Microfinance, Microentrepreneurship and Misallocation*

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Abstract

Microfinance has been shown to have limited average impacts on incomes and profits in developing countries. In addition to credit constraints, the poor also face labor market frictions which may lead them to make constrained occupational choices and investments in businesses. Some entrepreneurs start a business due to lack of alternatives ("involuntary entrepreneurs") while others do so by choice ("voluntary entrepreneurs"). These two groups of entrepreneurs may respond very differently to microfinance and are difficult to distinguish empirically. We structurally estimate a heterogeneous agent model of occupational choices based on Karaivanov and Yindok (2022). We use data from two randomized experiments in microfinance to test the predictions of the model and differentiate voluntary from involuntary entrepreneurs. We find that the majority of entrepreneurs are involuntary who earn significantly lower income than voluntary ones. This misallocation at the extensive margin translates into significant misallocation in capital and labor investments in businesses. Microfinance leads to a positive impact on incomes for both types of entrepreneurs and wage workers by increasing credit and labor investments, but reduces the overall entrepreneurship rate. Income gains are driven by voluntary entrepreneurs and those with lower wealth levels. Simulating policy counterfactuals provides evidence that relaxing credit constraints lead to lower impacts than relaxing labor market constraints and thus, labor market policies may deserve relatively more consideration.

Keywords: microfinance; misallocation; involuntary entrepreneurs; market frictions

JEL Codes: D1; D2; D5; D6; J6; O1

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1 Introduction

For almost half a century, microfinance has been seen as a powerful tool to improve access to credit for the poor. In 2018, Microfinance Institutions (MFIs) lent approximately $124.1 billion to 139.9 million borrowers, the majority of whom were women and from rural areas. The average cost per borrower of providing microfinance is about $106.7 (Convergences, 2019), making it one of the lowest-cost and most-scalable interventions to reach poor unbanked households. However, the evidence on microfinance in developing countries is characterized by modest take up and limited average impacts on income, profits and consumption, raising questions about the extent to which microfinance can catalyze significant growth.

Another major challenge faced by the poor are imperfect labor markets, characterized by a lack of wage work or large search frictions. The interplay of both imperfect credit and labor markets may lead poor households to make constrained occupational choices. Those who prefer to do wage work may start a small business for sustenance due to lack of appropriate jobs or out of necessity ("involuntary entrepreneurs") while those who prefer to start a business ("voluntary entrepreneurs") may face credit constraints and not be able to grow their business optimally. The presence of involuntary entrepreneurs signifies excess entrepreneurship in the economy. For example, in India, the self-employment to total population ratio in 2010 was 83.3% (Bank, 2010).[1] These constrained occupational choices may lead to over- or under-investment of resources in businesses, i.e., allocative inefficiency of resources and hence, lower returns to credit or investments.

In this paper, we focus on the interplay between credit and labor market frictions and their role in generating misallocation in occupational choice and business investments.[2] We then investigate whether this interplay can help explain the low average returns of microfinance. Specifically, we evaluate the following research questions: Do credit and labor market frictions lead to involuntary entrepreneurs with low entrepreneurial productivity and lower capacity to invest and cause them to grow their business sub-optimally? What is the prevalence of involuntary and voluntary entrepreneurs given these market frictions? And to what extent do microfinance treatment impacts differ by these entrepreneur types? We build on the occupational choice framework in the presence of credit and labor market frictions, developed

[1] Donovan et al. (2021) estimate that the key transition rates of employment exit, job finding and job-to-job transition (i.e., from self-employment to wage work or between wage works) is 2-3 times higher in poorer countries. These transition rates highlight the labor market frictions related to lack of outside opportunities and matching and search frictions faced by the poor.

[2] We define "misallocation" as any deviation from the first-best preference of occupations and allocation of inputs in businesses. Hence, we refer to misallocation in occupational choice as the prevalence of excess entrepreneurship as compared to first-best and in business investments as the ratio of capital and labor investments when compared to first-best (described in detail in Section 5).

by Karaivanov and Yindok (2022), to classify involuntary and voluntary entrepreneurs and wage workers. We further allow for two modifications in the model. First, the entrepreneur is not the only labor input and hires wage workers. Second, access to microfinance leads to crowding-in of additional loans from formal and/or informal sources. We use the Simulated Method of Moments (SMM) to estimate parameters related to credit and labor market frictions, to simulate policy counterfactuals of microfinance and other credit and labor market policies, to quantify their impacts and understand the mechanisms of change.

We use data from two randomized controlled trials (RCTs): one in Hyderabad (Telengana, India) and one in Bosnia and Herzegovina - Banerjee et al. (2015) and Augsburg et al. (2015) - respectively, to structurally estimate the model. With randomized access to microfinance and different experimental contexts, the RCTs provide us with causal identification and lend internal and external validity to the results. These RCTs span two different economic environments: high economic growth and widespread lending from MFIs between 2005 and 2010 in Hyderabad and economic recession of 2008-09 in Bosnia and Herzegovina. Moreover, in Bosnia and Herzegovina, microfinance was available to only those who were previously rejected by MFIs and hence, could lead to relatively more credit constrained participants.

However, it is not possible to directly observe in data whether a given entrepreneur is voluntary or involuntary.[3] This kind of classification requires inferring counterfactual incomes had they chosen a different occupation or faced different constraints, and, by definition, these counterfactual outcomes are not directly observable: they must be inferred. We use observable schooling and wealth levels from the data and structural modeling to infer counterfactual incomes and distinguish these entrepreneur types. We find that a majority of entrepreneurs in our sample are involuntary entrepreneurs, providing consistent evidence of misallocation at the extensive margin, i.e., occupational choice or labor rationing (Breza et al., 2021; Donovan et al., 2021) or "forced entrepreneurs" (Hacamo & Kleiner, 2021).[4] We further match the model-implied predictions of entrepreneur types with survey data to provide insights into characteristics of involuntary entrepreneurs. These involuntary entrepreneurs, on average, earn much lower incomes than voluntary ones. They are older, more likely to be female, more likely to be married and have larger households and lower educational qualifications. This description of these low-return involuntary entrepreneurs is also consistent with previous literature on own-account workers being similar to wage workers

[3]There is documentation of people preferring jobs with steady wages when asked about their job preferences but unobservables drive these occupational preferences and decisions (Günther & Launov, 2012; Calderon et al., 2016).

[4]In developing countries, self-employment mostly acts as a "search technology" and not as an "absorbing state" (Donovan et al., 2021).

(de Mel et al., 2009; Schoar, 2010; Grimm et al., 2012; Gindling & Newhouse, 2014; Falco & Haywood, 2016; Karaivanov & Yindok, 2022).

