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Gender Specific Distortions, Entrepreneurship and Misallocation

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Abstract

Women account for a small share of all business owners and a small share of the market in India's manufacturing sector. To account for these patterns, I estimate the extent of gender-specific distortions to operating a business using firm-level data. Feeding these estimates that differ across gender into a standard framework of heterogeneous producers replicates key features of the firm size distribution, on aggregate and across gender. While women face higher entry barriers into entrepreneurship, they have modest impacts on female market shares when there are sharp differences in distortions across gender along the intensive margin of entrepreneurship. Policies that promote female entrepreneurship are effective, yet have only modest impacts on aggregate productivity. These findings are not unique to India, and apply across a broader set of countries.

JEL: J16, O1, O4, O5.

Key Words: gender, entrepreneurship, misallocation, productivity, micro data.

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1 Introduction

Women face considerable barriers in the labour market and are particularly under-represented in owning and operating a business, patterns that are especially stark in poorer countries (Jayachandran, 2015, 2020). While gender equality is a human rights issue, it is also related to economic development. In this context, the misallocation literature has shown that frictions, whether implicit or explicit, that affect businesses differently can be important for understanding cross-country aggregate productivity differences (Restuccia and Rogerson, 2017). Less explored are whether these frictions differ across male and female business owners, if they matter for understanding female entrepreneurship and economic development. This paper examines the extent that barriers to operating a business differ across entrepreneur gender in India, its quantitative relevance for female entrepreneurship and market shares, and its implications for aggregate productivity.

Based on micro-level data for India's manufacturing sector from the World Bank Enterprise Surveys (WBES), there are considerable differences in the firm size distribution, productivity and market shares across entrepreneur gender. For instance, women account for 12 percent of firms and 20 percent of sales among formal firms in manufacturing. Importantly, they are more productive—measured by output per worker—and operate larger firms on average, implying considerable misallocation across entrepreneur gender in India. I interpret these differences as stemming from distortions that differ across gender along the extensive and intensive margins of entrepreneurship, and which alters the optimal size distribution of firms. Quantitatively, when women face a similar range of distortions as men, there is a 2-fold increase in female entrepreneurship rates and in their share of sales. However, on aggregate there are modest impacts on output and TFP (in the range of 2-4 percent) from the reallocation of resources across entrepreneur gender.

I explore differences in entrepreneurship across gender more formally in a standard model of heterogeneous producers. As a starting point, men and women are heterogeneous in ability but draw from the same distribution of entrepreneurial talent. The only source of difference across gender are from barriers to entry and the extent that distortions on production, in particular its distribution, varies across gender. Differences in barriers to entry are inferred from the share of female entrepreneurs implied by the model, and distortions are estimated as implicit wedges that alter optimal firm size. I find that women face higher entry barriers into entrepreneurship than men, and that even among a more talented subset of women who overcome these barriers and become entrepreneurs, they still face higher distortions on production.[1] Even though average distortions are similar across gender, accounting for the distribution of distortions provides a clearer view of the differential constraints on production across gender and is important for informing appropriate policy responses.

I focus on formal firms who account for the majority of production in India and keep the model intentionally simple to highlight the impact of differential distortions on female entrepreneurship and productivity.[2] While more elaborate settings can be readily included, I show that a model of heterogeneous producers together with distortions that vary across gender can quite remarkably replicate key features of the firm size distribution and market shares across male and female entrepreneurs. Importantly, the quantitative findings I report are robust to various extensions (e.g., accounting for labour force participation and informality) and sensitivity analysis. Specifically, while I focus on an aggregated manufacturing sector with labour as the only input in production, the central results are robust to including capital in production as well as focusing on sub-industries within manufacturing.

I use the model to simulate various experiments that promote female entrepreneurship to evaluate its impact on the aggregate economy and to assess which frictions most stifle female entrepreneurship. There are three main results that I highlight. First, even though women face higher entry barriers than men—about 20 times the male entry barrier—equalizing

[1]I provide evidence these higher distortions are associated with women facing higher crime, or perceptions of crime, which lowers their optimal firm size.

[2]While informality is high in India, especially for labour, the share of output produced by formal firms in the manufacturing sector is about 90 percent.

them has only modest impacts on female market shares (relative to equalizing distortions on production).[3] For instance, female sales shares rise from 17 to 21 percent, but there is no movement in female shares among the top decile of producers. The reason is that lowering entry barriers induce more low ability women to select into entrepreneurship—more than a 2.5-fold increase in female entrepreneurship—but as long as women face higher distortions on production post-entry, they continue to operate small scale firms, reducing average firm size upwards of 50 percent.

Second, a policy that equalizes the distribution of distortions across gender while leaving differences in entry barriers unchanged has a large quantitative impact on female market shares. While there is a smaller influx of women into entrepreneurship, they are higher ability on average and compete for resources on par with men. As a consequence, female entrepreneurs operate closer to their optimal scale and account for over 40 percent of the market (sales and labour) and 50 percent of all producers at the top decile of the distribution. From a policy perspective, lowering differences in distortions across gender at the intensive margin of entrepreneurship is more relevant for promoting female entrepreneurship than lowering barriers at the extensive margin. Notably, these results are not unique to India. Across a broader sample of countries in the WBES, a consistent pattern is that women face higher distortions on production and entry barriers, the latter which is negatively related to development. Despite the magnitude of entry barriers, in all countries higher distortions on production are quantitatively more important for understanding female entrepreneurship.

Third, while policies that equalize distortions across gender have significant implications for female entrepreneurship and market shares, they nevertheless have only modest impacts on aggregate output and productivity, which rises by no more than 4 percent. Despite the considerable re-sorting across incumbent firms, TFP gains are small because there is more misallocation *within* than across gender. For instance, if men and women face their respective

[3] The entry barrier serves as a 'catch-all' term accounting for direct barriers as well implicit ones such as social norms that shape preferences and other simplifying modelling assumptions. See also Fattal-Jaef (2022) who also finds high entry barriers in poor countries (for all firms).

average distortions—that is, remove misallocation within gender but allow for misallocation across gender where women still face higher distortions—aggregate output and TFP rises by 10-fold relative to a policy that equalizes the distribution of distortions across gender. Said differently, while removing gender specific distortions promotes female entrepreneurship, improving aggregate productivity requires lowering distortions for *all* firms, which as a byproduct raises female entrepreneurship, albeit more modestly. The take away is that policies that promote female entrepreneurship are valuable of itself, but should not be necessarily evaluated by its impact on overall productivity.

There are few papers that examine the implications of distortions and misallocation on female entrepreneurship and aggregate outcomes. Closely related is Chiplunkar and Goldberg (2021) who using a rich setting rationalize differences in female labour force participation and entrepreneurship in India to infer average distortions (and wages) by gender, across formal and informal firms.[4] Similar to my results, they find that distortions on production have a larger impact on female entrepreneurship than barriers to entry. While they infer average distortions using industry aggregates from the Economic Census, my work emphasises differences in the distribution of output distortions using micro-level data among formal firms in manufacturing (and includes versions that account for the distribution of capital distortions with similar implications). By accounting for differences in the distribution of distortions, I find polices that promote female entrepreneurship have smaller impacts on TFP. Also related is Angel (2023) who examines informality in Mexico with a focus on aggregate barriers to female labour market participation and entrepreneurship and quantifies its importance on productivity.

Lee (2022) examines gender specific distortions across sectors, modelled as a gender tax on wage income, to show that women face higher distortions in non-agriculture (manufactur-

[4]In the context of the U.S., Hsieh et al. (2019) focus on the allocation of talent across occupations with a focus on race and gender, Bento (2021) examines the rise in female entrepreneurship in the U.S. since the 1980s, and Morazzoni and Sy (2021) quantify the relevance of access to credit on female entrepreneurship and capital misallocation.

ing) sectors which can account for the large agricultural productivity gaps across countries. In line with the predictions of my model, he shows that women face higher distortions in manufacturing, and which is negatively related with GDP. Also related are Cuberes and Teignier (2016, 2017) who examine the implications of labour market gender gaps using aggregate statistics in models featuring occupation choice. They find that barriers to entry, that differ across entrepreneur gender and productivity, can account for sizeable productivity losses. My paper emphasises both entry barriers and distortions on production that differ across gender. While entry barriers certainly matter, as in Cuberes and Teignier (2017), my quantitative results imply that differences in the distribution of distortions are more pressing for female entrepreneurship. Ranasinghe (2023) documents misallocation across gender for over 30 countries and shows that women face higher distortions on production on average, which is especially acute in poorer countries, but abstracts from selection into entrepreneurship. This paper models both misallocation and selection to quantify the impact on female entrepreneurship rates and market shares when distortions are equalized.

The rest of the paper proceeds as follows. Section 2 documents differences in market shares and the firm size distribution across gender in India using the WBES (2014). Section 3 presents a standard model of misallocation that imbeds gender-specific distortions to production. Section 4 presents the quantitative analysis. Specifically, Section 4.1, 4.2 and 4.3 describe the data, the model calibration strategy and model fit. Section 4.4 presents the quantitative impacts from policies that promote female entrepreneurship, and Section 4.5 examines the sources of these gender based distortions. Section 5 considers various sensitivity tests and Section 6 examines the cross-country implications of gender specific distortions. Section 7 provides concluding remarks.

2 Some facts on firm size across gender in India

A growing literature finds that female business owners operate both smaller businesses and under-perform relative to males, particularly among small or micro-scale enterprises, and is a pattern that holds across rich and poor countries (Fairlie and Robb, 2009; Hardy and Kagy, 2018; Jayachandran, 2020). Here, I use data from the WBES and focus on *formal* manufacturing firms in India (2014) to examine differences across male and female business owners.[5] The data covers both micro-scale enterprises as well as small, medium and large firms. The surveys for India have the most number of observations of all countries in the WBES, and India is of particular interest given its population size, poverty, and evidence of gender bias (Jayachandran, 2015, 2020). The WBES reports industry classification up to the 2-digit ISIC level but there are limited observations at this level of disaggregation, which is further amplified when examining across gender. For this reason, I primarily focus on an aggregated manufacturing sector (ISIC 15-37); in Appendix A.1 and A.2 I focus on sub-industries within manufacturing. While the WBES data is at the establishment level, I use firm for ease, and also use firm and entrepreneur interchangeably when convenient (all statistics and results that follow hold for firms and establishments).

The WBES is especially useful because it reports business owner categories by gender (all, majority, minority or none of the owners are male/female) and also the top manger's gender. I define a firm as female owned if any of the business owners are female (i.e., not all business owners are male), which is both a conservative way to measure female entrepreneurship and maximizes the sample of observations.[6] In the Appendix A.4, I show the results are robust to using the top manager's gender to define a firm.

[5]There are considerably fewer observations for the service sector (about 25 percent of manufacturing) and so I focus on manufacturing firms. Nonetheless, the data patterns I document for women in manufacturing also hold in services with women accounting for slightly higher market shares in services.

[6]If women face higher discrimination on average, defining a firm 'female' that is primarily male owned would understate female discrimination. In addition, in poorer countries, including India, women often require men to co-sign business ownership. Of note, there are too few observations if a female firm is defined as majority or equally owned by women.

Table 1: Statistics for India's Manufacturing Sector

	Panel A All Firms			Panel B Firms reporting Capital		
	All	Male	Female	All	Male	Female
# of firms (un-weighted)	6313	5302	1011	2778	2351	427
share of entrepreneurs		0.877	0.123		0.873	0.127
share of sales		0.801	0.199		0.821	0.179
share of labour (wage bill)		0.844	0.156		0.840	0.160
share of employees		0.853	0.147		0.855	0.145
share of capital		—	—		0.841	0.159
Average firm size (employees)						
$\ln(n)$	3.44	3.42	3.57	3.40	3.38	3.52

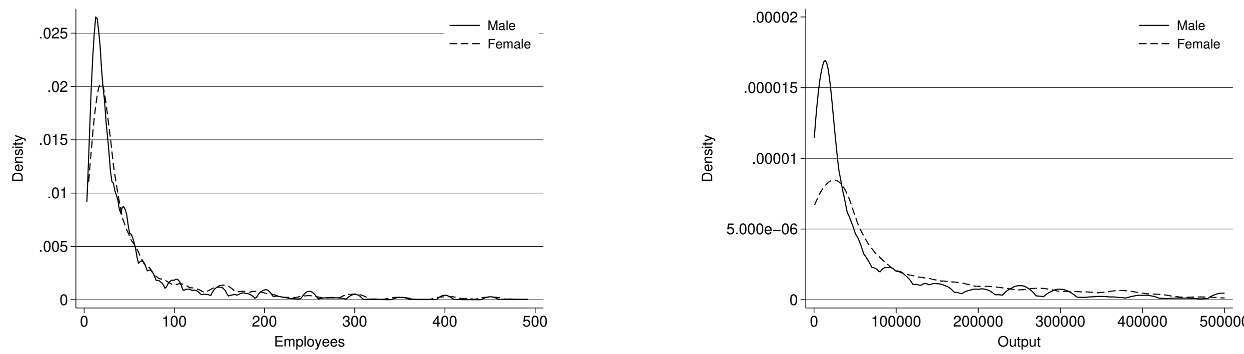
Notes: Statistics are based on sample weights, except for number of firms, and are based on the sample described in the text. A firm/entrepreneur is defined 'female' if any one of the owners is female.

To get a sense of the differences between male and female firms in India, Table 1 provides descriptive statistics for the manufacturing sector. All reported statistics are based on sample weights unless otherwise stated, excludes firms that have more than 1000 employees (less than 1 percent of the sample), those whose responses are deemed unreliable, and if business owner gender is not reported.[7] Panel A shows statistics for the full sample of firms where women account for 12 percent of all firms and a small share of the market—20, 16 and 15 percent of sales, labour costs and workers. To the extent the distribution of innate entrepreneurial talent is common across gender, the above statistics can imply the following: First, that women do not account for half of all firms is suggestive of substantial entry barriers that preclude female entrepreneurship.[8] Second, that women account for a large share of sales relative to their share of entrepreneurs (and employees) suggests that female entrepreneurs are more productive on average. This interpretation is also supported looking at firm size, where women operate larger firms on average, and is a robust pattern across various cuts to the data. This finding is also confirmed by Chiplunkar and Goldberg (2021), who using India's

[7]The sample is also restricted to firms that report positive annual sales, employees and total labour costs.

[8]Entry barriers here can reflect outright gender discrimination to implicit social norms that shape preferences and dissuade women from entrepreneurship (and labour force participation). Also of note, that women account for only a small share of firms is not unique to India or low-income countries. For instance, the share of female firms in the U.S. was below 20 percent in 2018 based on the Census Bureau (see also Fairlie and Robb (2009)). Although the type and scale of barriers can vary across countries, it is a common hurdle women face across the range of development.

