (w_{og}); and (iii) average human capital (h_{og}) for each gender g in occupation o.

Let $X_o = x_{of}/x_{om}$ be the empirical gender gap in labor supply or labor demand distortions in occupation o, that is, the excess distortions faced by women relative to men. The occupation-specific labor-demand distortion Λ_o and labor-supply distortion Ξ_o are given by:

$$\Lambda_o = \left(\frac{P_o^{1/\theta} \cdot \overline{W}_o}{H_o} \right)^{-1} \tag{6}$$

$$\Xi_o = \frac{\overline{W}_o}{\overline{W}_H} \tag{7}$$

These can be derived by re-arranging Equations (2) and (3) and using the assumptions discussed in Section 4.2. Appendix Section B.1 provides the details of the calculations.

Before we proceed, two clarifications are in order. First, identifying Ξ_o in Equation (7) requires us to know the relative earnings at home (W_H), which are not observable in the data. We resolve this by assuming that women do not face any demand-side distortions at home (λ_H=1) and using Equation (6) to back out W_H.

Second, Equations (6) and (7) demonstrate that distortions can only be identified if we adjust observed gender gaps in occupational shares not only for labor force participation (as we did in empirical Section 2), but also for gender differences in human capital. Without this adjustment, the observed gaps may confound differences in productivity with distortions. Specifically, we can re-arrange Equations (6) and (7) to obtain:

$$\frac{P_o}{P_H} = \left(\frac{H_o}{H_H}\right)^{\theta} \cdot (\Xi_o \Lambda_o)^{-\theta} \tag{8}$$

Equation (8) shows that it is not sufficient to condition occupational shares on gender-specific LFP rates by dividing by P_H (note that the LFP rate is equal to $1-P_H$) to identify distortions; occupational shares also need to be adjusted for gender differences in average human capital which proxy for gender-specific productivity differences. This LFP- and human capital-adjusted ratio then identifies excess barriers faced by women when working in occupation o.

These clarifications highlight the importance of moving beyond raw occupational shares and relying on micro-founded expressions showing which factors need to be taken into account to identify distortions. Finally, note that gender-differences in occupation shares, even when adjusted for human capital, are not sufficient for identifying demand-side and supply-side distortions separately. They only allow us to identify a composite of demand- and supply-side distortions. To identify those separately, we also need to know gender differences in average wage earnings (relative to home), as shown in Equation (7).

4.4. Estimated Distortions

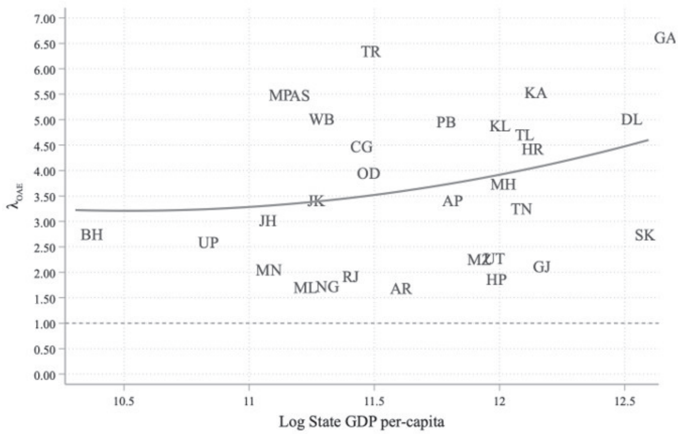
We use Equations (6) and (7) to identify distortions faced by women in the labor market. We follow Goldberg et al. (2024) and Hsieh et al. (2019) and set θ=1.5.

Figure 5 presents state-level estimates of labor demand distortions Λ_o for self-employed women (Figure 5a) and entrepreneurship (Figure 5b). On average, we estimate that women face a labor demand distortion of 3.68 in self-employment and 12.53 in entrepreneurship. These magnitudes imply that, relative to men, women receive only 27 percent of the effective returns of self-employment and a mere 8 percent of entrepreneurship.[4] Put differently, this means that even if women had identical talent and worked under identical market conditions, the effective returns they get from self-employment and entrepreneurship are drastically lower than those for men.