We then introduce access to microfinance and its crowding-in effects of additional credit supply from other formal and/or informal sources in the model to explore the distributional impacts of microfinance. We find that by relaxing credit constraints, microfinance improves credit and labor investments and improves entrepreneurial incomes by 30%. Microfinance reduces total entrepreneurship by 5% and increases voluntary entrepreneurship by 8%. We validate these results by matching households in the survey data with their model-predicted probability of involuntary entrepreneurship and running heterogeneous treatment effects regressions. The treatment effects we estimate using the model complement the findings on lack of transformative impacts on incomes and profits on average and on the important role of entrepreneurial heterogeneity (Karlan & Zinman, 2011; Angelucci et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Banerjee et al., 2015; Crépon et al., 2015; Tarozzi et al., 2015). Most of the entrepreneurial income gains are driven by voluntary entrepreneurs and those in lower terciles of wealth, who face binding credit constraints. We also find that involuntary entrepreneurs who have access to microfinance earn lower business revenue and more wage income than those without, consistent with microfinance inducing some involuntary entrepreneurs to shift away from self employment and toward wage employment. The presence of uneven distributional impacts is consistent with recent literature documenting large heterogeneous results of microfinance.[5]

We also contribute to recent literature exploring general equilibrium effects of microfinance (Buera et al., 2020; Banerjee et al., 2020; Fink et al., 2020; Karaivanov & Yindok, 2022; Breza & Kinnan, 2021).[6] By modeling entrepreneurs as potential employers and not just own-account workers, we find that access to microfinance leads to increased labor demand from existing businesses and hence, leads to higher equilibrium wages. We further

[5]While some studies suggest that entrepreneurs with prior business experience are more likely to take up credit offers and experience large long-run positive treatment effects of microfinance (Chernozhukov et al., 2018; Meager, 2019; Banerjee et al., 2019), loan contract type and information about the borrower held by the community are also relevant in explaining the heterogeneity (Crépon et al., 2020; Beaman et al., 2014; Jack et al., 2016; Maitra et al., 2017; Hussam et al., 2021). Banerjee et al. (2020) show that while households with higher prior productivity may not explain selection, it explains large heterogeneous treatment effects of microfinance. See Cai et al. (2021) for an overview of the microfinance literature.

[6]Buera et al. (2020) show that microfinance has adverse allocative efficiency effects: some individuals with marginal entrepreneurial productivity switch into entrepreneurship, leading to a fall in aggregate total factor productivity in the short run. Karaivanov and Yindok (2022) find that poorer households and involuntary entrepreneurs benefit significantly with access to microfinance. Fink et al. (2020) find that in rural Zambia during lean seasons, households reallocate family labor to wage work and that small loans lead to increase in on-farm family labor and agricultural output and wages in local labor markets. Breza and Kinnan (2021) show that negative credit supply shocks, such as the emergency halting of microfinance lending in the state of Andhra Pradesh (India) led to a reduction in daily wages, wage incomes and consumption.

show that with microfinance, while voluntary entrepreneurs now pay higher wages for labor inputs into their businesses, some involuntary entrepreneurs switch to wage jobs in response to higher equilibrium wages and hence earn higher wage incomes.

Constrained occupational choices and lower incomes of involuntary entrepreneurs provide further evidence to the existing literature explaining the dispersion in marginal products of capital and labor observed in businesses in developing countries (Hsieh & Klenow, 2014; Foster & Rosenzweig, 2017; Restuccia & Rogerson, 2008). We further use model simulations to compare the entrepreneurship rates and the business investments in scenarios with different credit and labor market frictions such as the first-best scenario with a scenario featuring only of labor market frictions or only of credit market frictions. We find that misallocation in occupational choices decreases with schooling and initial wealth. We also find that relaxing labor market frictions leads to significantly greater improvements in allocative efficiency at both extensive and intensive margins than relaxing credit market frictions through microfinance.

These findings highlight the powerful role of labor market policies for improving welfare outcomes relative to increasing credit access, i.e., microfinance with small loan size is not a panacea. Recent studies have shown that very large asset transfers (Bandiera et al., 2020) or asset-based microfinance (Bari et al., 2021) help the poor to escape poverty traps by reducing misallocation in occupations. Efficient targeting of loans to high-return borrowers or voluntary entrepreneurs is another possible solution (Hussam et al., 2021). Moreover, labor market policies such as public works programs (Imbert & Papp, 2015; Muralidharan et al., 2021); provision of adult education, skills or vocational training (Chakravorty et al., 2021); and, removal of hiring barriers (Chiplunkar & Goldberg, 2021) may be more effective at reducing involuntary entrepreneurship and lead to large welfare gains.

The rest of the paper is structured as follows. Section 2 describes occupational choice model for heterogeneous agents in the presence of credit and labor market frictions. Section 3 discusses the RCTs used for this study. Section 4 outlines the estimation strategy combining both structural and reduced form methods. Section 5 examines the structural results including its validation and policy counterfactuals and Section 6 describes robustness checks. Section 7 provides an overall discussion of the findings and its policy implications.

2 Model

Building on the framework developed by Karaivanov and Yindok (2022), we describe a heterogeneous agent model of occupational choice that explicitly allows a distinction between involuntary and voluntary entrepreneurs in the presence of credit and labor market frictions.

We make the following key modifications that are useful for the contexts of randomized experiments: First, Karaivanov and Yindok (2022) assume only the agent i.e., the entrepreneur is required to operate the business. We allow entrepreneurs to also be potential employers and participate in the local economy along with a third party employer. To this effect, we use a more general production function, allowing for both capital and labor inputs. We implement this modification because the average enterprise size (i.e., number of employees hired) observed in some of the RCTs is more than 1.[7] This also helps us understand misallocation not just in capital investments but also in enterprise size. Second, we build in crowding-in effects of credit through other formal and/or informal loans that agents experience as they get access to microfinance. Banerjee et al. (2019) find evidence of crowding-in of other credit sources, especially for "Gung-Ho Entrepreneurs". These additional lines of credit not only have further impacts on business investments and hence, profits but are also reflective of borrowers knowing their "type" and using it as a signal to borrow more.

2.1 Agents

In this model, there are N number of households who are risk-neutral and have strictly increasing preferences over income.[8] The agents differ in their initial level of wealth or endowments (z) and labor productivity characteristics or educational qualifications (s). Both z and s are given and observable in the data. Each agent is also characterized by "entrepreneurial talent or productivity", θ, which is known in the model but unobservable to the econometrician *(unobservable heterogeneity)*. We assume that θ has a log-normal distribution with a stochastic productivity shock (ϵ) (Evans & Jovanovic, 1989; Paulson et al.,

[7]The mean enterprise size in Banerjee et al. (2015) is 1.4 while for Augsburg et al. (2015), it is 7.8 (majority non-family labor).

[8]The risk neutrality assumption ensures that an agent is interested in expected incomes i.e., expected values over stochastic technology shocks for the output production or inherent riskiness of the wage job. Small businesses can be inherently more risky, and households with higher risk tolerance have a higher propensity to start a business. Previous literature has documented an absence of correlation between wealth and propensity to start a business except at very high wealth levels. Hence, risk aversion may not be a concern except for households with very high wealth levels with a higher propensity to take on risk (Bond et al., 2015; Hurst & Lusardi, 2004). In Section 5, we find a weak positive relationship between wealth and entrepreneurial productivity, determining an agent's propensity to become an entrepreneur. These results are consistent with previous literature and, we conclude that the assumption of risk-neutrality is valid.

2006; Karaivanov & Yindok, 2022).[9]

$$\ln \theta = \delta_0 + \delta_1 \ln z + \delta_2 \ln(1+s) + \epsilon; \quad \epsilon | z, s \sim N(0, \sigma^2) \tag{1}$$

We assume that wealth and schooling are orthogonal to each other and also to ϵ.[10] We will jointly estimate the model parameters of δ_0, δ_1, δ_2 and σ given the observed distribution of s and z through structural methods (described in Section 4).