Figure 1: Size Distributions



(a) Size

(b) Output

Notes: The plots are based on the sample of all firms (Table 1 Panel A). An unweighted Kolmogorov-Smirnov test for equality of distributions is rejected ($p < 0.01$) for both panels.

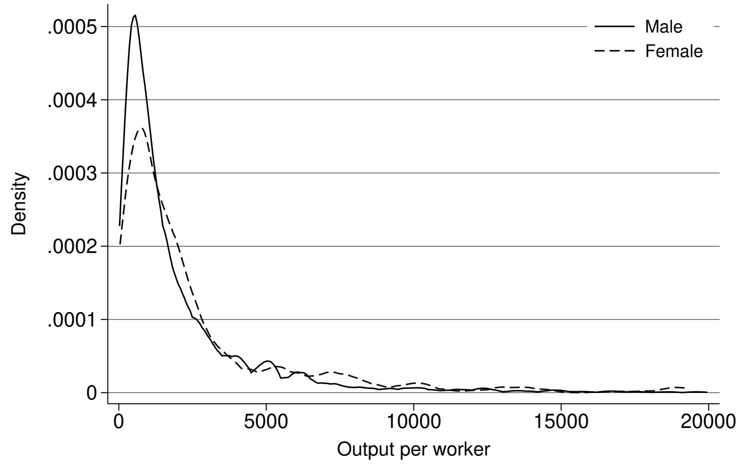
Economic Census, find that women operate larger firms in the formal sector (measured by workers).[9] The statistics in Table 1 may also be shaped from women facing higher distortions to operating a business and is taken up in Section 3.

Table 1 Panel B restricts the sample to capital reporting firms (i.e., excludes firms that do not report values for capital). An issue with the WBES is that many firms do not report values for capital, and in this instance lowers the sample size by more than half, in total and for female firms. While capital certainly plays an important part of the production process, it is reassuring the implications for female entrepreneurship rates, market shares and relative firm size differences are virtually unchanged. Going forward I exclusively focus on the sample of all firms (panel A) to maximize the number of observations. Appendix A.3 considers the sample of capital reporting firms (panel B) and where capital plays a role in production.

Moving beyond averages, Figure 1 shows the distribution of firm size (based on employees) and output (based on sales) across gender. The right-hand tails are trimmed for emphasis. On firm size, the range is similar across gender though there is a higher proportion of small

[9] The Economic Census is nationally representative and has considerably more observations than the WBES. An advantage of the WBES is that it reports firm-level sales/output (and capital) which is crucial for backing out differences in the distribution of distortions across entrepreneur gender, and facilitates cross-country comparisons.

Figure 2: Output per worker



Notes: The plots are based on the sample of all firms described in the text, and trimmed for emphasis. An unweighted Kolmogorov-Smirnov test for equality of distributions is rejected ($p < 0.01$).

male firms. A similar pattern is also evident for output where there is a higher proportion of male firms that produce very little. To get a sense of whether these differences are tied to productivity, Figure 2 plots output per worker across gender. To the extent that output per worker is a reasonable proxy for productivity, female firms are more productive on average, and there is a higher proportion of high productivity female firms.

To further get at the differences across gender, Table 2 shows (non-causal) regression estimates on firm sales and size (in logs) of being a female entrepreneur, while controlling for urban population, registration status, entrepreneur experience, firm size classifications and 2-digit manufacturing industry fixed effects (see table notes for details). The female estimate is positive and significant implying that female entrepreneurs on average have higher sales and operate larger firms. For instance, when accounting for all controls women are associated with having 27 percent higher sales (column 4) and operating firms that are 13 percent larger based on employees (column 7)—the latter is identical to the estimate Chiplunkar and Goldberg (2021) find for formal firms using the Indian Economic Census and a finer level of industry controls.[10] These results, by focusing on a broader range of firm size in formal

[10]It is reassuring the estimates for firm size using the WBES matches the census data estimates, and provides

Table 2: Female estimates: Sales and Employees

	Sales				Employees		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.43***	0.42***	0.36***	0.24***	0.16***	0.15***	0.12**
	(0.10)	(0.09)	(0.09)	(0.07)	(0.05)	(0.05)	(0.05)
City			-0.02	0.05			-0.03
			(0.06)	(0.05)			(0.03)
Register			0.44***	0.30**			0.16**
			(0.16)	(0.13)			(0.08)
Experience			0.13***	0.07***			0.05***
			(0.03)	(0.03)			(0.02)
Industry fixed effects	–	✓	✓	✓	–	✓	✓
Size fixed effects	–	–	–	✓	–	–	–
N	6313	6313	6313	6313	6313	6313	6313
R^2	0.017	0.094	0.106	0.464	0.005	0.095	0.100

Notes: Columns (1)–(4) and (5)–(7) show estimates when the dependent variable is sales and employees, in logs, for all manufacturing firms (ISIC 15-37) in the sample. Female is an indicator whether the business owner is female; City is an indicator whether the firm operates in a city with a population of <50, 50-250, 250-1000, >1000 (in thousands) or is the capital; Experience is the manager/owner's experience working in the industry (less than 5, 5-10, 10-15, 15-20, >20 years); Register is an indicator whether the firm was formally registered when it began operations; and size is an indicator based on the WBES definition whether a firm is small, medium or large. Industry fixed effects account for about 20 sub-industries in manufacturing. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

manufacturing are in contrast to earlier cited work that find women operate smaller micro-scale businesses, and which are primarily in the service sector. In addition, estimates for profit—measured as sales minus labour costs—are similar in magnitude to what is reported in columns (1) through (4). Table 3 reports female estimates when sales/output per worker is the dependent variable. The estimates are positive and significant implying that female entrepreneurs are 25 percent more productive (based on column 4).

One interpretation of the facts presented above, and consistent with the emphasis in the misallocation literature, is that women face larger frictions to operating a business than men. These frictions can stem from barriers to starting a business (distortions at the extensive margin of entrepreneurship) and/or distortions to operating a business post entry (distortions

additional credibility for other estimates using the WBES. In addition, the estimates in Table 2 and 3 also hold when restricting the sample to firms that have fewer than 30 employees and also when focusing on the sample of firms that report capital. There are insufficient observations to focus on micro-scale firms (fewer than five employees).

Table 3: Female estimates: Output per worker

	Sales per worker			
	(1)	(2)	(3)	(4)
Female	0.28***	0.27***	0.24***	0.22***
	(0.07)	(0.07)	(0.07)	(0.07)
City			0.01	0.02
			(0.05)	(0.05)
Register			0.28*	0.27*
			(0.15)	(0.15)
Experience			0.08***	0.08***
			(0.02)	(0.02)
Industry fixed effects	–	✓	✓	✓
Size fixed effects	–	–	–	✓
N	6313	6313	6313	6313
R^2	0.013	0.061	0.071	0.080

Notes: Columns (1)–(4) show estimates when the dependent variable is output per worker, in logs, for all manufacturing firms (ISIC 15-37) in the sample. All other variables are as defined in Table 2. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

at the intensive margin). To the extent that female firms are more productive on average, reallocating inputs in production towards female firms can raise overall productivity, as well as the proportion of women that operate a business. In what follows, I explore a model of heterogeneous producers to measure the extent of these differential barriers to entrepreneurship across gender and to quantify its implications for market shares and productivity.

3 Model

I now consider a standard model of heterogeneous producers with occupation choice that operate in a perfectly competitive setting as in Lucas (1978). People differ in entrepreneurial ability/productivity for running a business and choose whether to operate a firm (entrepreneur) or work for a firm earning a wage (worker). I abstract from labour force participation and assume every person is an entrepreneur in the formal sector or a worker earning a common wage.[11] The emphasis is on gender. Specifically, men and women are heterogeneous in entrepreneurial ability, the distortions on production they face, and in an entrepreneurial entry cost, all of which are static and known in advance as is typical in the misallocation literature. Apart from these, there are no other differences across gender. Differences in ability together with differential distortions across gender affect the set of men and women that select into entrepreneurship (extensive margin gender misallocation), and has implications for market shares across gender (intensive margin gender misallocation), as well as macroeconomic aggregates. While more elaborate settings can be readily included, features of the model are kept to a minimum as they are sufficient to account for the facts reported in Section 2 and highlight the main channels that affect productivity, firm size and differences across gender. The specifics of the model are described below.

3.1 Environment

People are heterogeneous in entrepreneurial ability $z \in Z$ which is drawn from a distribution $F(z)$. This distribution *can* differ across gender to reflect gender specific frictions that affect human capital accumulation and productivity prior to labour market entry. Specifically, $F^j(z)$ $j \in \{m, f\}$ is the gender specific distribution males (m) and females (f) draw ability from. Each person lives forever, has one unit of labour that is supplied inelastically every period, and works either as an entrepreneur in a formal manufacturing sector operating an individual specific technology, or as a worker earning a wage w by supplying labour to hiring firms. (In what follows I use the term entrepreneur and firm interchangeably.)

Entrepreneurs operate in perfectly competitive markets, using capital k_{ij} and labour n_{ij} together with ability z_{ij} to produce a homogeneous good/output y_{ij}. The production function

[11] The informal sector can be sizeable in developing countries. In the context of the model, one can think of a subset of workers as operating micro scale informal firms—own account workers—that produce very little while supplying labour to hiring firms.

is a span-of-control type and exhibits decreasing returns to scale in inputs,

$$y_{ij} = (z_{ij})^{1-\eta} \left(k_{ij}^{\alpha} n_{ij}^{1-\alpha}\right)^{\eta}$$

where $0 < \alpha, \eta < 1$ (and $\alpha = 0$ when there is no capital in production). The decreasing returns to scale assumption ensures there is a distribution of firms in equilibrium, and the span of control parameter η affects how important entrepreneurs are in production.

Entrepreneurs also face distortions on production which are modelled as implicit taxes (or subsidies) on output τ_{ij}^{y} and capital τ_{ij}^{k} that affect the marginal product of inputs used in production. These distortions include an idiosyncratic component to reflect random frictions firms face, as well as a gender specific component that is common across firms of a given gender to reflect gender barriers to production. Specifically, the distortion on output and capital are $\tau_{ij}^{y} = \bar{\tau}_{j}^{y} + \tau_{i}^{y}$ and $\tau_{ij}^{k} = \bar{\tau}_{j}^{k} + \tau_{i}^{k}$, where the 'bars' reflect the gender specific distortion on output and capital and the second part reflects an idiosyncratic component that is not tied to gender. On average, female entrepreneurs face a higher distortion on output when $\bar{\tau}_{m}^{y} < \bar{\tau}_{f}^{y}$, and on capital when $\bar{\tau}_{m}^{k} < \bar{\tau}_{f}^{k}$.

I abstract from dynamic considerations by assuming entrepreneur ability and distortions are fixed over the life-cycle, consistent with Hsieh and Klenow (2014) who document very little growth for firms in India. The decision for an entrepreneur is to choose capital and labour to maximize profit,

$$\pi(z_{ij}, \tau_{ij}^{y}, \tau_{ij}^{k}) = \max_{k_{ij}, n_{ij} \geq 0} (1 - \tau_{ij}^{y}) y_{ij} - w n_{ij} - (1 + \tau_{ij}^{k}) r k_{ij}, \tag{1}$$

where $-\infty < \tau_{ij}^{y} < 1$, $-1 < \tau_{ij}^{k} < \infty$, w is a common wage across workers, and $r = R + \delta$ is the user cost of capital where R and δ are the real interest and depreciation rate. The first order conditions for (1) imply

$$\frac{y_{ij}}{n_{ij}} = \frac{w}{\eta(1-\alpha)} \cdot \frac{1}{1-\tau^y_{ij}}, \tag{2}$$

$$\frac{k_{ij}}{n_{ij}} = \frac{\alpha}{1-\alpha} \cdot \frac{w}{r} \cdot \frac{1}{1+\tau^k_{ij}}, \tag{3}$$

which show that output and capital per worker are proportional to the distortions on production they face. These ratios will differ across entrepreneur gender to the extent that capital and output distortions differ across gender, and reflect gender misallocation at the intensive margin. That is, firms exhibiting high (low) output per worker relative to $w/(\eta(1-\alpha))$ are those facing high (low) output distortions; similarly, firms that exhibit low (high) capital-labour ratios (relative to $\alpha/(1-\alpha) \cdot w/r$) are those facing high (low) capital distortions. Equations (2) and (3) are especially useful to examine how output and capital distortions, in particular their distributions, vary across entrepreneur gender.

Figure 2 showed that female entrepreneurs on average have higher output per worker than males, which is also supported by the estimates in Table 3. Interpreting these patterns based on equations (2) and (3) suggests that female entrepreneurs face higher output (and capital) distortions in production.

Following Hsieh and Klenow (2009), it also useful to combine the expressions above to obtain a composite measure of distortions at the firm level based on revenue productivity,

$$tfpr_{ij} \equiv \frac{y_{ij}}{k^{\alpha}_{ij} n^{1-\alpha}_{ij}} = \chi \cdot \frac{(1+\tau^k_{ij})^{\alpha}}{1-\tau^y_{ij}}, \tag{4}$$

where $\chi = \left(\frac{r}{\alpha\eta}\right)^{\alpha} \left(\frac{w}{\eta(1-\alpha)}\right)^{1-\alpha}$ is common across all firms. Equation (4) shows that when distortions are common across firms (or when equal to zero), $tfpr_{ij}$ reduces to a constant, which is to say all firms have the same revenue productivity. Hence, dispersion in $tfpr$ across firms provides a measure of misallocation and where high values imply a firm faces high distortions.

The optimal solutions for capital, labour and output (which are not presented) imply that high ability entrepreneurs use more inputs, produce more output and earn more profit from operating a business, but the strength of this correlation with ability is muted by the distortions they face. Put differently, holding ability fixed, high $tfpr_{ij}$ firms use fewer inputs in production, produce and earn less profit relative to a low $tfpr_{ij}$ firm.

Of note, I have assumed a common production function across gender. Conceptually, differences in inputs across gender can be attributed to differences in η or α across gender, which I assume away. That is, the primitives of the model related to technology are common across all entrepreneurs—men and women use the most efficient production technology—and differences in inputs are only due to differences in distortions and ability.