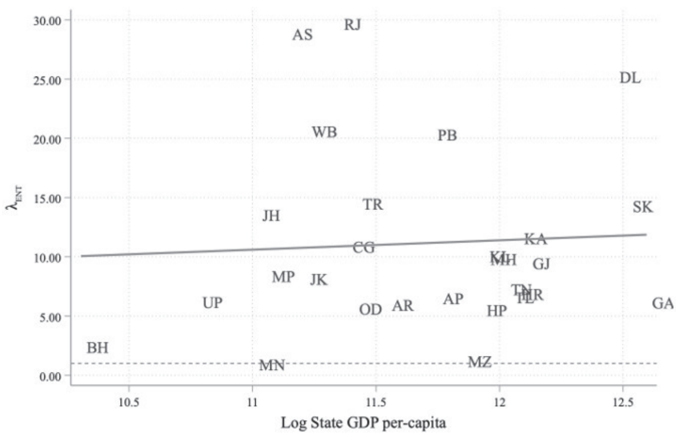
4. We calculate these as $1/\Lambda$.

FIGURE 5. Labor Demand Distortions

(a) Self-employment



(b) Entrepreneurship



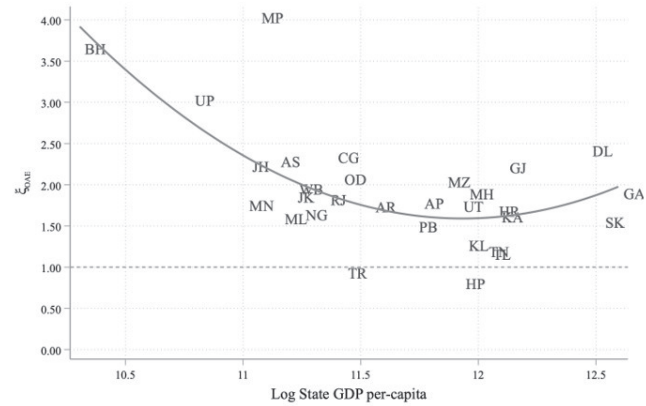
Source: The figure reports model parameter estimates using data from the 2023 PLFS.

Note: We restrict the sample to individuals aged 21-65 years. The figure plots estimates of labor demand distortions (λ) for self-employed women (Figure 5a) and entrepreneurs (Figure 5b) against log state GDP per-capita. They are calculated using Equation (6).

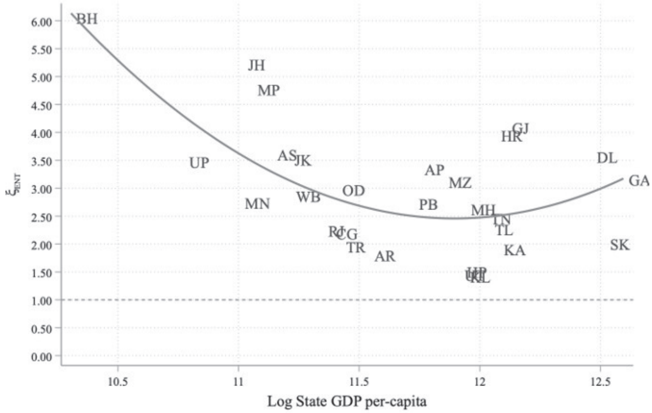
In addition, low correlation between these demand-side distortions and state-level income (Figure 5) suggests that richer states do not necessarily have lower demand distortions. This implies that economic development alone is not sufficient to remove structural barriers to female entrepreneurship. These findings are consistent with prior discussions in Sections 2 and 3, where richer states displayed persistent gender gaps in entrepreneurship, even after adjusting for LFP, and female-owned firms reported larger (demand-side) constraints in accessing key inputs to production, along with credit and transport, among others.

FIGURE 6. Comparing Distortions in Self-employment and Entrepreneurship

(a) Self-employment



(b) Entrepreneurship



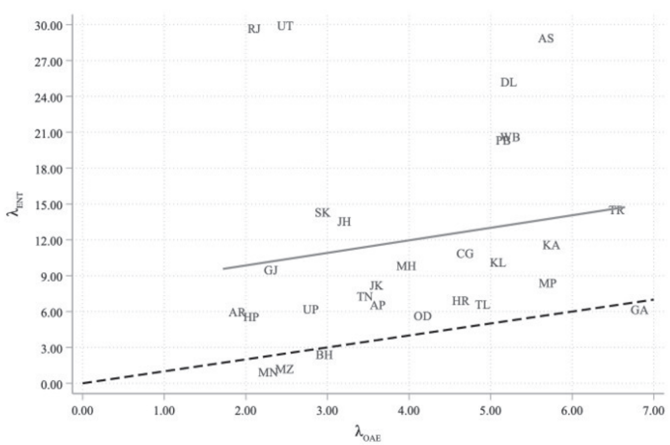
Source: The figure reports model parameter estimates using data from the 2023 PLFS.
Note: We restrict the sample to individuals aged 21-65 years. The figure plots estimates of labor supply distortions (ξ) for self-employed women (Figure 6a) and entrepreneurship (Figure 6b) against log state GDP per-capita. They are calculated using Equation (7).