In a given period, every agent has two occupational choices (occ): to be a wage worker (W) or an entrepreneur (E).[11] That is, $occ \in \{W, E\}$. Occupational choice is observable and endogenous. We now describe the two occupations available to an agent.

Entrepreneur: Karaivanov and Yindok (2022) assume agent i.e., entrepreneur to be the only labor input to operate the business. Following Lucas (1978) and Buera (2009), we use a general Cobb-Douglas production function with constant returns to scale and hence, assume a closed local (village) economy consisting of not just a third party employer but also local entrepreneurs employing wage workers. That is, an entrepreneur uses both capital (k) and efficiency units of labor (n) (defined below). This modification also provides us with insights on credit constraints that entrepreneurs face not just to make capital investments but also in hiring labor for their businesses. We assume that there is no minimum scale or fixed cost ($F = 0$) to start a business (Karaivanov & Yindok, 2022; McKenzie & Woodruff, 2006). The entrepreneur's production function or gross income (R^E) is specified as:[12]

$$R^E \equiv \tilde{f}(\theta, k, n) = \theta^{\nu}(k^{\alpha} n^{(1-\alpha)})^{(1-\nu)}; \quad \alpha, \nu > 0$$

where, ν is span of control parameter or "managerial or entrepreneurial technology". It reflects both variable skill or talent or productivity to manage the production as well as diminishing marginal returns to scale. We assume that the agent puts her own labor as well in the business activity. We first solve for optimal amount of labor and then solve for

[9]A log-normal specification avoids spurious inference that wealth or labor market qualifications rather than entrepreneurial productivity are the sources of constraints faced by an entrepreneur. It allows entrepreneurial productivity to be correlated with wealth and schooling, through δ_1 and δ_2, respectively (Paulson et al., 2006). δ_1 may reflect greater past savings by higher productivity entrepreneurs, knowing their θ type, of becoming an entrepreneur in future or could reflect lower absolute risk aversion among agents with high levels of wealth inclined to become entrepreneurs (Evans & Jovanovic, 1989). The log-normal specification also ensures that lower bound of θ is always 0 (i.e., $\theta \geq 0$ and that distribution of θ is skewed to the right i.e., has a long right tail.

[10]If correlation between wealth and schooling were allowed, we could have poverty traps as in Banerjee and Newman (1993).

[11]An entrepreneur E can either be a sole proprietor of the business or can hire other workers.

[12]The properties of an entrepreneur's production function are described in Appendix A.1.

optimal amount of capital given the following optimization problem, where r is net interest rate (given) and w is wage paid per efficiency unit of labor (endogenous):

$$f(\theta, k) = \arg\max_{n} \ \tilde{f}(\theta, k, n) - r(z - k) - w(n - 1)$$

This gives us the following:

$$\begin{aligned} f(\theta, k) &= B^E \theta^{(1-\phi)} k^{\phi} + r(z - k); \\ B^E &= (1 - (1-\nu)(1-\alpha)) \left[\frac{(1-\nu)(1-\alpha)}{w} \right]^{\frac{(1-\nu)(1-\alpha)}{1-(1-\nu)(1-\alpha)}} \\ \phi &= \frac{(1-\nu)\alpha}{1 - (1-\nu)(1-\alpha)} \end{aligned} \tag{2}$$

Wage worker: A wage worker earns income (R^W) equal to ws^{γ} where s^{γ} is efficiency units of labor supplied by the agent with labor market qualifications s and γ determines the sensitivity of labor income to labor market qualifications ($\gamma \geq 0$). A wage worker consumes at the end of the period and saves all her wealth. Her gross income is $y^W \equiv ws^{\gamma} + rz$.

Thus far, we assumed that that there are no credit and labor market frictions. We will relax these assumptions in the section below.

2.2 Market frictions

Credit market frictions: All agents are assumed to have access to a financial intermediary, through whom they can either save or borrow. However, the agent faces credit constraints given by limited liability (Evans & Jovanovic, 1989; Karaivanov & Yindok, 2022). This implies that there is a limit to the maximum amount of capital that an agent can invest i.e., $k \leq \lambda z$ where $\lambda > 0$. We assume that all assets owned by an agent are not productive assets and hence, agent can invest or borrow up to a fraction λ of the wealth. We check for validity of this assumption by modifying λ to be greater than 1 in Section 6. While $\lambda \to \infty$ implies a perfect credit market, $\lambda > 0$ implies an imperfect credit market. Given the production function, $f(\theta, k)$, and subject to the credit constraint $k \leq \lambda z$, the optimal amount of capital, $k_u(\theta)$, is given by:

$$k_u(\theta) = \left(\frac{\phi B^E \theta^{(1-\phi)}}{r} \right)^{\frac{1}{1-\phi}}$$

An entrepreneur chooses k such that $k \in \min\{k_u(\theta), k_c\}$ where $k_c = \lambda z$. For large values of z, credit constraint does not bind and agents have access to the first-best amount of capital. This implies that $k_u(\theta)$ is increasing in θ i.e., high productivity entrepreneurs would like to invest more capital, but may be constrained given z. Given $k_u(\theta)$, there is a threshold level of entrepreneurial productivity ($\tilde{\theta}(z)$) above which entrepreneurs would be capital constrained.[13] If $\theta > \tilde{\theta}(z)$, then the entrepreneur is unconstrained and if $\theta < \tilde{\theta}(z)$, then the entrepreneur is constrained. This further implies that there is a threshold level of initial wealth ($\tilde{z}(\theta)$) below which entrepreneurs are constrained and if $z > \tilde{z}(\theta)$, then the entrepreneur is unconstrained. The threshold level of entrepreneurial productivity and wealth are defined in Appendix A.2. Thus, the income schedule for an agent will be:

$$y(\theta, z, w) = \begin{cases} ws^{\gamma} + rz, & z \in [0, \tilde{z}(\theta)), \qquad \textit{Wage Worker} \\ B^E \theta^{(1-\phi)} (\lambda z)^{\phi} + (\lambda - 1) rz, & z \in [\tilde{z}(\theta), \frac{k_u(\theta)}{\lambda}), \qquad \textit{Constrained E} \\ B^E \theta^{(1-\phi)} k_u(\theta)^{\phi} + (z - k_u(\theta)) r, & z \in [\frac{k_u(\theta)}{\lambda}, \infty), \qquad \textit{Unconstrained E} \end{cases}$$

Labor market frictions: Following Karaivanov and Yindok (2022), labor market frictions are introduced with respect to wage jobs in the form of an agent not having access to a wage job with some probability (i.e., $P(s, \theta, z, w) \in [0, 1]$). An agent puts some effort (e) to search for a wage job (called search effort or intensity), which is endogenous. Let $p(e^*(s, \theta, z, w), s)$ be the probability of finding a wage job W which is increasing in e and s, with $p(0, s) = 0$ such that $p(e^*(s, \theta, z, w), s) = 1 - P(s, \theta, z, w)$.[14] It is assumed that search effort in finding a wage job is associated with some cost, $c(e, s)$. We also assume $c(e) = e$ such that $c(0) = 0$.[15] The optimal effort choice (e^*) chosen by an agent is described in Appendix A.3.