Occupation Choice. A person chooses an occupation—entrepreneur or worker—that generates the highest income over their life time. While I assume no differential cost to being a worker across gender, there is a one-time start up or entry cost to operating a firm $\xi_j > 0$ that can differ by gender, and serves as a 'catch-all' term. This is to capture implicit costs stemming from cultural and social norms to more explicit forms of discrimination, such as access to start-up funds, that on *average* make entry costs differ by gender. In this regard, ξ_j has a first-order impact on gender based misallocation at the extensive margin. Given profit, and noting that ability and distortions are static over the life-cycle, a person chooses to operate a firm if

$$\frac{\pi_{ij}}{1-\beta} - \xi_j \geq \frac{w}{1-\beta}, \tag{5}$$

and is a worker otherwise, where $\beta = 1/(1+R)$ is a discount rate. Given a distribution $F^j(z)$, let Ω^j represent the set of gender j people choosing to operate a firm.

I have assumed perfect capital markets so that entrepreneurs can freely borrow to pay the entry cost, and thereby overlook the need to self-finance prior to entry.[12] While adding a

[12] See Morazzoni and Sy (2021) who examine differences in access to finance across gender in the U.S.

savings motive allows for an additional dimension of misallocation, I instead calibrate the entry cost to match the share of entrepreneurs by gender. This will imply a higher entry cost than if savings or financing is required but is functionally equivalent.

3.2 Aggregation and Equilibrium

Given optimal factor demands and output, the economy aggregates up to provide convenient expressions for aggregate distortions by gender. Specifically, the aggregate output distortion, capital distortion, and $TFPR$ by entrepreneur gender are

$$1-\bar{\tau}_j^y=\frac{1}{\eta(1-\alpha)}\cdot\frac{wN_j}{Y_j},\qquad 1+\bar{\tau}_j^k=\frac{\alpha}{1-\alpha}\cdot\frac{wN_j}{rK_j},\qquad TFPR_j=\chi\cdot\frac{(1+\bar{\tau}_j^k)^\alpha}{1-\bar{\tau}_j^y},\tag{6}$$

where N_j, K_j and Y_j correspond to aggregate labour demand, capital demand, and output for gender j entrepreneurs (Ω^j). These expressions are useful to evaluate whether female entrepreneurs face higher output and capital distortions on aggregate, and where $TFPR_j$ serves as a summary statistic of these distortions. It follows that overall economy wide aggregate distortions can be represented as a weighted average of gender specific aggregate distortions;

$$1-\bar{\tau}^y=\theta_m^y\cdot(1-\bar{\tau}_m^y)+\theta_y^f\cdot(1-\bar{\tau}_f^y),$$

$$1+\bar{\tau}^k=\theta_m^k\cdot(1+\bar{\tau}_m^k)+\theta_f^k\cdot(1-\bar{\tau}_f^k),$$

$$TFPR=\varphi_m\cdot TFPR_m+\varphi_f\cdot TFPR_f,$$

where $\theta_j^y\equiv Y_j/Y$ and $\theta_j^k\equiv K_j/K$ are the share of total output (Y) and capital (K) used by gender j entrepreneurs, and $\varphi_j\equiv\left(\theta_j^k\right)^\alpha\left(\theta_j^n\right)^{1-\alpha}$, $\theta_j^n\equiv N_j/N$. Of note, $TFPR$ is especially high when the gender that accounts for the majority of inputs in production faces high distortions.

The above equations show that data on aggregate labour, capital and output by gender

j entrepreneurs together with production elasticities are sufficient recover gender specific distortions to production. These expressions can be especially useful when micro-level data is unavailable or not as reliable as observed aggregates.

Finally, aggregate output is

$$Y = TFP\left(K^{\alpha}N^{1-\alpha}\right)^{\eta},$$

and economy wide productivity is $TFP = \left(\sum_j \int_{z_{ij}\in\Omega^j} z_{ij} dF^j(z)\right)^{1-\eta}$.

Representative Household. There is a representative household consisting of all people, and serves to pin down the interest rate. In particular, the household maximizes lifetime consumption $\sum_{t=0}^{\infty}\beta^t U(C_t)$ subject to $C_t + K_{t+1} + \Xi = w_t N_t^s + r_t K_t^s + \Pi_t + T_t$, where N_t^s and K_t^s are the aggregate supply of workers and capital, Π_t is total entrepreneur profit, and Ξ is the total cost related to business start-up.[13] T_t is the sum of output and capital distortions that are rebated back to the household, and has no impact on savings decisions.

Equilibrium. I focus on a long run competitive equilibrium for this economy, all of which are standard. In particular, (a) the representative household chooses consumption-savings resulting in the standard Euler condition for the interest rate, $1+r=\beta^{-1}$; (b) people choose entrepreneurship based on equation (5); (c) entrepreneur capital and labour demands k_{ij} and n_{ij} are based on equation (1), and (d) capital, labour, goods market clearing and government budget balance are

$$\sum_j \int_{z_{ij}\in\Omega^j} k_{ij} dF^j(z) \equiv K^s,$$

$$\sum_j \int_{z_{ij}\in\Omega^j} n_{ij} dF^j(z) = \sum_j \int_{z_{ij}\notin\Omega^j} dF^f(z) \equiv N^s,$$

[13]The entry cost is paid only in the first period. If there is exogenous exit with re-entry so that population size is unchanged, Ξ is paid every period with a slight adjustment in β in equation (5).

$$C + \delta K + \Xi = \sum_j \int_{z_{ij} \in \Omega^j} y_{ij} dF^j(z) \equiv Y,$$

$$T + \sum_j \int_{z_{ij} \in \Omega^j} \left(\tau_{ij}^y y_{ij} + \tau_{ij}^k k_{ij} \right) dF^j(z) = 0$$

where $\Xi = \sum_j \xi_j \int_{z_{ij} \in \Omega^j} dF^j(z)$ are total start-up costs paid (only) in the first period. The left-hand side of the labour market clearing condition shows the sum of male and female entrepreneur labour demand, and the right-hand side is the supply of male and female workers. This equation determines the wage in equilibrium. The capital and goods market clearing conditions have an analogous interpretation. Lastly, the government budget balance condition shows the tax T rebated to the household is the sum of output and capital distortions across entrepreneurs.

3.3 Remarks

In modelling entrepreneurship across gender I have made some simplifying assumptions to present a standard framework, which I use in the next section to quantify the impact of policies that promote female entrepreneurship. Specifically, I have focused on a formal manufacturing sector and abstracted from decisions related to informality, labour force participation, investment in productivity, and assumed common wages, all of which are likely to vary across gender. Nevertheless, and as I explain below, explicitly modelling some of these abstractions will serve mainly to affect the calibrated entry barrier ξ_j. In this sense, ξ_j should be understood as a 'catch-all' term that accounts for the impacts of these abstractions. And since the quantitative results that follow show that entry barriers play a minor role on female entrepreneurship and aggregates when there are sharp differences in the distribution of distortions across gender, I opt for a simpler setting that abstracts from these concerns.[14]

Informality: I have abstracted from informality, which can be in the range of 70 percent of the workforce and 90 percent of firms in India, and also has a gender dimension where women are more likely to be workers or business owners in the informal sector. Informality can be modelled through a less efficient production technology and/or a detection constraint that restricts firm size as in Leal-Ordonez (2014) and Lopez-Martin (2019). As the model in this paper is calibrated to match the share of female entrepreneurs in the formal sector, modelling informality will only lower the calibrated entry barrier ξ_j, which has modest impacts on aggregates and female market shares as will be shown in Section 4.4.[15] Of course, central to this point is that higher (lower) ability entrepreneurs operate in the formal (informal) sector and account for the bulk of production, which is a standard feature in these class of models. Said differently, if informal sector entrepreneurs are low-to-moderate skilled who produce very little (i.e., draw from the lower tail of the ability distribution), then policies that promote female entrepreneurship will raise the number of women in entrepreneurship but have little impact on female market shares or economy-wide aggregates in the formal sector.

Labour force participation: The labour force participation (LFP) rate for men and women are 77 and 21 percent (ILOSTAT, India 2014). Differences in LFP can be included in the model with an additional parameter, say disutility of working or a labour entry barrier, that differs by gender. Similar to modelling informality, adding this parameter will only lower the entry barrier ξ_j since the model is calibrated to match statistics related to formal entrepreneurship, statistics that are independent of LFP, and will not affect the main quantitative results. Allowing for LFP will affect measures related to income inequality across gender, and for

[14] To be clear, entry barriers affect selection in to entrepreneurship (extensive margin) but as long as distortions on production vary across gender entry barriers have a modest impact on female production and market shares (intensive margin).

[15] Allowing for informality implies that lower ability people will forgo being a worker to opt into informal entrepreneurship, which means a lower calibrated entry barrier is needed to match the female share of formal entrepreneurship.

this reason I do not focus on these statistics.[16] In addition, policies that promote female entrepreneurship will raise female LFP as in Cubas (2016) and Chiplunkar and Goldberg (2021) through changes in the wage, which I do not account for. But again, as long as those who enter the labour force from such policies are from the lower tail of the ability distribution, then this will only raise the share of female workers and entrepreneurs but have little to no effect on female market shares and on aggregate outcomes.

Common wages: I have assumed a common wage and abstracted from wage differences across gender. Based on the Human Development Report from the United Nations Development Program, the average female worker earns about 1/3 the wage a man earns in India (see also Lee (2022) who uses wage gaps from this data source to assess gender specific frictions). A wage gap can be included in the model as an implicit tax on female wage income, or more explicitly through an elasticity of substitution for male and female workers. In either case, a lower female wage must imply a higher calibrated entry barrier, which as shown in Section 4.4 has little impact on female market shares and aggregates.[17]

Productivity Investment: The data I use (WBES) does not include measures related to firm investment and so I have abstracted from investment in productivity, which have been shown to amplify aggregate losses when distortions vary across firms (Bhattacharya et al., 2013; Gabler and Poschke, 2013; Ranasinghe, 2014; Da-Rocha et al., 2022). Allowing for this channel in my setting will imply women make fewer investments in productivity as they face higher distortions (as implied by the data), and will amplify differences across gender. However, the aggregate implications will be minor since women account for a small share of

[16] In my framework, female income shares are overstated and income inequality understated, especially given common wages across gender.

[17] A lower female wage will make entrepreneurship more attractive and so the female entry barrier ξ_f must rise to match the targeted share of female entrepreneurs in the formal sector. This condition is based on the occupation choice condition in equation (5) and approximately equivalent to

$$\xi_f(1-\beta) + w = \bar{z}_{if}\left(\frac{\eta(1-\tau_f^y)}{w}\right)^{\frac{\eta}{1-\eta}} \cdot \left(1-\eta(1-\tau_f^y)\right),$$

where $w_m = w_f \equiv w$, and $\bar{z}_{if}$ is the female ability threshold required for entry in to entrepreneurship. If women earn a lower wage $w_f < w$, then ξ_f must rise to keep the share of female entrepreneurs constant.

entrepreneurs.

4 Quantitative Analysis

I now evaluate the quantitative implications of the model using firm level data for India and assume there is no capital in production to maximize the sample size. The model is calibrated to match key features of the firm size distribution, entrepreneurship rates, and sales shares by gender, taking the estimated distribution of distortions as given. I then consider experiments that alter the extent that distortions differ across gender to evaluate their impacts on female entrepreneurship and aggregate productivity. I asses the sensitivity of the results, including the importance of capital in production, in the next section.

4.1 Data: Sample Statistics and Distortions

The data for India is from the WBES and is based on the sample of firms reported in Table 1 Panel A. In addition to reporting business owner gender, the surveys also report balance sheet data (annual sales, employees, and labour costs) which allows me to infer distortions on production, and by gender. The output distortion τ_{ij}^y is identified from equation (2) using firm sales and labour costs (wage bill).[18] To account for outliers in the data, I drop the bottom one and top five percent of tails for τ_{ij}^y *by gender*.[19] The final sample includes 5931 firm level observations, of which 935 are female firms.

I focus on an aggregated manufacturing sector by pooling across sub-industries (ISIC 15-37), and assume a common span-of-control η across manufacturing sub-industries which affects the estimates of τ_{ij}^y. An alternative is to allow η to vary by each sub-industry (at the 2-digit

[18] I assume $\eta = 0.85$ and $\alpha = 0$ to infer the distortions. I later calibrate η to match relevant targets and obtain a similar value.

[19] The data for capital, which I later use for sensitivity, is especially noisy and therefore useful to drop the top five percent of the distribution. For consistency and for comparison across results, I drop the top five percent of tails for τ_{ij}^y as well.

ISIC which is the finest level of disaggregation feasible in the WBES) so that the estimates of τ_{ij}^{y} can reflect differences in sub-industry production technologies. I show in Appendix A.1 (see 'Sub-industry specific factor shares') that this does not affect the relative differences in the distribution of distortions across gender, which drives the quantitative results that follow, and so for sake of simplicity I assume η is common across sub-industries.[20]

Table 4: Descriptive Statistics: All firms

	All	Male	Female
# of firms	5931	4996	935
share of entrepreneurs		0.881	0.118
share of sales		0.833	0.167
share of labour		0.856	0.144
share of employees		0.862	0.138
Average firm size (employees)			
$\ln(n)$	3.43	3.42	3.57
Agg. Distortion			
Output, $\bar{\tau}_y$	0.900	0.897	0.914

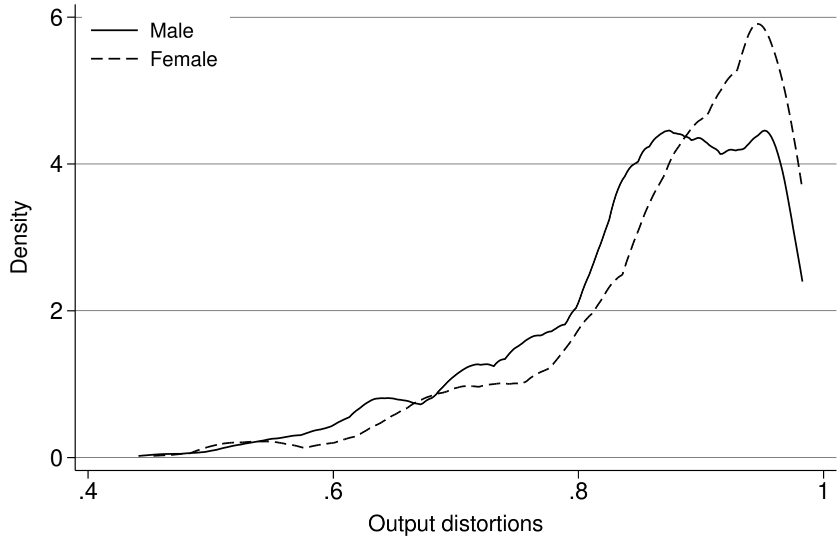
Notes: See text for details. Statistics are based on sample weights except for number of firms.