Turning to labor supply distortions, Figure 6 reports estimates of E_o, again for both self-employment and entrepreneurship. On average, we find values of 1.95 for self- employment and 3 for entrepreneurship. These figures imply that women, on average, receive only 51 percent and 33 percent, respectively, of the utility that men derive from working in the same occupation for the same level of income. These supply-side frictions could reflect norms around mobility, safety, household responsibilities, or other non-monetary constraints that reduce women's willingness or ability to work. Unlike labor demand distortions, however, supply-side distortions show a strong negative correlation with state income levels (Figure 6). This suggests that constraints to female labor supply may erode with development, that is, women in wealthier states appear to face fewer non-monetary frictions in entering the labor market or choosing among occupations. However, this does not automatically translate into higher female entrepreneurship, reinforcing the idea that demand-side barriers persist even when supply-side frictions weaken.

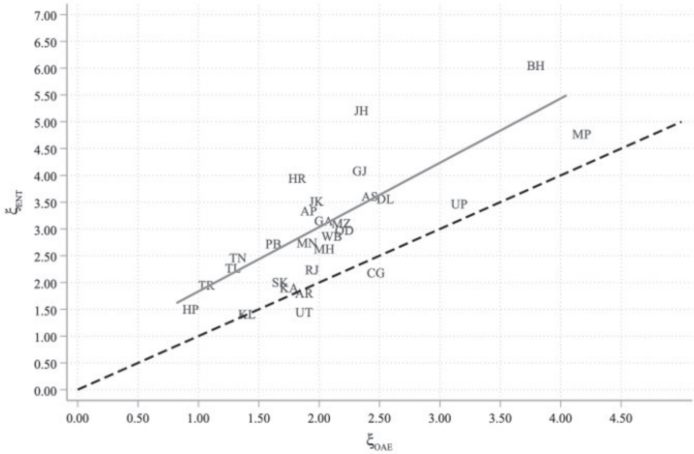
Lastly, Figure 7 plots the relationship between distortions across occupations. In Figure 7a, we observe a strong positive correlation between labor demand distortions in self-employment and entrepreneurship across states. States with high Λ_{OAE} tend to also have high Λ_E. Moreover, there is an order of magnitude difference in the level of distortion in entrepreneurship as compared to self-employment. This pattern suggests that structural barriers compound as women attempt to rise from self-employment to more demanding entrepreneurial roles by extending the scale of their firms. In Figure 7b, labor supply distortions are positively correlated across states as well, though the difference in magnitudes between self-employment and entrepreneurship is smaller as compared to the difference in the demand-side distortions Λ. This indicates that the same non-monetary frictions that discourage women from entering self-employment may also deter them from expanding into entrepreneurship.

FIGURE 7. Comparing Distortions in Self-employment and Entrepreneurship

(a) Demand Distortions



(b) Supply Distortions



Source: The figure reports model parameter estimates using data from the 2023 PLFS.

Note: We restrict the sample to individuals aged 21-65 years. The figure plots estimates of Λ and Ξ in self-employment and entrepreneurship across states. We also show the line of linear fit (solid line) and the 45-degree line (dotted black line).

5. Implications For Policy

Our findings establish that entry into entrepreneurship and entrepreneurial growth are shaped by both supply- and demand-side dynamics. Unlocking women's entrepreneurial potential, therefore, requires targeted interventions at both margins, tailored to the specific frictions that operate at individuals' occupational choices.

Our insights carry several implications for policy design. First, efforts to improve female labor force participation remain fundamental. Policies that reduce the opportunity cost and non-monetary burdens of working, such as investments in safety, public transportation, childcare infrastructure, and social norm change campaigns, can help shift the extensive margin of female labor supply. These interventions are particularly relevant in poorer states, where supply-side distortions remain most binding.

Second, fostering entrepreneurship among women already in the workforce requires a different set of tools aimed at reducing structural, demand-side barriers. Expanding access to formal finance through gender-sensitive credit schemes, streamlining regulatory processes for business registration and compliance, and expanding public procurement for women-owned firms can raise the effective returns to entrepreneurship. In parallel, initiatives that connect women to mentorship, skill development, and professional networks are essential to ensure that women can scale their businesses and participate in broader market ecosystems.