An agent's probability of finding a job is parameterized as: $p(e, s) = \frac{se}{\eta + se}$, where η is the labor market friction parameter such that $\eta > 0$ for different values of s. Hence, if $\eta = 0$, then there are no labor market frictions or search costs and all agents can freely choose their preferred wage job such that $P(s, \theta, z, w) = 0$ for all values of s. As η increases labor market frictions increase and the marginal return to agents' efforts falls. Also, for a given $\eta > 0$, $p(e, s)$ is decreasing in s i.e., if an agent has higher labor market qualifications, the effect of labor market frictions in finding a wage job is lower.

We now describe how agents make occupational choices in the presence of both credit and labor market frictions.

[13]This underlines the importance of the orthogonality assumption between labor market qualifications and initial wealth.

[14]This implies that if an agent puts more effort, her probability of finding a wage job increases. Also, an agent with higher labor qualifications will find it easier to navigate the labor market, will have more job opportunities and hence, has a higher likelihood of finding a wage job.

[15]An assumption of linear cost function would ensure a corner solution for optimal search effort which is desirable to get an estimate of an agent's probability of finding a wage job. This helps classify agents as wage workers or involuntary entrepreneurs as described later in the section.

2.3 Occupational choices

Given an agent has strictly increasing preferences over income, an agent chooses wage work or entrepreneurship depending on expected income from choosing that occupation. Let income differential between entrepreneurship and wage work, $\Delta(s, \theta, z, w)$ be given by:

$$\Delta(s, \theta, z, w) = y^E(\theta, z) - y^W(s, w) \tag{3}$$

Let the indicator function for whether a person is an entrepreneur or not be given by 1_E such that $1_E = 1$ if the agent chooses entrepreneurship and $1_E = 0$ if the agent chooses wage work. Given Equation (3), if $\Delta(s, \theta, z, w) \geq 0$ then, an agent prefers entrepreneurship over wage work, and hence, chooses entrepreneurship ($1_E = 1$). We term this agent a **"Voluntary Entrepreneur"**. However, there are also agents for whom $\Delta(s, \theta, z, w) < 0$. They may prefer wage work but are not able to find one due to labor market constraints or their labor market qualifications and hence, may end up choosing entrepreneurship. We term such an agent an **"Involuntary Entrepreneur"**. While some agents with $\Delta(s, \theta, z, w) < 0$, may choose W as the labor market constraints are not binding for them (also called **"Wage Workers"**). These different occupational choices are more formally defined below.

Definition 1 *Voluntary Entrepreneur: An agent who earns more expected entrepreneurial income than wage income will always choose E in the presence of both credit and labor market constraints. The probability of being a voluntary entrepreneur, $P_V(s, \theta, z, w)$, is given by:*

$$P_V(s, \theta, z, w) \equiv Prob\,\{1_E = 1 \mid \Delta(s, \theta, z, w) \geq 0\} \tag{4}$$

Definition 2 *Involuntary Entrepreneur: An agent who prefers wage job may also choose E depending on severity of labor market constraints and her labor market qualifications. The probability of being an involuntary entrepreneur, $P_I(s, \theta, z, w)$, equals her probability of being constrained by labor market frictions, $P(s, \theta, z, w)$ and is given by:*[16]

$$P_I(s, \theta, z, w) \equiv Prob\,\{1_E = 1 \mid \Delta(s, \theta, z, w) < 0\} \equiv P(s, \theta, z, w) \tag{5}$$

Definition 3 *Wage Worker: An agent with lower income differential ($\Delta(s, \theta, z, w) < 0$) will choose W, if labor market constraints are not binding. The probability of being a wage worker, $P_W(s, \theta, z, w)$ is given by:*

$$P_W(s, \theta, z, w) \equiv Prob\,\{1_E = 0 \mid \Delta(s, \theta, z, w) < 0\} \tag{6}$$

[16]This implies that all agents who are constrained by labor market frictions and hence, can't choose to be a wage worker, would prefer to choose wage work if available.

Hence, any agent choosing to be an entrepreneur either voluntarily or involuntarily can be defined as follows:

Definition 4 *Entrepreneur: An agent chooses entrepreneurship, E, either because the income differential is large or because of severity of labor market frictions and/or its direct impact on y^W, given agent's labor productivity s.*[17]

$$\{1_E = 1\} = \underbrace{\{1_E = 1|\Delta(s,\theta,z,w) \geq 0\}}_{\textit{Voluntary Entrepreneur}} \cup \underbrace{\{1_E = 1|\Delta(s,\theta,z,w) < 0\}}_{\textit{Involuntary Entrepreneur}}$$

Agents with low s may be more likely to face labor market constraints and have subsequent low effort choice (e^*) and hence, are more likely to start a business involuntarily. These agents are also less likely to prefer wage work due to lower y^W. As an agent's labor market qualifications increases, effect of labor market constraints decreases, and she is able to find a wage job more easily. However, higher labor market qualifications may also be associated with higher entrepreneurial productivity, making entrepreneurship more attractive. Hence, her decision to choose entrepreneurship depends on indirect effect on entrepreneurial income through entrepreneurial productivity and on direct effect on wage income due to higher returns to education. With respect to initial wealth, agents with very high z may have higher returns to entrepreneurial activity as they are able to invest more capital and hire more labor. While agents with low z may choose an occupation depending on the severity of credit and labor market frictions.

As labor market becomes more imperfect i.e., η increases, the marginal return to agents' search efforts falls and hence, an agent may find it harder to find a wage job. On the other hand, as credit market becomes more imperfect i.e., λ decreases, an agent may find it hard to borrow credit and hence, capital and labor investments decline, leading to lower marginal products and lower entrepreneurial income. Hence, she may choose to not start a business and put effort in searching for a wage job.

[17] The probability of being an entrepreneur, $P_E(s,\theta,z,w)$, can also be written as:

$$\begin{aligned} P_E(s,\theta,z,w) &\equiv 1_{\Delta(s,\theta,z,w)\geq 0} + P(s,\theta,z,w)1_{\Delta(s,\theta,z,w)<0} \\ P_E(s,\theta,z,w) &= Prob\,(\Delta(s,\theta,z,w) \geq 0) + P(s,\theta,z,w)1_{\Delta(s,\theta,z,w)<0} \end{aligned} \tag{7}$$

Empirically, given an agent's observable characteristics, s and z and unobservable heterogeneity, θ (given by (1)), the expected probability that an agent will be an entrepreneur or involuntary entrepreneur is given by:

$$\begin{aligned} P_E(s,z,w) &= \int_\theta P_E(s,\theta,z,w)\,d\theta \\ P_I(s,z,w) &= \int_\theta P_I(s,\theta,z,w)\,d\theta \end{aligned}$$

Therefore, severity of labor (η) and credit market frictions (λ) and agent's labor productivity s, initial wealth level z and income differential $\Delta(s, \theta, z, w)$ will jointly determine her occupational choice set. This leads us to the following four testable predictions:

Testable prediction 1 *For a given η and λ, the likelihood of an agent being an involuntary entrepreneur is decreasing in s.*

Testable prediction 2 *For a given η and λ, the probability of being an involuntary entrepreneur is decreasing in z. If the agent's z is below $\tilde{z}(\theta)$, then the agent chooses to be either a wage worker or becomes an involuntary entrepreneur, depending on the labor market constraints. But as z increases, returns to entrepreneurial activity increases and hence, the likelihood of involuntary entrepreneurship decreases.*

Testable prediction 3 *For a given agent's characteristics, as λ increases, the likelihood of voluntary entrepreneurship increases due to an increase in credit availability which leads to an increase in capital and labor investments. This further leads to an increase in entrepreneurial output and revenue.*

Testable prediction 4 *For a given agent's characteristics, as $\eta \to \infty$, labor market gets more imperfect and binding (and probability of finding a wage job decreases) and hence, the likelihood of involuntary entrepreneurship increases.*

We will test the first two predictions by examining the relationship between prevalence of involuntary and voluntary entrepreneurs estimated using the model against distribution of years of schooling (proxy for labor market qualifications) and initial wealth as observed in the data. The last two predictions related to η and λ will be tested by simulating counterfactual by varying each parameter value and examining the model predicted prevalence of different occupations. We now describe how the equilibrium wage w earned by the wage workers is determined in the local economy.