Table 4 reports descriptive statistics for the manufacturing sector in India. Women account for 12 percent of all firms, 17 percent of sales, 14 percent of labour costs and employees, and operate larger firms, similar to what is reported in Table 1. The bottom panel in Table 4 reports the aggregate output distortion for all firms and by gender. The numbers imply high distortions on production with implicit taxes in the range of 90 percent. While it is difficult to rule out the potential of measurement error in the data, what matters is the differential across gender rather than the level, where female entrepreneurs face about a 2 percent higher distortion on output.

Figure 3 shows the raw plot of output distortions by gender. The data imply that all firms face high distortions, where the least distorted firm faces about a 45 percent implicit tax on production. Of particular interest, the distribution for women is more left-skewed implying they consistently face higher distortions on production relative to males. That is, while the aggregate distortion in Table 4 suggests small differences in distortions across gender,

[20]This is mainly because there are no strong selection effects across sub-industries by gender (see Table A.2).

Figure 3: Distribution of output distortions τ_{ij}^{y}



Notes: Shown is the kernel density plot for output distortions. The mean and standard deviation of output distortions for male and females are: 0.848 (0.103) and 0.872 (0.099). A Kolmogorov-Smirnov test for equality of distributions across males and females is rejected (p-value < 0.01).

Figure 3 shows sizeable differences in the magnitude of distortions across the distribution by gender.

4.2 Calibration

There are several ways to incorporate distortions in the model, which can range from using averages to using the entire distribution. The approach I take is to approximate the output distortions shown in Figure 3 by focusing on deciles. In particular, I take the average at each decile of the distribution for males and females, respectively, where $\bar{\tau}_{d,j}^{y}$ $d = \{1, 10\}$ is the average at each decile by gender (see Table A.3).[21] The advantage of this approach is its transparency while allowing for heterogeneity across entrepreneur gender by approximating its distribution closely.

In calibrating the model, I assume entrepreneur ability is described by a Pareto distribution

[21] An alternative is to use the mean and variance of the distribution to generate distortions along a number of grid points. This is conceptually similar and does not affect the results.

with shape parameter θ. I take the stance the ability distribution is common across gender, i.e., $\theta_f = \theta_m \equiv \theta$ (I discuss the relevance of this assumption below). As a starting point, I assume that distortions are not related to entrepreneur ability, such that $\bar{\tau}^y_{d,j}$ are independently and identically distributed across z_{ij}. I then allow for a correlation between female entrepreneur ability and distortions, based on a parameter ν_f, to better match the data. Specifically, female distortions are $\bar{\tau}^y_{d,f} + \varepsilon_{if}$, where $\varepsilon_{if} = z_{if}^{\nu_f} - 1$ is a constant that scales up with *female* productivity.[22] In total, there are nine parameters to calibrate: the household discount factor β; production function elasticities η and α; the depreciation rate δ, the real interest rate r, entry costs that differ by gender ξ_m and ξ_f, the Pareto distribution parameter θ, and the correlation between distortions and female productivity ν_f. These parameters are calibrated taking the average distortion at each decile $\bar{\tau}^y_{d,j}$ as given.

Parameters β and δ matter only insofar as their impact on the interest rate r. Based on the IMF's International Financial Statistics, the lending rate in India is 10 percent and so r is set to this value. The household discount factor is set to $\beta = 0.96$ as is standard, which implies a capital depreciation rate of $\delta = 0.06$. For the production function, $\alpha = 0$ to shut-down capital in the model.

The remaining parameters (θ, η, ξ_j and ν_f) are jointly calibrated to capture relevant statistics across the size distribution of firms, and by gender. While no one parameter uniquely identifies a target moment they have some direct impact on a specific moment, and so I describe these to motivate the data moments I target. The Pareto shape parameter θ influences dispersion in entrepreneur ability, where higher values lower ability dispersion and thereby increase the number of people that select into entrepreneurship. As such, θ is used to target the entrepreneurship rate. Based on the Global Entrepreneurship Monitor Report (GEM), the overall entrepreneurship rate in India is 16.05 percent (the WBES does not provide

[22] More generally, distortions are $\bar{\tau}^y_{d,j} + \varepsilon_{ij}$, and $\varepsilon_{ij} = z_{ij}^{\nu_j} - 1$; where for males $\nu_m = 0$, and for females $\nu_f > 0$. Note, calibrating $\nu_m \neq 0$ alters the calibrated value for ν_f, so it is simpler and approximately equivalent to set $\nu_m = 0$ and calibrate ν_f.

entrepreneurship rates).[23] The Indian economy, however, is characterized by a large informal sector, with some estimates suggesting that upwards of 90 percent of firms operate in the informal sector. Since I focus on formal firms, I apply a 10 percent formality rate and target an entrepreneurship rate of 1.6 percent. In the context of this framework, one can interpret informal firms as own-account workers that produce very little output and supply labour to the formal sector. (Of note, the quantitative results, specifically the relative impacts across gender, are not sensitive to targeting an entrepreneurship rate of 1.6 percent instead of 16.05 percent, as it would mainly alter the calibrated values for θ and η.) The span-of-control parameter η affects entrepreneur operation scale, specifically the share of sales across the distribution of firms where lower values imply entrepreneurs play a more central role managing the business. And so, η is chosen to match the share of sales among the top ten percent of all firms, which based on the WBES is 68 percent. Entry costs affect the share of entrepreneurs in the economy by affecting the ability threshold required for entry. I normalize $\xi_m = 1$ and calibrate ξ_f to match the share of female entrepreneurs, which is 12 percent. Lastly, ν_f affects the correlation between female productivity and distortions and primarily affects the female share of sales, which is 17 percent.

To sum up, parameters β, δ, r, α, and $\bar{\tau}^y_{d,j}$ (for each decile) are set apriori. Parameters η, θ, ξ_f ($\xi_m = 1$) and ν_f are jointly calibrated to match the entrepreneurship rate, share of sales in the top decile of all firms, the share of female entrepreneurs and their share of sales.

I have taken the stance that men and women have similar entrepreneurial ability which is modelled via a common distribution of ability across gender based on a Pareto shape parameter θ. This can be a strong assumption if women have a comparative advantage in and are more represented in other sectors (e.g., services), such that the women who select into manufacturing are less productive than men on average. This can be modelled by assuming

[23] This is based on taking an average between 2013 to 2018. The entrepreneurship rate from the GEM is based on the sum of early-stage entrepreneurial activity, which are new businesses that have operated for fewer than 42 months, and the established business ownership rate which are businesses operating for more than 42 months.

$\theta_f > \theta_m = \theta$ such that women have lower ability on average and calibrating θ_f to match average ability differences across male and female workers. However, and similar to the arguments made in Section 3.3, the model is calibrated to match formal entrepreneurship targets and so allowing for different ability distributions (i.e., $\theta_f > \theta_m$) will primarily lower the calibrated entry barrier ξ_f, which does not affect the main results.[24] And so accounting for differences in ability across gender does not play an important role for the results that follow.

4.3 Model Fit

Table 5 reports parameter values from the joint calibration, the model fit based on targeted moments, as well as non-targeted moments. The calibrated model closely matches all targeted moments, and notably the share of female entrepreneurs and the share of female sales which are non-standard. The returns to scale parameter is $\eta = 0.84$ and the Pareto distribution parameter is $\theta = 5.3$, which are consistent with the values used in the literature. The model implies that entry, or start-up, costs are 21 times higher for women, implying considerable entry barriers are needed to rationalize that women account for 12 percent of all entrepreneurs. Again, this entry cost serves as a catch-all term and accounts for both implicit barriers—social norms broadly defined such as those affecting LFP and informality—and explicit discrimination that make entry into entrepreneurship more costly for women. Additionally, this cost also reflects any gender bias against women related to human capital, mentoring and training deficiencies that get absorbed by assuming a common distribution of entrepreneurial ability across gender. An implication of higher of entry costs in the model is that female entrepreneurs are more productive than male entrepreneurs on average, consistent with the evidence presented in Section 2. The correlation between distortions and female productivity is $\nu_f = 0.05$ implying that distortions have a slight increase with productivity.

[24] Quantitatively, ξ_f marginally falls because the value for ν_f falls to match female entrepreneurship targets. As such, policies that promote female entrepreneurship will imply even smaller TFP gains than what is reported in Table 7.

Table 5: Model Fit

Target Moments	Data	Model	Parameter
Entrepreneurship Rate	0.016	0.016	$\theta = 5.292$
Sales share (top decile)	0.678	0.663	$\eta = 0.844$
Female share of:			
Entrepreneurs	0.118	0.118	$\xi_f = 20.831$
Sales	0.167	0.167	$\nu_f = 0.052$
Non-targeted moments			
Log avg. firm size (female/male)	1.045	1.052	
Female share of:			
Workers	0.139	0.142	
Labour Costs	0.144	0.142	
Aggregate Distortions:			
Output, $(1-\bar{\tau}_f^y)/(1-\bar{\tau}_m^y)$	0.824	0.838	
$TFPR_f/TFPR_m$	1.194	1.213	

Notes: See text for details.

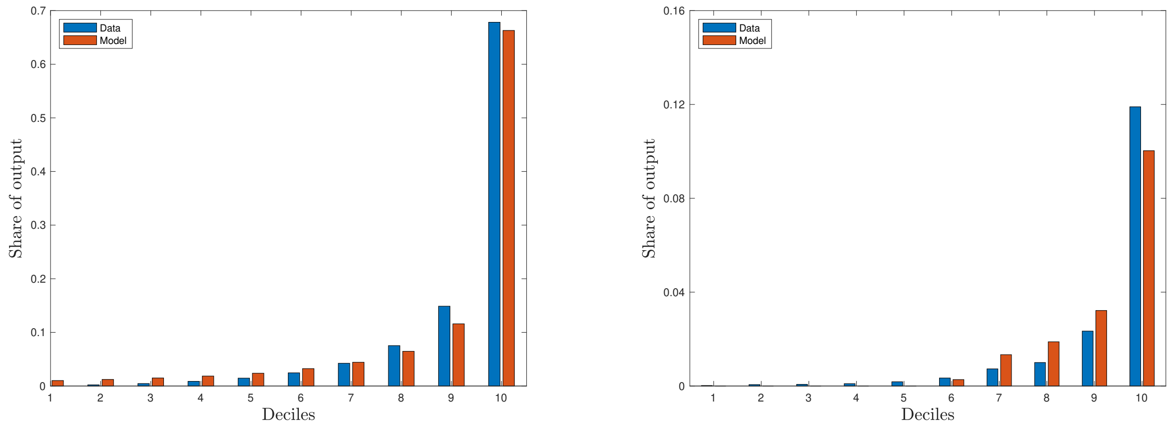
For example, the highest ability female entrepreneur faces a 7 percent higher distortion than the lowest ability female entrepreneur (in levels).

The bottom panel in Table 5 reports *non*-targeted moments, specifically female market shares, firm size differences and relative distortions across gender. The model predicts very closely female market shares for labour (workers and labour costs) and average firm size differences. The model also does reasonably well matching relative aggregate distortions across gender, for output and $TFPR$. Figure 4 panel (a) shows the distribution of output across all firms implied by the model against the data (and, noting that only the top decile is targeted in the calibration). While most models of heterogeneous producers can reasonably capture the output distribution, it is reassuring that it also does in this model which includes differences in the distribution of distortions across gender. Panel (b) shows female output shares across deciles in the model and data, and in particular that the majority of female sales are concentrated in the top deciles.[25]

While this simplified model can replicate key features of the firm size distribution and market shares for the Indian economy, both as a whole and by gender, there are some limitations to

[25] Female output share in the top 2 deciles are 16 and 18 percent in the model and data, and where the top 2 deciles account for 85 percent of aggregate output.

Figure 4: Model Fit



(a) Distribution of output

(b) Female output shares

Notes: Panel (a) shows output/sales in the data and as predicted by the model for all firms across deciles, relative to total output, and panel (b) shows female output shares across deciles, relative to total output. The distribution across deciles for labour are similar to what is shown for output in panels (a) and (b).

highlight. One issue is there are no firms that face the upper deciles of distortions reported in Table A.3 (specifically, deciles $6-10$). This is a feature of any standard model that allows for selection into entrepreneurship where highly distorted potential entrepreneurs forgo entrepreneurship.[26] Nevertheless, the model replicates that women face higher distortions across the distribution and on average, along with matching relative distortions and firm size differences across gender, as well as statistics related to market shares. Related, there are no female firms in the bottom deciles of the output distribution (deciles 1–5 in Figure 4 panel b). While this is consistent with the data that female output is essentially zero in the lower deciles, it does mean there are no very small female firms. For context, the model implies there are no female firms that have fewer than 25 employees (which account for about one-third of all female firms in the data). However, these firms account for less 0.5 percent of total output in the data and so will have little impact on the quantitative results.

[26]All distortions can be made active in the model by scaling down distortions—leaving relative differences across gender in each decile unchanged—and would deliver roughly the same quantitative results that follow.

4.4 Experiments

I now evaluate the impacts of specific policies that promote female entrepreneurship and their implications on economy wide aggregates. Recall, differences in entrepreneurship across gender are from two sources: the distribution of output distortions and entry costs.

Table 6 and 7 present the results: Column (1) shows the impact when women face the same entry costs as men, $\xi_f = \xi_m$; in essence, removing gender discrimination along the extensive margin of entrepreneurship. In column (2) women face the same distribution of output distortions as men ($\bar{\tau}^y_{d,f} = \bar{\tau}^y_{d,m}\ \forall d$), and where the correlation between female ability and distortions remains fixed ($\nu_f > 0$); column (3) is the same as column (2) but where $\nu_f = 0$. These relate to policies that remove gender discrimination along the intensive margin of entrepreneurship. Column (4) shows the impact when men and women, respectively, face a common average distortion based on their distribution of distortions, and where entry costs are equalized ($\xi_f = \xi_m$). In essence, the policies in columns 1–3 remove misallocation *across* gender to varying degrees while allowing for misallocation *within* gender, and the policy in column (4) removes misallocation within gender while allowing for misallocation across gender (where women still face a higher distortion on average). The impact of these policies on the sales/output distribution for women is shown in Figure 5. While each hypothetical policy has an overall positive impact on female entrepreneurship, I highlight three main points of interest.