Third, the design and targeting of entrepreneurship promoting policies should be state-and occupation-specific. Our analysis shows that both the nature and magnitude of gender-related distortions vary substantially across states and across self-employed individuals and entrepreneurs. In poorer states, entry-level self-employment support and labor inclusion policies may be more effective. In richer states, the bottleneck shifts to firm growth and formalization, where reforms must focus on credit access, taxation, and easing entry into higher-return markets.

Finally, the empirical approach used in this paper highlights the value of data-driven policy-making. Building state-level gender distortion indices as in Goldberg et al. (2024) and incorporating them into policy evaluation frameworks can help prioritize resources and monitor progress. Embedding experimental designs and feedback loops into the rollout of entrepreneurship programs will also be critical for ensuring that policies effectively reach and empower the women they are designed to support.

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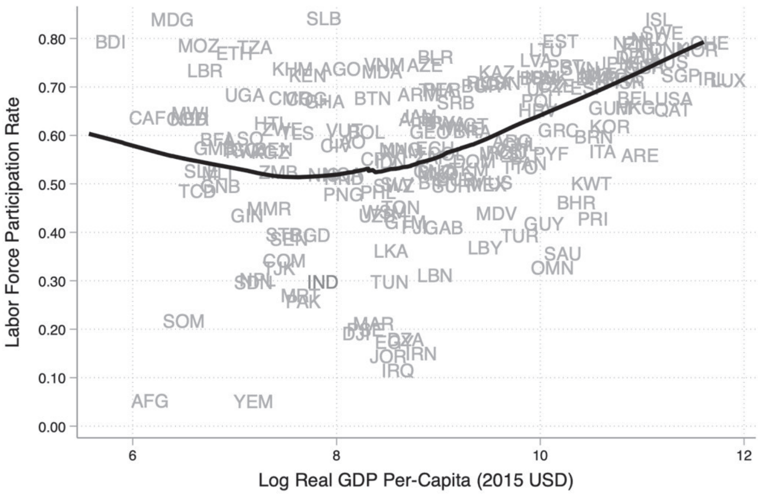
APPENDIX A: Additional Figures

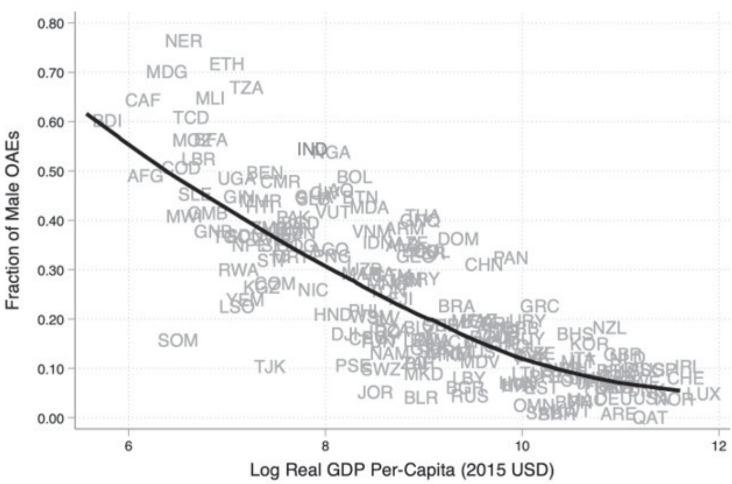
FIGURE A1. Female LFPR across Countries

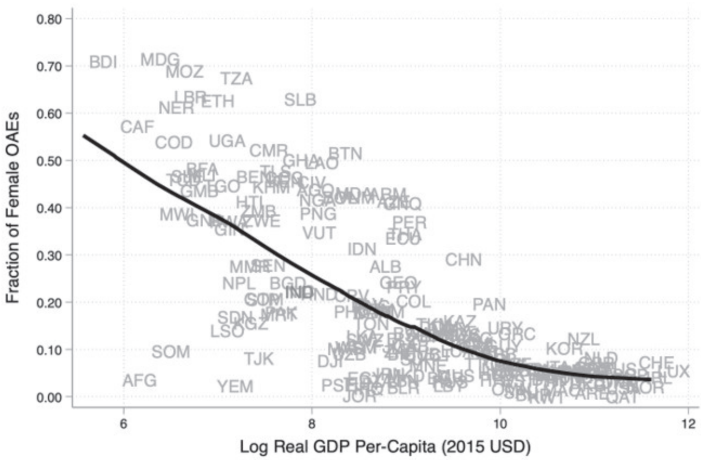


Source: The figure uses data from the World Bank across 186 countries in 2022.