2.4 Labor market

Third party employer: In the economy, there is also a third party employer, either public or agriculture sector, who hires wage workers at equilibrium market wage, w, per efficiency unit of labor.[18] The Cobb-Douglas production function for this third party employer is $B^W L^{\psi} K^{\tau}$, where $B^W, \psi, \tau > 0$, $\psi + \tau < 1$, L is total efficiency units of labor hired (each wage worker supplies s^{γ} units of efficiency labor) and K is aggregate capital, normalized to be 1, for simplicity. Hence, the labor demand function (L_d^{TP}) is given by $(\frac{B^W \psi}{w})^{\frac{1}{1-\psi}}$.

[18]This third party employer is not a price-taker but determines wage in the local economy.

Labor Market Equilibrium: The labor market clears when aggregate labor demand from entrepreneurs and third party employer (L_d^{TP}) equates aggregate labor supply from agents ($L^s(w)$), determining equilibrium wage per efficiency unit of labor (w^*).[19] That is,

$$L^s(w) \equiv \iint_{s,z} (1 - P_E(s, \theta, z, w)) s^\gamma g(s, z)\, ds\, dz = \sum_{i=1}^{N} (n_i - 1) + L_d^{TP}$$

At equilibrium with given η and λ, agents with lower entrepreneurial productivity and income, search for wage jobs and choose to either be a wage worker or become an involuntary entrepreneur. Wage workers contribute to total labor supply in the economy while others who face constraints in choosing their preferred occupation get rationed out of labor market.

2.5 Microfinance

Following Karaivanov and Yindok (2022), with microfinance, credit market constraints are relaxed. Each agent is assumed to now borrow up to an additional amount M, that can be used either to rent or buy capital at net interest rate r. That is, the new credit constraints are: $k \leq \lambda z + M$. We assume that all microfinance loans are used for business activity and make no distinction between consumption loan or business loan for simplicity purposes.[20] Hence, the optimal amount of capital than an agent can now choose ($k_u^M(\theta)$), subject to new credit constraints, will be given by:

$$k_u^M(\theta) \equiv \underset{k \leq \lambda z + M}{\arg\max}\ B^E \theta^{(1-\phi)} k^\phi + r(z - k) \tag{8}$$

While unconstrained entrepreneurs may be unaffected by access to microfinance, constrained entrepreneurs will additionally borrow up to M, increasing capital investments as marginal product of capital would be positive.[21] This would increase entrepreneurial income and hence, increase the likelihood of an agent being a voluntary entrepreneur. However, impact of microfinance on involuntary entrepreneurship is ambiguous. Microfinance raises business investments and entrepreneurial income but increased labor demand from businesses raises equilibrium wages and wage income. For a given distribution of s and z and

[19] Empirically, $L^s(w)$ can be written as: $L^s(w) = \sum_{i=1}^{N} (1 - P_E(s, \theta, z, w)) s^\gamma$

[20] In Augsburg et al. (2015), 23.7% of treatment loans were reported to be used for business purposes. In Banerjee et al. (2019) it was 40.5%, However, Gung-Ho Entrepreneurs reported spending almost all of their treatment loans for business purposes relative to Reluctant Entrepreneurs.

[21] An entrepreneur who is not credit constrained could still be affected by changes in equilibrium wage which may have an impact on her labor demand. Recent evidence on general equilibrium effects of microfinance suggests that equilibrium wages rise after new credit is made available (Fink et al., 2020; Breza & Kinnan, 2021; Buera et al., 2020)

given η, while increased labor demand would ease job availability for some agents and some agents may still find it hard to find a wage job and hence, still choose to be an involuntary entrepreneur. The relative effects of increased entrepreneurial and wage income for some agents and severity of labor market constraints for remaining agents would determine prevalence of involuntary entrepreneurship with microfinance. This leads us to our final testable prediction:

Testable prediction 5 *With microfinance, as k and n increases, expected income y^E also increases. For an agent with given characteristics, an increase in y^E, increases the likelihood of being a voluntary entrepreneur but the likelihood of being an involuntary entrepreneur is ambiguous and depends on expected entrepreneurial income and ease in finding a wage job given the severity of labor market constraints.*

We simulate and quantify the impacts of microfinance on entrepreneurship, incomes and business investments by allowing all agents to borrow up to an additional amount M with microfinance. For empirical purposes, we use maximum amount of microfinance loan available to participants as maximum credit an agent can borrow.

2.6 Crowding-in effects of microfinance

The evidence on the impacts of microfinance from previous RCTs suggests that microfinance may lead to crowding-in of credit from other formal and/or informal sources.[22] The crowding-in effects of credit are important for several reasons: First, access to newer and cheaper credit through microfinance can help re-finance older and more expensive loans for the households. This may or may not affect their liquidity but brings down their marginal net interest rate on loans. Second, from supply-side perspective, an agent's access to microfinance can signal to other formal and informal sources of the borrower's quality or "type" and hence, further increase their credit access and hence, impact on their business investments and profits.

The crowding-in effects of microfinance can be modeled as credit constraints in simplest form as $k \leq \lambda(z + M) + M$. That is, an agent can invest an additional fraction (λ) up to microfinance amount (M) in business from other sources, on top of the microfinance amount already borrowed. Hence, the optimal amount of capital in this case ($k_u^{M(II)}(\theta)$) is given by:

$$k_u^{M(II)}(\theta) \equiv \underset{k \leq \lambda(z+M)+M}{\arg\max} \quad B^E \theta^{(1-\phi)} k^{\phi} + r(z - k - M) \tag{9}$$

[22] Banerjee et al. (2019) find that while total and informal credit do not increase with microfinance, informal credit taken for business purposes increases. On average, Gung-Ho Entrepreneurs witness a significant increase in informal loan size compared to Reluctant Entrepreneurs. Augsburg et al. (2015) find that credit access from a bank decreases with microfinance but overall there is an increase in borrowings.