First, while women face high entry barriers relative to men it has a relatively modest impact on female market shares. As seen in Table 6 column (1), when entry barriers are equalized female output shares rise from 17 to 21 percent, which is lower than the impacts when distortions on production are equalized (columns 2 or 3). Equalizing entry barriers have the biggest impact on entry into entrepreneurship—more than a two-fold increase in the share of female entrepreneurs—but this is primarily from low ability women entering.[27] Increased

[27]The share of female entrepreneurs is the number of female entrepreneurs relative to all entrepreneurs; the female entrepreneurship rate is the number of female entrepreneurs relative to number of females.

Table 6: Female entrepreneurship and market shares

	Benchmark Economy	(1) Entry ξ	(2) Output τ^y & $\nu_f > 0$	(3) Output τ^y & $\nu_f = 0$	(4) Average $\overline{\tau}_j^y$ & $\xi_f = 1$
Female share of:					
Entrepreneurs	0.12	0.30	0.18	0.28	0.28
Output	0.17	0.21	0.26	0.47	0.25
Labour	0.14	0.18	0.24	0.47	0.22
Female share in top decile:					
Output	0.15	0.16	0.25	0.50	0.19
Labour	0.12	0.12	0.21	0.50	0.15
Entrepreneurship rates:					
Female	0.004	0.012	0.006	0.008	0.016
Male	0.028	0.027	0.026	0.020	0.039

Notes: Reported are female entrepreneurship shares and rates from equalizing distortions across entrepreneurs. See text for details.

Table 7: Economy wide aggregates

	(1) Entry ξ	(2) Output τ^y & $\nu_f > 0$	(3) Output τ^y & $\nu_f = 0$	(4) Average $\overline{\tau}_j^y$ & $\xi_f = 1$
Output, Y	1.01	1.02	1.04	1.34
Productivity, TFP	1.01	1.02	1.03	1.35
Males	1.01	1.02	1.07	1.34
Females	0.99	0.94	0.87	1.31
Average Firm Size	0.82	1.01	1.18	0.58
Males	0.99	0.97	0.89	0.65
Females	0.40	1.10	1.65	0.37
Wage	1.01	1.02	1.07	0.54

Notes: Reported are the aggregate impacts of equalizing distortions across entrepreneurs relative to the benchmark economy. The columns correspond to those in Table 6.

entry does not translate to women operating 'efficient' large-scale firms as there is no impact on female shares among the top decile of producers (see also Figure 5 panel (a) for the distribution across deciles). Put differently, equalizing entry barriers induce more women into entrepreneurship, but as long as distortions on production affect women more severely they continue to operate small scale firms. As a consequence, the impacts on aggregate output and TFP are marginal (about 1 percent higher), and average firm size falls by 18 percent on aggregate and by 60 percent for women (Table 7).

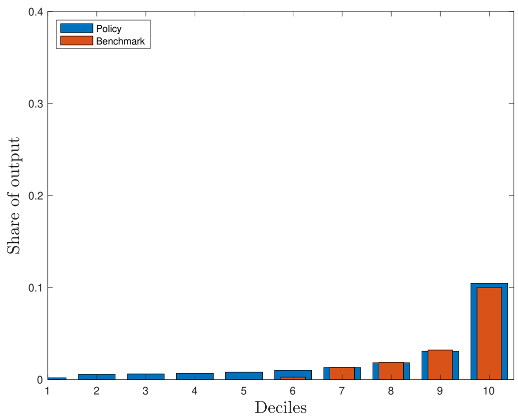
Of note, the impacts from equalizing entry barriers are especially modest when recognizing that ξ_f is overstated due to assuming a common distribution of talent, labour force participation and informality across gender (and understated due to assuming common wages). That is, the policy in column (1) goes beyond equalizing 'true' entry barriers into entrepreneurship. Nevertheless, Table A.5 shows the results hardly change when ξ_f is equalized within a plausible range of its calibrated value.

Second, a policy that equalizes the distribution of output distortions has a large impact on female entrepreneurship. For instance, based on Table 6 columns (2) and (3), female market shares rise to a quarter and close to one-half, respectively, both on aggregate and among the top decile of producers. The quantitative impacts also show it is when distortions are correlated with productivity (column 3) that generate much of the quantitative impacts on female entrepreneurship, consistent with the misallocation literature.[28] The results in column (3) are especially striking—that women account for essentially 50 percent of the market and a two-fold increase in the entrepreneurship rate—despite that entry barriers remain 20-times higher for women. Moreover, average female firm size is over 65 percent higher despite a higher equilibrium wage.

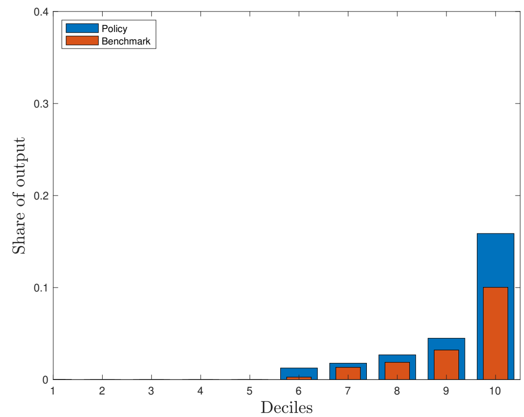
Taken together, these results are particularly relevant given the emphasis on promoting female entrepreneurship by incentivizing entry (i.e., policies that lower entry barriers). From a policy

[28]When both entry barriers and output distortions are equalized (column 1 plus column 3) women account for 50 percent of entrepreneurs and market shares.

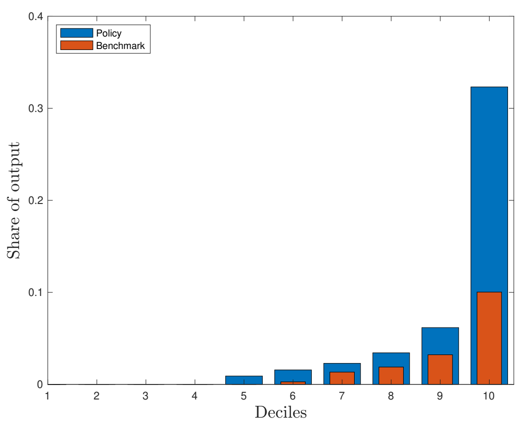
Figure 5: Distribution of Female Sales across Deciles



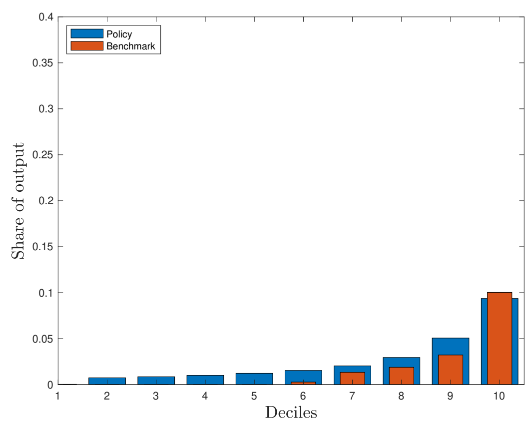
(a) Common Entry Costs, ξ



(b) Common $\bar{\tau}_d^y$, $(\nu_f > 0)$



(c) Common $\bar{\tau}_d^y$, $(\nu_f = 0)$



(d) Average $\bar{\tau}_{d,j}^y$, and common ξ

Notes: The figure shows female sales in each decile relative to total sales (all firms). Panel (a) and (b) show the case when women face the same distribution of output and capital distortions as men, and panel (c) combines their effects; panel (d) shows the case when women face the same entry costs as men.

perspective, while lowering entry barriers are possibly more feasible they are not the primary barrier to women operating thriving businesses and accounting for a small share of the market. In fact, lowering entry barriers by itself, while failing to account for the higher distortions on production women face, may re-enforce the view of women as sub-par business owners that operate small-scale firms. This analysis shows, to promote female entrepreneurship requires policies to circumvent the differential distortions among incumbent firms. To be clear, this is not to say that women do not benefit from policies that lower entry costs—female earnings, both in entrepreneurship and wages, are higher. Rather, women are better off from policies that lower discrimination along the intensive margin of entrepreneurship than those that lower discrimination along the extensive margin.

Third, while each of these policies promote female entrepreneurship to varying degrees, a common feature is that they have small impacts on aggregate output and productivity, where TFP rises by no more than four percent in each case (Table 7).[29] Despite considerable re-sorting across incumbent firms and entry/exit, TFP gains are small because much of the misallocation is among male entrepreneurs who account for the majority of firms. Key to this is accounting for the distribution of distortions rather than focusing on averages. To make this point clear, column (4) shows that aggregate output and TFP rise by over 30 percent when men and women face their respective *average* distortion. Said differently, removing misallocation within gender (column 4) generates about a 10-fold larger impact on aggregate output and TFP than removing misallocation across gender (columns 1–3). While equalizing distortions across gender promotes female entrepreneurship to varying degrees, improving aggregate productivity requires limiting misallocation across *all* firms, although with more modest impacts on female entrepreneurship. Again, this highlights the relevance of accounting for differences in the distribution of distortions, rather than averages which would otherwise misleadingly suggest that high female output distortions are important for

[29]There are differential impacts on TFP across gender, where TFP is calculated as Y_j/N_j (output divided by a Cobb-Douglas function of inputs, as is standard). Since female labour input shares rise from a policy that equalizes distortions, and noting that production at the firm-level is decreasing returns to scale, female TFP falls and male TFP rises.

understanding income and productivity differences across countries.

4.5 Distortions

I have modelled distortions in a reduced-form way, measuring them as 'wedges' that equalize marginal products of inputs to prices. An ideal feature of the WBES is that it reports firm responses to whether specific distortions, or obstacles, are a severe, major, moderate, minor or non obstacle to business operation. There are over 15 obstacles reported and cover a wide range of frictions that affect production, which can be useful to asses which frictions are related to distortions on production and whether it varies by gender.

I set these obstacles equal to one if a firm reports they are a severe or major obstacle, and follow Kalemli-Ozcan and Sørensen (2014) by grouping obstacles into four broad categories—infrastructure, red-tape, rule of law and finance obstacles. I then regress the obstacles with interactions on entrepreneur gender, and other controls, on the distortion on production τ_{ij}^{y}. The estimates in Table A.1 show that, (1) female entrepreneurs face higher distortions on production, and (2) the rule-of-law obstacle is positively associated with higher distortions across all specifications (about six percent higher).

I further assess whether specific obstacles that makeup the rule of law—obstacles related to functioning of courts, political uncertainty, corruption, crime, informality—affect distortions on production, and particularly by gender. Table 8 reports the estimates, where columns (1) and (2) show the impact of the obstacles without and with controls, and columns (3) and (4) include female interactions on these obstacles. The first two columns show that political uncertainty is associated with firms facing distortions that are 2 percent higher. Columns (3) and (4) show that crime is a distortion that primarily affects women, and quantitatively in the range of 11 percent higher relative to men.[30] While few papers have focused on the impacts of

[30]Of note, crime is not whether a firm has faced crime but rather a firm's perception of it and how it might impact business operation. The WBES reports whether a firm has faced 'crime', with 3 percent of male and female entrepreneurs reporting facing crime. Also reported are losses associated with facing crime but there

Table 8: Rule of Law Obstacles to Doing Business

	(1)	(2)	(3)	(4)
Female	0.02***	0.02***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Courts	-0.01	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Political	0.02*	0.02**	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Corruption	0.01	0.00	0.02***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)
Crime	0.02	0.01	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Informal	-0.00	0.00	0.01*	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)
Courts × Female			-0.00	0.00
			(0.02)	(0.03)
Political × Female			0.02	0.02
			(0.01)	(0.01)
Corruption × Female			-0.02	-0.02*
			(0.01)	(0.01)
Crime × Female			0.08***	0.08***
			(0.02)	(0.02)
Informal × Female			-0.03	-0.02
			(0.02)	(0.02)
Controls	–	✓	–	✓
N	5931	5931	5931	5931
R^2	0.021	0.080	0.029	0.089

Notes: Rule of law obstacles include functioning of Courts, Political uncertainty, Corruption, Crime and practices of Informal firms as obstacles to operating a business. Controls include industry fixed effects, city fixed effects, entrepreneur experience, whether the firm is registered and size controls. See text for additional details. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

crime as a distortion on business performance (Ranasinghe, 2017; Ranasinghe and Restuccia, 2018; Piemontese, 2021), this result is one of the first to find that female entrepreneurs are more affected by crime and relevant for accounting for differences in distortions across gender, at least in India. Corruption is also associated with high distortions, with some evidence that it affects men more than women.

are too few observations to make comparison.

5 Sensitivity

I now evaluate the sensitivity of the results to focusing on sub-industries within manufacturing, including capital in production, and defining gender based on the top manager's gender. Overall, I find the central results in Section 2 and 4 are robust to each of these specifications.

Sub-industry level analysis: To maximize the number of observations I have focused on an aggregate manufacturing sector by pooling sub-industries within manufacturing (ISIC 15−37). This aggregation can skew the results if women select into specific sub-industries *and* if the elasticity in production η—which affects how distortions are measured—varies considerably across these sub-industries; that is, if women select into highly distorted sub-industries within manufacturing (although this too would be a form of gender specific friction).

In Appendix A.1, I allow the elasticity in production η to vary by sub-industry. I find the relative difference in the distribution of distortions do not change by much (though in levels they are lower). And since it is the relative differences that affect the main results, the quantitative impacts from policies that promote female entrepreneurship are also similar.

Focusing on sub-industries, Table A.2 shows that the share of female entrepreneurs and their market shares are fairly stable across sub-industries, implying limited selection effects across gender. This also why allowing for variation in η across sub-industries does not alter the results. A common pattern when focusing on each of the ten largest sub-industries is that women operate larger firms and are more productive on average, consistent with Section 2.[31] Importantly, the quantitative results in Section 4.4 depend on the statistics used to calibrate the model (Table 4 and Figure 3). In 9 of the 10 sub-industries women face higher distortions on average and face a more left-skewed distribution of distortions, consistent with the statistics used to calibrate the model. While observations at the sub-industry level are limited, the overall evidence shows that focusing on an aggregated manufacturing sector is not

[31] Women operate larger firms and have higher average sales in 8 of 10 sub-industries, though not always statistically significant due to a smaller sample of firms. Also, I hold the value η fixed for easy comparison—what matters is how distortions vary across gender and so the exact value is not critical.

skewing the results. Said differently, that women operate larger firms, face higher distortions and account for a small share of the market also holds at the sub-industry level and is not an artifact of aggregation.

Nevertheless, in Appendix A.2 I re-evaluate the main results by focusing on the sub-industry that has the most number of observations (rubber and plastic products). The general patterns across gender related to entrepreneurship and market shares are similar except for differences in average firm size. The model calibration and quantitative implications of policies that promote female entrepreneurship, notably that entry barriers (distortions) have smaller (larger) impacts on female market shares continue to hold at the sub-industry level.