Note: The figure plots a non-parametric correlation between female labor force participation rate and log real GDP per-capita. India (IND) is highlighted in the figure.

FIGURE A2. Fraction of Male and Female OAEs across Countries

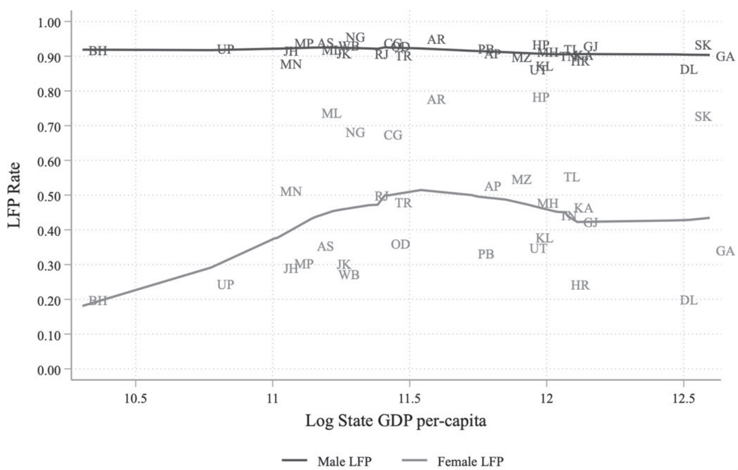




ource: The figure uses data from the World Bank across 186 countries in 2022.

Note: The figure plots a non-parametric correlation between the fraction of 15-64 years old male (panel on the left) and female (panel on the right) individuals who operate own-account enterprises (OAEs) and log real GDP per-capita. India (IND) is highlighted in the figure.

FIGURE A3. Labor Force Participation across Indian States



Source: The above figure uses data from the 2023 PLFS.

Note: The figure shows a non-parametric correlation between the male and female labor force participation rates for each state with log state GDP per-capita.

TABLE A1. Variable Definitions and Descriptions

Variable	*Table*	*Variable Description*
(1)	*(2)*	*(3)*
Intention	Table 2	Takes the value 1 if an individual reports planning to start a business
Networks	Table 2	Takes the value 1 if an individual knows an entrepreneur who has started a business in the last 2 years
Buss. Opp.	Table 2	Takes the value 1 if an individual believes there will be good business opportunities in the next six months
Skills	Table 2	Takes the value 1 if an individual reports having the knowledge, skills, and experience to start a new business
Prob. Success	Table 2	Takes the value 1 if an individual reports fear of failure will not prevent them from starting a business
Desirable Career	Table 3	Takes the value 1 if an individual agrees with the statement: "In my country, most people consider starting a business a desirable career choice''
Respect	Table 3	Takes the value 1 if an individual agrees with the statement: "In my country, those starting a business have a high level of respect and social status"
Media Coverage	Table 3	Takes the value 1 if an individual agrees with the statement: "In my country, you will often see stories in the media about successful entrepreneurs and businesses''

Source: The table uses data on India from the GEM between 2015 and 2018.

Appendix B: Theory

B.1 Derivation of Equations (6) and (7)

For a variable x_{og} (e.g., employment shares, wage earnings, etc.), define: $X_o = x_{of}/x_{om}$. Combining Equations (2) and (3) and using $\lambda_{om}=1$,

$$\left(\frac{p_{of}}{p_{om}}\right)^{1/\theta} = \Lambda_o^{-1} \cdot \frac{h_{of}}{h_{om}} \cdot \left(\frac{\overline{w}_{of}}{\overline{w}_{om}}\right)^{-}$$

$$\Rightarrow P_o^{1/\theta} = \Lambda_o^{-1} \cdot \frac{H_o}{\overline{W}_o}$$

Similarly, using the assumption that $E_H = \xi_{Hf} \backslash \xi_{Hm} = 1$, and from Equation (5),

$$\frac{\overline{w}_{of}/\overline{w}_{Hf}}{\overline{w}_{om}/\overline{w}_{Hm}} = \left(\frac{\xi_{of}/\xi_{Hf}}{\xi_{om}/\xi_{Hm}}\right)^{-1}$$

$$\frac{\overline{W}_o}{\overline{W}_H} = \Xi_o{}^{-1}$$