3 Data

We use datasets from two RCTs on microfinance: Augsburg et al. (2015) and Banerjee et al. (2015). These studies were chosen for three main reasons: first, these are randomized experiments and hence, we have exogenous variation in access to microfinance. This ensures that the treatment effects estimated in this study are unbiased i.e., our results are internally valid. Second, these are either individual- or household-level panel studies which enable us to follow household's occupational decisions over time i.e., track entry and exit of entrepreneurs across different survey rounds and with the introduction of microfinance. Third, the inclusion of these RCTs provides us with different settings in which these experiments were conducted, reflecting different credit and labor market frictions and hence, lend external validity to the results. Banerjee et al. (2015) implemented the study in the urban neighborhoods of Hyderabad (India) (hereafter, referred as "Hyderabad") during a period of high economic growth.[23] While Augsburg et al. (2015) conducted the experiment during economic recession with high unemployment rates across Bosnia and Herzegovina right after the financial crisis of 2008. The two studies also differ in their experimental design: while the Hyderabad study is a cluster RCT with an Intention-to-Treat design, the RCT in Bosnia and Herzegovina was randomized at individual-level with an over-subscription design. That is, microfinance in Bosnia and Herzegovina was offered to a subset of those who were originally rejected by the Microfinance Institution (MFI) as they failed to meet credit requirements (also called "marginal applicants") and hence, may reflect relatively higher credit market frictions.

These RCTs find an increase in outstanding credit from a MFI with mixed evidence on crowding-in effects of other sources of lending. There was an increase in self-employment activities and business profits but these results are inconclusive. The impacts on business profits are driven by those in the top of the distribution. However, they do find significant positive impacts on business investments or inventories. They find an increase in labor supply and decline in certain components of consumption. All effects are at the short to medium term. A brief overview of design and findings of these experiments is in Appendix B.1.

We harmonize the data from these experiments to provide comparable results. We exclude any observations not tracked in follow-up surveys and preserve the sample used for these studies (also referred to as the "study sample" in the text). However, the sample used for the model estimation (also referred to as the "model sample" in the text) differs from the study sample in two respects (see Table B.2). First, we exclude any observation for whom income was either not reported in the survey or they were reported to earn zero income. These observations are excluded because, using structural estimation methods, we match

[23] Between 2005 and 2010, average household consumption increased by about 80% for control households.

expected mean incomes as predicted by the model with mean incomes observed in the data to assign occupations to individuals or households. Second, we winsorize total assets value and incomes reported by the household at top 5 percentile to avoid observations with very high values from influencing the choice of parameters. For such agents, market frictions may also not be binding in the first place. We also consider winsorizing at top 1 percentile as one of the robustness checks described in Section 4.

For model estimation, an agent's occupational choice ($\mathbf{1}_E$) is determined by any business ownership at the household level. We conduct robustness checks using an alternative definition where an entrepreneur is an agent who owns a business and does not earn any wage income i.e., she does not have any other occupation other than owning a business. Initial wealth (z) is given by total value of assets owned by the household at the time of baseline survey, winsorized at top 5 percentile. The baseline value of assets helps avoid the simultaneity issue between occupational decisions and initial wealth to the extent possible.[24] An agent's labor productivity (s) is measured by years of schooling reported for the household head. An agent's income is defined as annual gross household earned income, excluding remittances, pensions, interest income, social security and other benefits, winsorized at top 5 percentile. For a wage worker, income (R_W) is defined as gross earnings from wage work and for an entrepreneur, income (R_E) is defined as total business revenue. The definitions of these key variables are presented in Table B.2.

4 Estimation strategy

A key implication of our theoretical framework is that credit and labor market interventions may have different impacts on involuntary and voluntary entrepreneurs. Previous literature documenting heterogeneity in impacts of microfinance have used different observable proxies to define entrepreneur status. For example, Banerjee et al. (2019) use previous business experience to distinguish "Gung-Ho Entrepreneurs" from "Reluctant Entrepreneurs". Since it is not possible to directly identify involuntary and voluntary entrepreneurs from data, we use structural methods to classify these entrepreneur types from observable distribution of schooling and initial wealth and unobserved heterogeneity in entrepreneurial productivity. We use structural modeling to conduct counterfactual simulations to understand and quantify the distributional impacts of microfinance and the mechanisms of change in the presence of credit and labor market frictions. We validate these results and provide more insights into the characteristics of involuntary entrepreneurs using reduced form methods.

[24] However, for Banerjee et al. (2015), initial wealth measure is only available for first and second endline survey and not for baseline.

4.1 Structural methods

We use Simulated Method of Moments (SMM) to estimate a set of parameters (Θ) of the structural model. SMM involves minimizing percentage deviation between simulated targeted moments from the model and sample moments calculated using the data. We use nine target moments to estimate seven parameters using observed distribution of years of schooling (s) and initial wealth (z). We use identity matrix as the weighting matrix to provide consistent estimates of the parameters. We perform SMM in MATLAB using hybrid global optimization routine of simulated annealing algorithm *(simulannealbnd)* along with pattern search algorithm *(patternsearch)* to find global minima and estimate true parameters. The standard errors for the parameters are estimated by bootstrapping 100 times. We also conduct Hansen's J-test for over-identification. A detailed description of the SMM approach is in Appendix C. We also conduct robustness and sensitivity analyses to check for both calibrated and estimated parameters, described in Section 6.

Parameters: Overall, there are fifteen parameters in this model, also outlined in Table 1. We calibrate eight parameters in the following manner: We calibrate four parameters based on recent literature: α, share of payments going to variable factors that is paid to the capital, is calibrated to 0.21 based on Karaivanov and Yindok (2022). Business technology parameter for an entrepreneur, ϕ, is calibrated to 0.27 based on Buera (2009). Span of control parameter, ν, is calculated to be 0.36 using Equation (2.1).[25] Fixed cost of starting a business is assumed to be 0, i.e., $F = 0$. As part of robustness checks, we also estimate F as an additional parameter using SMM.

We calibrate the other four parameters based on study-specific estimates or country-specific statistics. We estimate λ, γ and r using baseline pooled data from each experiment while ψ is calibrated to country-specific statistic in which the experiment is based. The parameter determining credit market constraints, λ, is given by mean ratio of total loan size held by the households to total value of assets possessed by them, winsorized at top 5 percentile. For robustness checks, we calibrate λ as an additional parameter, use an alternative credit constraints specification and winsorize assets and incomes at top 1 percentile. The robustness checks are discussed in detail in Section 6. The wage technology parameter, γ, is given by the coefficient on log of schooling for the linear regression of log of wage income on log of schooling. The net interest rate, r, is calibrated to median rate of interest on household

[25]The span of control parameter, ν, is given by:

$$\nu = \frac{\alpha(1-\phi)}{\phi + \alpha(1-\phi)}$$

loans for each experiment. The technology parameter for the third party employer, ψ, is calibrated to country-specific share of labor compensation in Gross Domestic Product (GDP) at current national prices using Penn World Tables (PWT) for the study period (Feenstra et al., 2015).

The remaining seven parameters are: η, the labor market friction parameter; δ_0, conditional mean of log of entrepreneurial productivity, θ; δ_1, elasticity of θ with respect to initial wealth z; δ_2, elasticity of θ with respect to schooling s; σ, standard deviation of θ; B^E, total factor productivity for entrepreneur and B^W, total factor productivity for third party employer. These are denoted by $\Theta = \{\eta, \delta_0.\delta_1, \delta_2, \sigma, B^E, B^W\}$ and estimated using SMM.