Capital in production: Capital plays an important role in production, especially in the manufacturing sector. While Table 1 shows that female entrepreneurship and market shares are consistent across the sample with and without capital, it is nevertheless useful to evaluate the results when capital is part of the production process. In Appendix A.3, I set $\alpha = 1/3$ so that the distribution of output and capital distortions vary across gender (and $\eta = 0.85$). Consistent with the facts presented in Section 2, women operate larger firms, have higher sales and are more productive when accounting for capital (see Tables A.9 and A.10). I also recalibrate the model and show the quantitative implications of the model continue to hold when capital is included (Table A.12 and A.13).

Top Manager gender: The results are based on defining a firm as female owned if any one of the owners is a woman, which as already discussed is a conservative way to define entrepreneur gender. The WBES also reports the top manager gender, which is a useful sensitivity check for defining firm/entrepreneur gender, especially if the top manager is most encumbered by frictions that affect day-to-day business operation. Appendix A.4 shows that women operate larger firms, have higher sales and are more productive on average when entrepreneur gender is based on the top manger (see Tables A.14 and A.15). The quantitative results and policy implications remain robust when using the top manager's gender as well

(Tables A.16, A.17 and A.18). While these results are based on the sample of firms that excludes capital in production, the results also hold when restricting the sample to capital reporting firms.

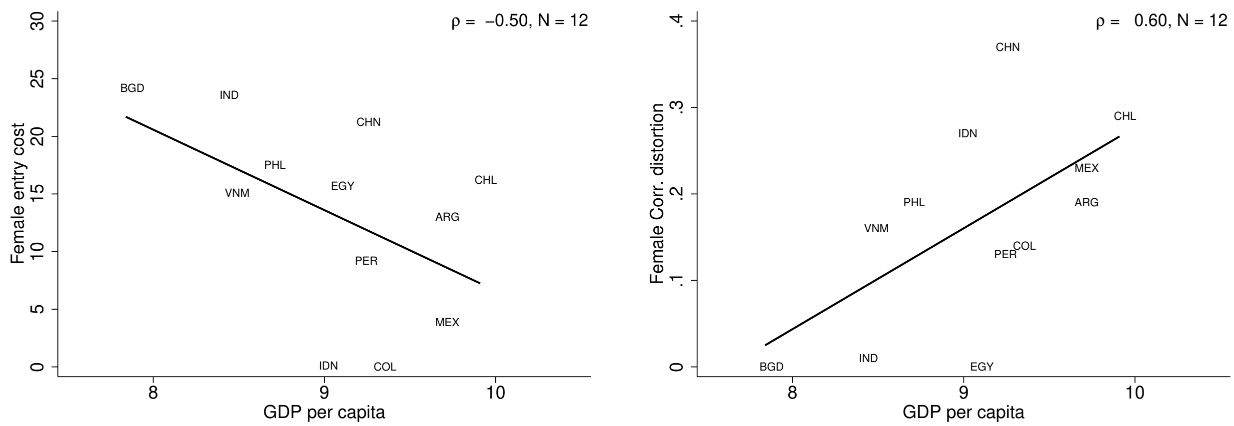
6 Cross-country Analysis

The main results in this paper are that women in India face higher entry costs and output distortions which encumber female entrepreneurship, and that output distortions are quantitatively more important for understanding female entrepreneurship than entry costs. I now evaluate whether these predictions generalize across countries. A main upside of the WBES is that data collection is harmonized across countries making it suitable for cross country comparisons. I examine low and middle income countries in the WBES that have at least 500 observations, and focus on an aggregate manufacturing sector with labour as the only input in production ($\alpha = 0$). For each country, I back-out the country specific distribution of distortions for men and women, and calibrate the female entry cost ξ_f and the correlation between distortions and female productivity ν_f to match the country specific female share of entrepreneurs and sales. All other parameters are kept the same as in section 4.2. In essence, to facilitate meaningful cross-country comparisons I think of parameters affecting the productivity distribution, the production function, and the time-preference discount rate as fundamental parameters that are common across countries.[32]

I begin by evaluating the calibrated parameters across the sample of countries. Figure 6 panel (a) shows the calibrated female entry cost is negatively related to GDP per capita, and panel (b) shows the correlation between distortions and female productivity is positively related to GDP per capita. A consistent pattern across countries is that women face higher

[32] Of course, all parameters can be re-calibrated for each country but this will obfuscate any meaningful comparisons across countries. Also of note, I define gender based on the top manager to maximize the sample of countries; unlike in India, most countries have more observations based on the top manager. There are 13 countries in the sample, however, I drop Brazil because it is an extreme outlier with respect to its calibrated entry cost.

Figure 6: Cross country calibration



(a)

(b)

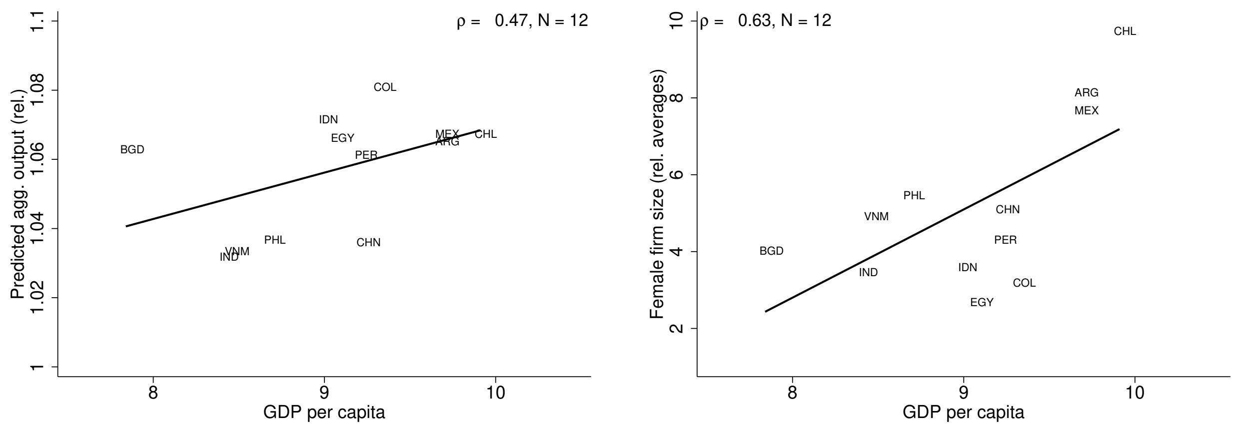
Notes: Panel (a) plots the country specific calibrated female entry cost ξ_f against against GDP per capita (in logs); panel (b) plots the country specific calibrated female correlated distortion ν_f against GDP per capita (in logs). All country statistics are based on the most recent year in WBES between 2009-2019.

entry costs ($\xi_f > 1$) and correlated distortions on production ($\nu_f > 0$) relative to men.[33] Panel (a) is particularly related to Fattal-Jaef (2022), who also allows distortions to vary across firms and finds that entry costs (for all firms) are negatively related to development. My results highlight that women face disproportionally higher entry costs than men, and is a pattern that is also negatively related to development. For instance, female entry costs are six times higher in India than in (relatively richer) Mexico. Together with panel (b), in poorer countries it is harder for women to enter into entrepreneurship (higher entry costs) and in relatively richer countries it is harder to operate a business after entering (higher distortions to operate).

An implication in this paper is that while women face high entry costs, a policy that equalizes output distortions has a larger impact on female entrepreneurship than a policy that equalizes entry costs. I evaluate whether this prediction holds across the sample of countries and how it relates to development. Figure 7 shows the impact on aggregate output and average firm

[33] Colombia and Indonesia are notable exceptions where women face lower entry costs. Also of note, the calibrated parameters match the country specific targets for share of female entrepreneurs and sales very closely.

Figure 7: Policy impact of equalizing distortions relative to entry costs



(a) Aggregate output

(b) Female average firm size

Notes: This figure shows the policy impact if women face the same output distortions as men relative to a policy if women face the same entry costs as men. Panel (a) shows the relative impact on aggregate output in the model, and panel (b) shows the relative impact on average female firm size, against GDP per capita (in logs).

size of a policy that equalizes output distortions *relative* to a policy that equalizes entry costs, plotted against GDP; that is, the impacts if women face the same output distortions as men relative to if women face the same entry costs as men. Both panel (a) and (b) show that equalizing output distortions have a larger quantitative impact than equalizing entry costs (all values on the y-axis are bigger than 1), and is positively related with development. That is, even among the poorest countries where women face higher entry costs, a policy that equalizes distortions is more effective for promoting female entrepreneurship than lowering female entry barriers. Panel (b) shows large impacts on average female firm size, where in Argentina and Chile there is more than an 8-fold increase. The impacts are large because lowering entry costs lowers female average firm size and lowering output distortions raises it, and so the relative impact on firm size is magnified. A similar pattern also holds for female sales shares. The model also implies that relatively richer (or less poor) countries benefit more from equalizing gender based distortions—this is mainly because the correlated distortion is positively related with GDP.

A final implication is that equalizing distortions across gender—both entry costs and output distortions—have a small quantitative impact for understanding cross-country income differences. Panel (a) shows modest impacts on aggregate output across countries, where Colombia has the highest increase in output of 8 percent.[34] While 8 percent is a sizeable increase in output it remains marginal compared to a more than 6-fold gap in GDP between Colombia and the OECD average. The main message in Figure 7 is that equalizing distortions across gender is effective for promoting female entrepreneurship, but will have more modest impacts on overall development because the extent of misallocation is wide-spread across *all* firms.

7 Conclusion

In India's formal manufacturing sector, women account for a small share of entrepreneurs and share of the market, but on average operate larger firms than men. Interpreted through a setting of heterogeneous producers that face differential distortions across gender, the model implies that women face both higher entry costs into entrepreneurship and higher distortions on production, on average and across the distribution of producers. I find that high entry costs affect female entrepreneurship rates but are secondary for understanding their low market shares, especially when there are gender specific differences in the distribution of distortions across production. That is, lowering barriers along the extensive margin of entrepreneurship without addressing those along the intensive margin will result in women operating small-scale firms, which can further perpetuate the narrative of women as reluctant, ineffective business owners. While average distortions are similar across gender, accounting for the distribution of distortions is critical to get a clearer picture of the differential barriers to production women face in entrepreneurship. In particular, policies that promote female

[34] To be clear, panel (a) shows the *ratio* of output gains from equalizing output distortions and entry costs. However, since the impact on aggregate output of equalizing entry barriers is marginal, panel (a) essentially shows the quantitative impact of equalizing both entry costs and output distortions.

entrepreneurship have a modest impact on productivity and are not central for understanding the vast income differences across countries. This is because there is more misallocation within gender than across gender. These patterns are not unique to India, and hold across a range of low to middle income countries.

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A Appendix

A.1 Sub-industry and entry cost sensitivity

Sub-industries: Table A.2 reports descriptive statics for the ten largest manufacturing sub-industries in the WBES for India, which accounts for about 85 percent of the sample, in total and for females. While there is some variation, the female share of entrepreneurs, sales, employees and labour are fairly stable across industries. Sub-industry 28 (metal products) is an outlier where women account for 51 percent of total sales—the statistics in Table 4 are not sensitive to excluding this sub-industry. Aside from this, variation across sub-industries are fairly limited and has a reasonably small standard deviation. Also reported is the female share of capital which is also stable across sub-industries. Taken together, the evidence points to limited sorting and market share differentials across sub-industries by gender, and suggests that aggregating to a manufacturing sector is not driving the main results. (Though not reported, relative firm size and relative aggregate distortions by gender are also exhibit little variation across sub-industries, with standard deviations of 0.7 and 0.3, respectively.)

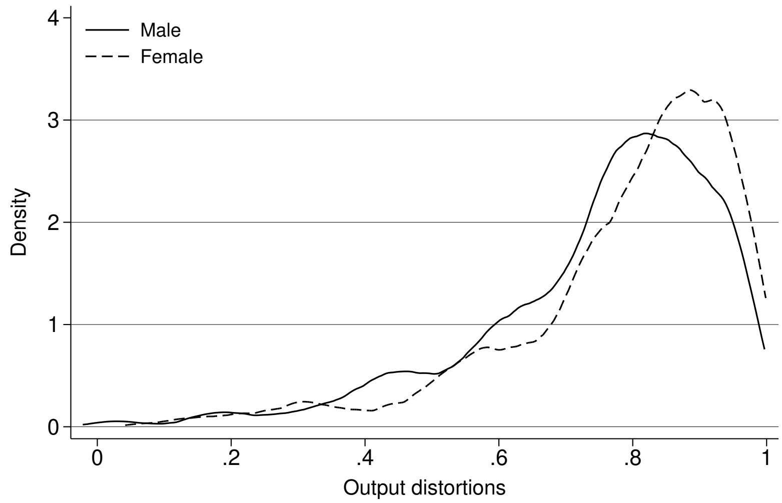
Table A.3 reports the average output distortion at each decile of the distribution by gender which approximates the distribution in Figure 3. Women face higher distortions at every decile, and is in the range of 2–4 percentage points higher in deciles 1 through 8. Also reported are the overall averages and standard deviation across deciles, and shows the variation in distortions are similar across gender.

Sub-industry specific factor shares: In presenting the main results I have pooled all firms in manufacturing together and assumed common factor shares in production across sub-industries ($\eta = 0.85$ and $\alpha = 0$). This assumption affects how distortions are measured and the resulting distribution of distortions across gender if production elasticities differ across sub-industries (see equation (2)). Put differently, if $\eta(1-\alpha)$ varies across sub-industries and a specific gender is more prominent in that sub-industry, the resulting estimates of τ_{ij}^{y} can be skewed across gender. While there is limited variation in share of male and female entrepreneurs across sub-industries as noted above (see Table A.2), it is nevertheless useful to evaluate the sensitivity of assuming common factor shares. To this end, I measure τ_{ij}^{y} by allowing factor shares to vary across sub-industries; specifically the elasticity on production with labour as the only input is $\tilde{\eta} = \eta(1-\alpha^k)$ where $\eta = 0.85$ as before but now α^k is specific to each ISIC.[35]

Figure A.1 plots the pooled distribution of output distortions across gender when $\tilde{\eta}$ varies across sub-industries. I highlight two points of interest. First, the distributions are fairly similar to what is shown in Figure 3 and where women still face higher distortions on average. This implies that assuming common factor shares across sub-industries are not skewing the relative estimates across gender. Second, the mean (standard deviation) of the distributions are lower (higher) when allowing factor shares to vary across sub-industries. This is because factor shares are $\tilde{\eta} = \eta(1-\alpha^k) < \eta$, since $\alpha^k < 1$, which lowers the estimate of τ_{ij}^{y}, and

[35] I map the average factor shares for 1998–2010 from North American Industry Classification System to the corresponding ISIC codes (15–37).

Figure A.1: Distribution of output distortions τ_{ij}^{y} with industry specific factor shares



Notes: Shown is the kernel density plot for output distortions for all firms but where factor shares vary by each sub-industry (ISIC). The mean and standard deviation of output distortions for male and females are: 0.749 (0.179) and 0.786 (0.173). A Kolmogorov-Smirnov test for equality of distributions across males and females is rejected (p-value < 0.01).

since $\tilde{\eta}$ varies by sub-industry there is more dispersion. Table A.4 reports the average output distortion at each decile of the distribution by gender shown in Figure A.1. While the averages at each decile are generally lower in comparison to what is shown in Table A.3, the differences in means across gender at each decile are quite similar (and mostly in the 2–5 percent range). And since it is the differences in distortions across gender, rather than the levels, that affect the quantitative results in section 4.4 the main implications of the various experiments are unchanged. In fact, the quantitative effects from equalizing output distortions and entry costs on economy wide aggregates are essentially unchanged and the impacts on female entrepreneurship are marginally higher when factor shares in production vary by sub-industry.

Entry costs: Table A.5 shows the impacts on female market shares from equalizing entry barriers to various degrees, and supports the view that entry costs affect the share of female entrepreneurs but have marginal impacts on female market shares. In columns (1)–(3) the entry barrier is set to 0.25 to 0.75 times the value of ξ_f; that is, assuming for the possibility that the true entry barrier—stripping away effects from assuming a common distribution of ability and common wages—accounts for 75, 50 and 25 percent of ξ_f, respectively. In column (4) the entry barrier is 1.25 times ξ_f—an instance when the impact of assuming common wages outweighs the impact from assuming a common distribution of talent. Despite the broad range of values for ξ_f considered it has limited impacts on female market shares; again, when there are sharp differences in the distribution of distortions across gender, entry costs are not of first-order importance for understanding female market shares. Aggregate statistics for the range of ξ_f are similar to those in Table 7 and not reported.

Table A.1: Obstacles to Doing Business

	(1)	(2)	(3)	(4)	(5)
Female	0.02***	0.02***	0.02***	0.03***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Infrastructure		-0.01	-0.01	0.01	0.00
		(0.02)	(0.02)	(0.01)	(0.01)
Red Tape		-0.03**	-0.02	-0.03***	-0.02*
		(0.02)	(0.02)	(0.01)	(0.01)
Rule of Law		0.06***	0.06***	0.05***	0.04***
		(0.02)	(0.02)	(0.01)	(0.01)
Finance		0.00	0.00	0.01*	0.01**
		(0.01)	(0.01)	(0.01)	(0.01)
Infrastructure × Female				-0.03	-0.02
				(0.04)	(0.04)
Red Tape × Female				-0.01	0.00
				(0.04)	(0.04)
Rule of Law × Female				0.03	0.02
				(0.05)	(0.05)
Finance × Female				-0.02	-0.02
				(0.02)	(0.02)
Controls	✓	–	✓	–	✓
N	5931	5931	5931	5931	5931
R^2	0.072	0.024	0.081	0.027	0.082

Notes: Controls include industry fixed effects, city fixed effects, entrepreneur experience, whether the firm is registered and size controls. See text for additional details. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

A.2 Results based on single sub-industry

The results in the main text are based on an aggregated manufacturing sector. Below I focus on the sub-industry that has the most number of observations (ISIC 25 - rubber and plastic products). Since there are about 600 observations I forgo the statistical analysis in Section 2 and focus on the quantitative implications of the model.

Table A.6 shows descriptive statistics for the rubber and plastics sub-industry. The shares are similar to the aggregated sector, with the exception that women have lower average firm size (this holds in 2 of the 10 sub-industries). The distribution of distortions is more left-skewed for women as it is in the aggregated sector. Table A.7 shows the calibrated model fit. The model matches all targets closely except for share of sales in the top decile for all firms, as well as the non-targeted moment that women operate smaller firms on average. The quantitative results in Table A.8 are similar in magnitude to those in Section 4.4, and in particular that equalizing distortions on production have a larger impact on female entrepreneurship than equalizing entry barriers.

A.3 Capital reporting firms

I show that the main results hold when the sample is restricted to firms that report values for capital (ISIC 15-37) and where production is $y_{ij} = (z_{ij})^{1-\eta} \left(k_{ij}^{\alpha} n_{ij}^{1-\alpha}\right)^{\eta}$ with $\alpha = 1/3$. Figures A.2 and A.3 reproduce Figures 1 and 2. Similarly, Tables A.9 and A.10 show the counterparts to Tables 2 and 3, where the broad patterns hold when the sample is restricted to capital reporting firms.

Table A.11 is the counterpart to Table 4 which shows descriptive statistics for capital reporting firms. As in Section 4.1 the bottom one and top five percent of the tails for τ_{ij}^{y} are removed, and now also for τ_{ij}^{k}, where τ_{ij}^{k} is identified from equation (3), using data on labour costs, capital (based on its replacement value) and an interest rate $r = 0.1$. The market shares across gender for capital reporting firms are similar to what is reported in Table 4. Average firm size and distortions are lower than in Table 4 since firms in the top five percent of capital distortions τ_{ij}^{k} by gender are dropped, and noting that distortions are positively correlated with firm size.

Figure A.4 shows the distributions for output and capital distortions (panels a and b), by gender, based on equations (2) and (3). The distribution of output distortions for females is skewed left of the distribution for male entrepreneurs, consistent with Figure 3. The distribution of capital distortions is skewed right and exhibits more dispersion than for output, suggestive of substantial capital misallocation. At the far tail, the distributions are similar across gender, suggestive that the higher capital distortions women face on average are primarily from men receiving higher subsidies ($\tau_{i}^{k} < 0$).

The model with capital reporting firms is calibrated in the same way as in Section 4.2 and where $\nu_f > 0$ is applied to both output and capital distortions. In this case, ν_f has a larger quantitative importance on the results. Table A.12 shows the model matches all targeted moments as well as non-targeted ones. Of note, entry costs are 279 times higher for females, implying enormous entry barriers. This is largely driven by capital subsidies which encourage female entry and requires higher entry costs to match the female share of entrepreneurs. The remaining parameters are fairly similar to what is in Table 5. While not reported, model also does well matching the distribution of output and capital across all firms and across females. Table A.13 shows the implications for female market shares when women face the same distribution of distortions as male entrepreneurs.

A.4 Results based on Top Manager Gender

This section presents results when entrepreneur gender is based on the top manager's gender. I assume $\alpha = 0$ such that production requires only labour inputs. I present a selection of statistics and results for brevity, and note that all the main results hold when using Top Manager gender. Figure A.5 and Tables A.14 and A.15 show the counterparts to the statistics reported in Section 2. Table A.16 is the counterpart to the descriptive statistics reported in Section 4.1, and Tables A.17 and A.18 show the quantitative implications of the model.

Table A.2: Descriptive Statistics by Sub-industry

ISIC	Observations All	Observations Female	Female share of: Entrepreneurs	Sales	Employees	Labour	Capital
15	467	75	0.14	0.24	0.15	0.15	0.23
17	426	84	0.16	0.17	0.17	0.15	0.14
24	428	67	0.10	0.11	0.09	0.10	0.17
25	592	109	0.14	0.14	0.13	0.14	0.20
26	469	46	0.07	0.11	0.08	0.13	0.08
27	568	69	0.10	0.28	0.16	0.14	0.15
28	490	80	0.11	0.51	0.16	0.21	0.18
29	592	87	0.08	0.16	0.12	0.15	0.06
31	463	91	0.16	0.14	0.12	0.12	0.07
34	466	74	0.09	0.17	0.14	0.15	0.14
Mean			0.12	0.20	0.13	0.14	0.14
Std. Dev.			0.03	0.12	0.03	0.03	0.06
All industries	**5931**	**935**	**0.12**	**0.17**	**0.14**	**0.14**	**0.16**

Notes: Reported are the ten largest sub-industries, and outliers are trimmed as in Table 4, but at the sub-industry level. Sales has a high standard deviation (relative to the other statistics) and is driven by ISIC 28.

Table A.3: Average output distortions by deciles

	Deciles 1	2	3	4	5	6	7	8	9	10	Avgs. Mean	S.D.
Output distortions												
Male $\bar{\tau}^y_{m,d}$	0.616	0.739	0.806	0.839	0.859	0.880	0.903	0.929	0.952	0.972	0.849	0.101
Female $\bar{\tau}^y_{f,d}$	0.642	0.775	0.828	0.868	0.890	0.908	0.931	0.949	0.962	0.976	0.863	0.099

Notes: Reported are the averages (and weighted) at each decile of the output distribution of distortions, for the sample of firms in Table 4. Means and standard deviations (S.D.) are based on a weighted average across the average at each decile. Standard deviations are similar across gender at each decile.

Table A.4: Average output distortions by deciles with industry specific factor shares

	Deciles 1	2	3	4	5	6	7	8	9	10	Avgs. Mean	S.D.
Output distortions												
Male $\bar{\tau}^y_{m,d}$	0.347	0.565	0.664	0.731	0.773	0.806	0.842	0.878	0.918	0.965	0.763	0.172
Female $\bar{\tau}^y_{f,d}$	0.373	0.623	0.718	0.772	0.818	0.849	0.877	0.909	0.941	0.973	0.785	0.172

Notes: Reported are the averages (and weighted) at each decile of the distribution of output distortions shown in Figure A.1, where production factor shares vary by sub-industries. Means and standard deviations (S.D.) are based on a weighted average across the average at each decile. Standard deviations are similar across gender at each decile.

Table A.5: Female entrepreneurship and market shares across values for ξ_f

	(1) $0.25 \times \xi_f$	(2) $0.50 \times \xi_f$	(3) $0.75 \times \xi_f$	(4) $1 \times \xi_f$	(5) $1.25 \times \xi_f$
Female share of all:					
Entrepreneurs	0.23	0.17	0.14	0.12	0.10
Output	0.19	0.18	0.17	0.17	0.16
Labour	0.17	0.16	0.15	0.14	0.14
Female share in top decile:					
Output	0.15	0.15	0.15	0.15	0.15
Labour	0.12	0.12	0.12	0.12	0.12
Entrepreneurship rates:					
Female	0.008	0.006	0.005	0.004	0.003
Male	0.028	0.028	0.028	0.028	0.028

Notes: Reported are female entrepreneurship shares and rates from equalizing entry barriers to vary degrees.

Table A.6: Descriptive Statistics for sub-industry (ISIC 25): Market shares and Distortions

	All	Male	Female
# of firms	592	483	109
share of entrepreneurs		0.863	0.137
share of sales		0.856	0.144
share of labour		0.855	0.145
share of employees		0.9006	0.094
Average firm size (employees)			
$\ln(n)$	3.24	3.26	3.09
Average Distortions			
Output, $\bar{\tau}_y$	0.890	0.890	0.890

Notes: Sample based on description provided in text.

Table A.7: Model Fit based on sub-industry (ISIC 25)

Target Moments	Data	Model	Parameter
Entrepreneurship Rate	0.016	0.016	$\theta = 3.509$
Sales share (top decile)	0.626	0.714	$\eta = 0.796$
Female share of:			
Entrepreneurs	0.137	0.137	$\xi_f = 10.325$
Sales	0.144	0.144	$\nu_f^k = 0.021$
NON-TARGETED MOMENTS:			
Log avg. firm size (female/all)	0.954	0.940	
Female share of:			
Workers	0.094	0.107	
Labour Costs	0.145	0.107	
$TFPR_f/TFPR$	0.996	1.35	

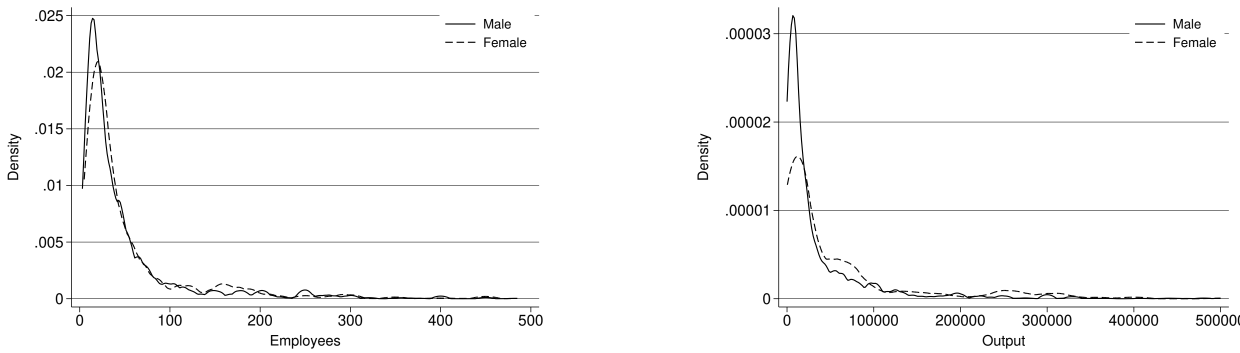
Notes: See text for detail.

Table A.8: Female entrepreneurship and market shares based on sub-industry (ISIC 25)

	Benchmark Economy	(1) Entry ξ	(2) Output τ^y & $\nu_f > 0$	(3) Output τ^y & $\nu_f = 0$
Female share of all:				
Entrepreneurs	0.14	0.22	0.33	0.39
Output	0.14	0.16	0.38	0.49
Labour	0.11	0.12	0.37	0.49
Female share in top decile:				
Output	0.12	0.12	0.37	0.50
Labour	0.08	0.08	0.35	0.50
Entrepreneurship rates:				
Female	0.004	0.008	0.011	0.012
Male	0.028	0.028	0.022	0.019

Notes: Reported are the quantitative impacts of equalizing distortions across entrepreneurs. Column (1) shows the impact when females face the same entry costs as men, $\xi_f = \xi_m = 1$. Column (2) shows the impact when output distortions are equalized and $\nu_f > 0$, and column (3) is the same as column (2) but where $\nu_f = 0$.