Target Moments: The nine target moment conditions to estimate seven parameters are related to observed distribution of entrepreneurs across s and z and based on Karaivanov and Yindok (2022) (outlined in Table 2). First seven target moments relate to distribution of entrepreneurship rate across observed tercile distribution of s and z and last two target moments relate to mean business revenue and wage earnings of entrepreneurs and wage workers, respectively. The model analogs for last two target moments are entrepreneurial revenue, R^E and wage earnings, R^W for entrepreneurs and wage workers, respectively.

4.2 Empirical validation of results

We validate model-predicted entrepreneur type and distributional impacts of microfinance using randomized variation in access to microfinance from the RCTs. The rich survey data from the RCTs also provide insights into key household (or individual) and business-related characteristics across entrepreneur types as predicted by the model. Given the observable distribution of assets z and schooling s and entrepreneurial productivity, θ, we predict the probability that an agent will be a voluntary or an involuntary entrepreneur, given by Equation (4) and (5) respectively, using structural methods. Then, we match these model-predicted probabilities of voluntary and involuntary entrepreneurship for each agent with the experimental datasets. This helps us analyze the following: (a) What are the distributional impacts of microfinance?; and (b) Who are these involuntary entrepreneurs and what are their characteristics? This analysis allows us to understand the extent to which misallocation in occupations implied by credit and labor market frictions can influence the impact of microfinance on a range of outcomes.[26]

First, we investigate the treatment effects of microfinance on a range of outcomes using

[26] We run these analyses on the model sample and hence, the results may not correspond to statistics and treatment effects as estimated in the original studies.

the following regression specification:

$$Y_{ivt} = \beta_0 + \beta_1 Treat_{vt} + \mathbf{X}_{i0} + \epsilon_{it} \tag{10}$$

where, Y_{ivt} is the outcome of interest measured for an individual i in village v at time t. At baseline, $t = 0$ and at endline $t = 1$. Given that the Hyderabad study is a cluster RCT, $Treat_{vt}$ is a dummy variable equal to 1 if the respondent lives in a treatment village. Since the study in Bosnia and Herzegovina involves individual-level randomization, the treatment variable will correspond to $Treat_{it}$. The key coefficient of interest is β_1 and represents Intention to Treat (ITT) effect of access to microfinance. $\mathbf{X}_{i0}$ is a set of study-specific respondent and household-level covariates measured at baseline. For the RCT in Hyderabad, we cluster standard errors at area level and for Bosnia and Herzegovina, we report robust standard errors. The key outcomes analyzed are: business ownership (or entrepreneurship), wage job, borrowings, loan take-up and size by sources, business revenue, expenditures and profits, enterprise size in terms of labor hired, gross household income and wage earnings. We also analyze transitions in occupations such as new business entries and exits because an aggregate change in entrepreneurship rate between baseline and endline hides heterogeneity in these transitions. Additionally, it helps us understand whether microfinance exacerbates misallocation at extensive margin.

Second, according to our theoretical framework, agents make constrained occupational choices in the presence of credit and labor market frictions. We analyze heterogeneity in impacts of microfinance using model-predicted probability of an agent being an involuntary entrepreneur, as per below:

$$Y_{iv1} = \beta_0 + \beta_1 Treat_v + \beta_2 IVEnt_{iv0} + \beta_3 IVEnt_{iv0} * Treat_v + \mathbf{X}_{i0} + \epsilon_{i1} \tag{11}$$

$IVEnt_{iv0}$ is model-predicted probability of an agent being an "involuntary entrepreneur" (given by Equation (5)) on baseline pooled sample.[27] The key parameter of interest is β_3 which captures difference in expected outcome to a marginal increase in predicted probability of involuntary entrepreneurship for treated compared to control households. We also report $\beta_1 + \beta_3$ which captures total change in expected outcome for treated households from a marginal increase in probability of being an involuntary entrepreneur.

Third, by matching predicted entrepreneurship type with rich survey data, we investigate several observable demographic and business-related characteristics and provide unique

[27] The left-out group consists of agents for whom predicted probability of involuntary entrepreneurship equals zero (i.e., $P_I = 0$). This corresponds to agents who are either voluntary entrepreneurs or wage workers.

insights into these involuntary entrepreneurs. Demographic characteristics include age, gender, marital status, household size, years of schooling, receipt of vocational training, assets ownership, occupations and income sources. Business characteristics include enterprise size (both family and non-family labor), revenues, expenditures and profits. For this analysis, we define "involuntary entrepreneur" as a binary variable based on appropriate probability threshold, discussed further in Section 5.

5 Results

In this section, we present the results from the analysis of Banerjee et al. (2015) because the fit of the structural model was better than for Augsburg et al. (2015). The sum of squared deviations ("criterion function") was 0.16 for Hyderabad and 0.39 for Bosnia and Herzegovina. We refer to the analysis from Bosnia and Herzegovina, where relevant, to check for external validity of our main results.

5.1 Model fit

Parameters: The calibrated parameters (upper panel) and parameters estimated using SMM (along with standard errors and 95% confidence intervals in lower panel) for Hyderabad are presented in Table 3. For the study-specific parameters, we calibrate credit market friction parameter, λ, to 0.98, i.e., 25^{th} percentile of distribution of ratio of total loan size to total value of assets possessed by households.[28] This implies that a client in Hyderabad can borrow up to 98% of their initial wealth. For example, an agent with median wealth of 3,235,000 INR in the model sample can borrow up to 3,170,300 INR in loans for investment purposes. It reflects relatively lower credit market frictions that can be explained by large presence of MFIs and high growth in lending in the state of Andhra Pradesh at the time of the experiment (Banerjee et al., 2015). The authors also note that even at baseline when there was no MFI borrowing in the sample areas, 68% of the households had at least one outstanding loan. It rose to 86.7% in first endline and 90.4% in second endline. Karaivanov and Yindok (2022) also estimated λ to be less than 1 for Thailand. We also check for robustness of these results using alternative definitions to calibrate and estimate λ, described in Section 6.

The wage technology parameter, γ, is calibrated to 0.14, which implies that a 1% increase in years of schooling raises household income by 14%. The net interest rate, r is calibrated

[28] We believe that using 25^{th} percentile of distribution is more representative of credit constraints faced by the population in developing countries. The parameter λ is estimated to be 0.04 for Bosnia and Herzegovina. This low credit access can be explained by the experiment design which only includes marginal applicants.

to median interest rate of 3% per month which corresponds to 36% Annual Percentage Rate (APR). This is higher than 24% APR as described in the study. The Third Party Employer's business technology parameter, ψ, is calibrated to 0.4819 for India for the year 2006 using PWT.

Among the estimated parameters, labor market friction parameter, η, is estimated to be 2.15 and its standard error is 0.76. This implies that, on average, at modal years of schooling (i.e., $s = 10$ years), the probability of an agent not having access to any wage job is about 30% (Figure 1). The country-level average employment to population ratio was 53.05% in India between 2005 and 2010 (Bank, 2010). The parameter, η, estimated by the model, reflects a relatively less imperfect local labor market in the context of high economic growth in the state of Andhra Pradesh.[29] The parameter η was estimated for Thailand by Karaivanov and Yindok (2022) implies that the probability that an agent has no access to a wage job at modal years of schooling (4 years) is 40%, lending external validity to our results.