Figure A.2: Size Distributions with capital in production

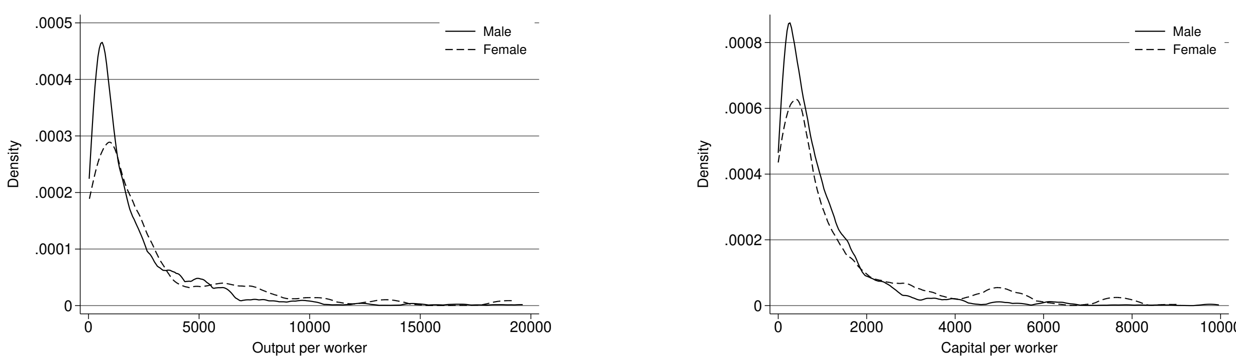


(a) Size

(b) Output

Notes: For emphasis, the sample in panel (a) is restricted to firms that have fewer than 500 employees, and in panel (b) for firms that have less than 500 million rupees in sales. Plots are based on sample weights. An unweighted Kolmogorov-Smirnov test for equality of distributions is rejected ($p < 0.01$) for both panels.

Figure A.3: Output and Capital per worker



(a) Output per worker

(b) Capital per worker

Notes: For emphasis, the sample is restricted to firms that have fewer than 500 employees and the right-hand tail of the weighted plots are trimmed. An unweighted Kolmogorov-Smirnov test for equality of distributions is rejected for panel a ($p < 0.01$) and panel b ($p < 0.05$).

Table A.9: Female estimates for capital reporting firms: sales and employees

	Sales				Employees		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.50***	0.52***	0.41***	0.32***	0.13*	0.16**	0.11
	(0.13)	(0.13)	(0.13)	(0.11)	(0.08)	(0.07)	(0.07)
City			-0.07	0.04			-0.04
			(0.07)	(0.05)			(0.04)
Register			0.54***	0.30			0.25**
			(0.21)	(0.19)			(0.11)
Experience			0.21***	0.13***			0.08**
			(0.05)	(0.04)			(0.03)
Industry fixed effects	–	✓	✓	✓	–	✓	✓
Size fixed effects	–	–	–	✓	–	–	–
N	2778	2778	2778	2778	2778	2778	2778
R^2	0.023	0.083	0.109	0.454	0.005	0.109	0.120

Notes: Columns (1)–(4) and (5)–(7) show estimates when the dependent variable is sales and employees, in logs, for the sample of firms reporting capital. All other variables are as defined in Table 2. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

Table A.10: Female estimates for capital reporting firms: output and capital per worker

	Sales per worker				Capital per worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.36***	0.36***	0.30***	0.28***	0.10	0.10	0.08	0.09
	(0.10)	(0.10)	(0.10)	(0.10)	(0.12)	(0.11)	(0.11)	(0.11)
City			-0.03	-0.02			0.22***	0.20***
			(0.05)	(0.05)			(0.05)	(0.05)
Register			0.28	0.25			0.13	0.17
			(0.18)	(0.18)			(0.18)	(0.18)
Experience			0.13***	0.12***			0.14***	0.16***
			(0.04)	(0.04)			(0.04)	(0.04)
Industry fixed effects	–	✓	✓	✓	–	✓	✓	✓
Size fixed effects	–	–	–	✓	–	–	–	✓
N	2778	2778	2778	2778	2778	2778	2778	2778
R^2	0.022	0.067	0.085	0.099	0.001	0.095	0.129	0.146

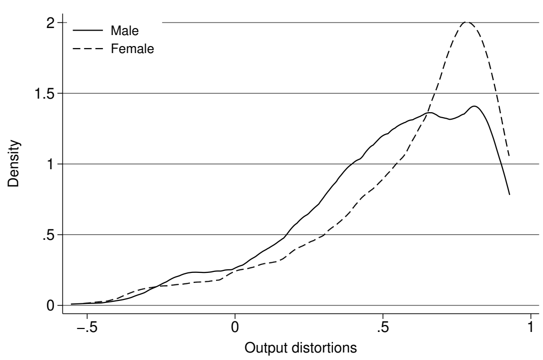
Notes: Columns (1)–(4) and (5)–(7) show estimates when the dependent variable is the output per worker and capital per worker, in logs, for capital reporting firms. All other variables are as defined in Table 2. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

Table A.11: Capital reporting firms: Market shares and Distortions

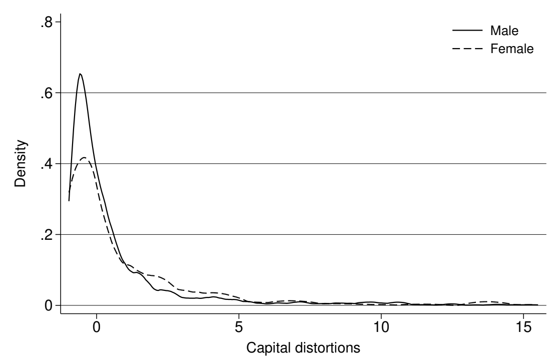
	All	Male	Female
# of firms	2452	2086	366
share of entrepreneurs		0.882	0.118
share of sales		0.816	0.184
share of labour		0.825	0.175
share of capital		0.834	0.166
Average firm size (employees)			
$\ln(n)$	3.37	3.35	3.53
Aggregate Distortions			
Output, $\bar{\tau}_y$	0.665	0.661	0.681
Capital, $\bar{\tau}_k$	-0.289	-0.297	-0.249
$TFPR$	2.747	2.708	2.938

Notes: Sample based on capital reporting firms as described in the text, and based on sample weights except for number of firms.

Figure A.4: Distribution of distortions for capital reporting firms



(a) Output distortions, τ_i^y



(b) Capital distortions, τ_i^k

Notes: The panel shows kernel density plots for output and capital distortions. See text for details. A Kolmogorov-Smirnov test for equality of distributions across males and females is rejected for τ^y (p-value = 0.012) and for τ^k (p-value = 0.06). The mean and standard deviation of output distortions for male and female entrepreneurs are: 0.519 (0.296) and 0.587 (0.294). The mean and standard deviation of capital distortions for male and female entrepreneurs are: 0.644 (2.332) and 0.880 (2.654).

Table A.12: Model Fit with Capital in production

Target Moments	Data	Model	Parameter
Entrepreneurship Rate	0.016	0.016	$\theta = 6.19$
Sales share (top decile)	0.663	0.664	$\eta = 0.857$
Female share of:			
Entrepreneurs	0.118	0.118	$\xi_f = 278.7$
Sales	0.184	0.184	$\nu_f^k = 0.129$
NON-TARGETED MOMENTS			
Log avg. firm size (female/male)	1.054	1.113	
Female share of:			
Workers	0.144	0.174	
Labour Costs	0.175	0.174	
Capital	0.166	0.159	
Aggregate Distortions:			
Output, $(1 - \bar{\tau}_f^y)/(1 - \bar{\tau}_m^y)$	0.943	0.935	
Capital, $(1 + \bar{\tau}_f^k)/(1 + \bar{\tau}_m^k)$	1.070	1.114	
$TFPR_f/TFPR_m$	1.085	1.102	

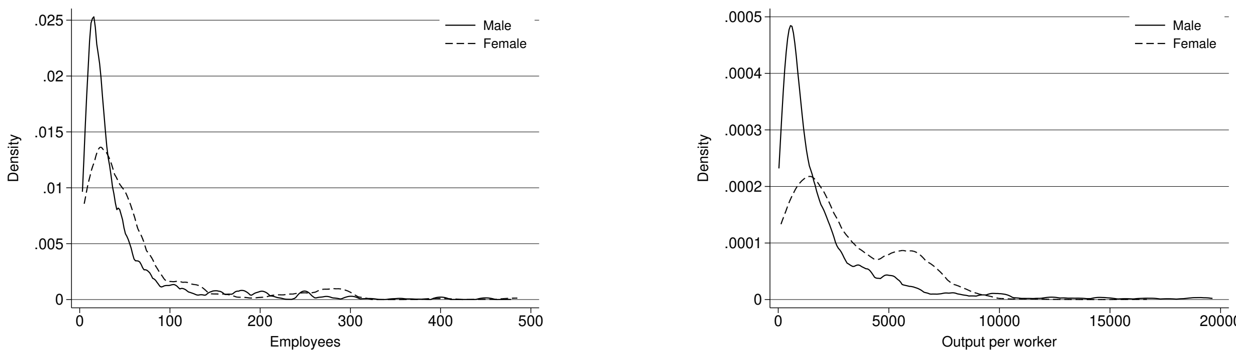
Notes: See text for detail.

Table A.13: Female entrepreneurship and market shares with Capital in production

	Benchmark Economy	(1) Entry $\xi_f = 1$	(2) Common τ_y and τ_k & $\nu_f > 0$	(3) Common τ_y and τ_k & $\nu_f = 0$
Female share of all:				
Entrepreneurs	0.12	0.46	0.08	0.16
Output	0.18	0.29	0.14	0.44
Labour	0.17	0.28	0.13	0.44
Capital	0.16	0.28	0.09	0.45
Female share in top decile:				
Output	0.16	0.18	0.12	0.50
Labour	0.14	0.16	0.11	0.50
Capital	0.11	0.14	0.06	0.50
Entrepreneurship rates:				
Female	0.004	0.022	0.003	0.004
Male	0.028	0.026	0.029	0.023

Notes: Reported are the quantitative impacts of equalizing distortions across entrepreneurs. Column (1) shows the impact when females face the same entry costs as men, $\xi_f = \xi_m = 1$. Column (2) shows the impact when output distortions are equalized and $\nu_f > 0$, and column (3) is the same as column (2) but where $\nu_f = 0$.

Figure A.5: Distributions with gender based on Top manager



(a) Size (b) Output per worker

Notes: For emphasis, the sample in panel (a) is restricted to firms that have fewer than 500 employees, and in panel (b) for firms that have less than 500 million rupees in sales. Plots are based on sample weights. An unweighted Kolmogorov-Smirnov test for equality of distributions is rejected ($p < 0.01$) for both panels.

Table A.14: Female estimates based on Top Manager gender

	Sales				Employees		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.75***	0.50***	0.43***	0.30***	0.34***	0.22***	0.20***
	(0.14)	(0.13)	(0.12)	(0.10)	(0.08)	(0.07)	(0.07)
City			-0.02	0.05			-0.04
			(0.10)	(0.08)			(0.04)
Register			0.99***	0.64***			0.45**
			(0.24)	(0.13)			(0.18)
Experience			0.13***	0.08***			0.04
			(0.04)	(0.03)			(0.03)
Industry fixed effects	–	✓	✓	✓	–	✓	✓
Size fixed effects	–	–	–	✓	–	–	–
N	6316	6316	6316	6316	6316	6316	6316
R^2	0.050	0.174	0.196	0.508	0.026	0.141	0.150

Notes: Columns (1)–(4) and (5)–(7) show estimates when the dependent variable is sales and employees, in logs, for all manufacturing firms (ISIC 15-37) in the sample. Female is an indicator based on the top manager's gender. All other variables and controls are as in Table 2. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

Table A.15: Female per worker estimates based on Top Manager Gender

	Sales per worker			
	(1)	(2)	(3)	(4)
Female	0.41***	0.27***	0.23**	0.22**
	(0.09)	(0.09)	(0.09)	(0.09)
City			0.02	0.02
			(0.07)	(0.08)
Register			0.54***	0.51***
			(0.11)	(0.10)
Experience			0.09***	0.09***
			(0.03)	(0.03)
Industry fixed effects	–	✓	✓	✓
Size fixed effects	–	–	–	✓
N	6316	6316	6316	6316
R^2	0.031	0.101	0.118	0.123

Notes: Columns (1)–(4) show estimates when the dependent variable is output per worker, in logs, for all manufacturing firms (ISIC 15-37) in the sample. All other variables are as defined in Table 2. Standard errors are in parenthesis and ***, **, * denote significance at the 1, 5 and 10 percent level.

Table A.16: Descriptive Statistics based on Top Manager Gender: Market shares and Distortions

	All	Male	Female
# of firms	5933	5523	410
share of entrepreneurs		0.922	0.078
share of sales		0.859	0.141
share of labour		0.872	0.128
share of employees		0.900	0.100
Average firm size (employees)			
$\ln(n)$	3.44	3.40	3.77
Average Distortions			
Output, $\bar{\tau}_y$	0.899	0.898	0.909
$TFPR$	11.69	11.52	12.88

Notes: Sample based on description provided in text.

Table A.17: Model Fit based on Top Manager gender

Target Moments	Data	Model	Parameter
Entrepreneurship Rate	0.016	0.016	$\theta = 4.907$
Sales share (top decile)	0.677	0.683	$\eta = 0.835$
Female share of:			
Entrepreneurs	0.078	0.081	$\xi_f = 22.850$
Sales	0.141	0.141	$\nu_f^k = 0.017$
NON-TARGETED MOMENTS:			
Log avg. firm size (female/all)	1.098	1.085	
Female share of:			
Workers	0.078	0.116	
Labour Costs	0.128	0.116	
$TFPR_f/TFPR$	1.102	1.223	

Notes: See text for detail. $TFPR_f/TFPR$ is total factor revenue productivity for females divided by its value for the entire economy. Log avg. firm size (female/all) is average firm size among females relative to the economy average, in logs.

Table A.18: Female entrepreneurship and market shares based on Top Manager Gender

	Benchmark Economy	(1) Entry ξ	(2) Output τ^y & $\nu_f > 0$	(3) Output τ^y & $\nu_f = 0$
Female share of all:				
Entrepreneurs	0.08	0.21	0.24	0.27
Output	0.14	0.17	0.40	0.47
Labour	0.12	0.14	0.39	0.47
Female share in top decile:				
Output	0.14	0.14	0.41	0.50
Labour	0.11	0.11	0.40	0.50
Entrepreneurship rates:				
Female	0.003	0.008	0.007	0.008
Male	0.030	0.029	0.022	0.020

Notes: Reported are the quantitative impacts of equalizing distortions across entrepreneurs. Column (1) shows the impact when females face the same entry costs as men, $\xi_f = \xi_m = 1$. Column (2) shows the impact when output distortions are equalized and $\nu_f > 0$, and column (3) is the same as column (2) but where $\nu_f = 0$.

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