Entrepreneurial productivity is weakly positively correlated with initial wealth, z ($\delta_1 = 0.002$) but strongly positively correlated with schooling, s ($\delta_2 = 5.26$). The standard error for δ_2 is 4.15. These results compare with Karaivanov and Yindok (2022) which find both δ_1 and δ_2 to be positive for Thailand, although small.[30]

Target moments: Table 4 shows the fit between nine target simulated moments and data moments, computed using SMM over seven parameters, for Hyderabad. According to data (Column (3)), the overall entrepreneurship rate is 36.4% and the model underestimates it by 10%. The model does a fairly good job at estimating entrepreneurship rate across different terciles of schooling and wealth. However, it estimates entrepreneurship rate at top tercile of wealth and at top and bottom tercile of schooling and wealth within ±18-20% range. The measurement errors in measuring wealth could be a potential explanation for poor model fit for these distributions. The standard deviation for wealth measure for Hyderabad is 28342. In terms of both mean entrepreneurial and wage incomes, the model estimates it within

[29] In contrast, η is estimated to be 36.73 for Bosnia and Herzegovina with probability of not having access to any wage job at about 45% at modal years of schooling (i.e., 12 years). In Bosnia and Herzegovina, the employment to population ratio was 34.72 in 2008 (Bank, 2010). This study was conducted in 2008-09, just after the 2008 financial crisis which was characterized by high unemployment and over-indebtedness. The authors also find that their pool of marginal loan applicants, on average, are less likely to hold full-time jobs compared to regular loan applicants.

[30] For Bosnia and Herzegovina, wealth is weakly negatively correlated with entrepreneurial productivity ($\delta_1 = -0.15$) but correlation between entrepreneurial productivity and schooling is highly negative ($\delta_2 =$ -7.82). One explanation could be loss of employment and switching to small-scale business for highly educated agents due to economic recession. Another potential explanation could be higher financial aspirations induced by higher educational qualifications leading to frustration with economic recession and hence, reduced business investments (McKenzie et al., 2021).

$\pm$10-15% range. The Hansen J-test does not reject the null hypothesis that over-identifying restrictions are satisfied and the model is valid.

5.2 Entrepreneurship rate and incomes

In this section, we compare entrepreneurship rate and mean entrepreneurial and wage incomes for different terciles of schooling and wealth in Figures 2, 3 and 4, respectively. The left panel of these figures shows entrepreneurship rate and mean incomes as predicted by the model and the right panel shows its sample analogs.

Entrepreneurship rate: First, we observe higher entrepreneurship rate for bottom tercile of schooling than for top tercile for both data and model. Second, both model and data predict a higher prevalence of entrepreneurship for higher wealth levels. Overall, qualitatively, the results are similar across both model and data. According to the data, majority of the entrepreneurs in bottom tercile of schooling are involved in services sector and those at top tercile of schooling are in agriculture sector. The majority in bottom and top tercile of wealth are involved in agriculture sector. The model fit for entrepreneurship rate by schooling and wealth is investigated using smoothing spline fit in Figure D.1.

Incomes: The model fit in terms of distribution of entrepreneurial income is mixed: for schooling, the model systematically underestimates entrepreneurial income for bottom tercile and overestimates it for top tercile. This could potentially be explained by large positive δ_2 for schooling predicted by the model. The model performs better with respect to wealth distribution. For mean wage incomes, the model underestimates mean wage income for bottom tercile of wealth but performs relatively better across the rest of the distribution.

5.3 Involuntary and voluntary entrepreneurs

In this section, we investigate the distribution of involuntary and voluntary entrepreneurs. Since these entrepreneurship choices cannot be directly observed in the data, the structural model allows us to differentiate between the two using observed variation in schooling and wealth. Using the model-predicted probabilities of involuntary and voluntary entrepreneurship among agents, we test how these occupational choices varies by schooling and wealth. It also helps us investigate incomes across these entrepreneurs, a reflection of misallocation at intensive margin.

We investigate prevalence of involuntary (left panel) and voluntary (right panel) entrepreneurship by terciles of schooling and wealth, as predicted by the model, in Figure 5.

First, majority of the entrepreneurs are involuntary entrepreneurs. In the model sample, 23.5% of agents are involuntary entrepreneurs while only 9.3% are voluntary entrepreneurs. Second, involuntary entrepreneurship is highest in bottom tercile of schooling, highlighting binding labor market frictions. On the other hand, voluntary entrepreneurship rate is highest in top tercile of wealth, reflecting less binding credit market frictions. Higher prevalence of voluntary entrepreneurs in top tercile of schooling reflects strong positive relationship between entrepreneurial productivity and schooling. Third, voluntary entrepreneurship rate is highest in top tercile of assets and schooling, reflecting both less binding constraints of credit and labor markets.

Figure 6 further shows how involuntary and voluntary entrepreneurship rate trends with years of schooling (left panel) and percentiles of initial wealth (right panel). Figure 6a provides evidence of a negative relationship between the probability of involuntary entrepreneurship and schooling (Testable prediction 1) i.e., as schooling increases, involuntary entrepreneurship decreases. This could be explained by large positive relationship between entrepreneurial productivity and schooling (i.e., positive δ_2) and relatively low labor market frictions. On the other hand, voluntary entrepreneurship rate increases as years of schooling increases. Figure 6b shows a weak relationship between initial wealth and both involuntary and voluntary entrepreneurship rate (Testable prediction 2). At all percentiles of wealth, there is a higher proportion of involuntary than voluntary entrepreneurs. Overall, these figures suggest that labor market frictions may be a larger binding constraint than credit constraints in determining occupational choices.

In Figure 7 we explore how entrepreneurial income is distributed for involuntary (left panel) and voluntary (right panel) entrepreneurs across different terciles of schooling and wealth. On average, voluntary entrepreneurs earn ten times more than involuntary ones. This difference in mean incomes between voluntary and involuntary entrepreneurs is driven by voluntary entrepreneurs in top tercile of schooling and wealth. This suggests constrained occupational choices leading to misallocation in business investments (explored further in the following section). Among involuntary entrepreneurs, incomes are higher for those in top tercile of schooling or wealth.

5.4 Misallocation at extensive and intensive margin

In this section, following Karaivanov and Yindok (2022), we analyze misallocation at extensive margin i.e., occupational choice and at intensive margin i.e., capital and labor invested in businesses, due to both labor and credit market constraints. Given credit and labor market frictions and agents observable characteristics, an agent makes the decision of being an entrepreneur or not. Once she decides to be an entrepreneur, she decides how much capital is allocated to businesses and how many labor to hire. If she makes constrained occupational choices (i.e., chooses to be an entrepreneur even if wage job is preferred), it may lead to allocative inefficiency of resources (i.e., she may invest more or less capital or hire more or less labor than what a business optimally requires). Hence, we compare misallocation between the first-best scenario (absence of both credit and labor market friction i.e., $\lambda = 10^8$ and $\eta = 0$) with three different scenarios: (a) where λ and η are at SMM estimates; (b) when there is only credit market friction (i.e., $\lambda =$ SMM estimate and $\eta = 0$); and, (c) when there is only labor market friction (i.e., $\lambda = 10^8$ and $\eta =$ SMM estimate).

Misallocation in occupational choice: Figure 8 shows misallocation effects in entrepreneurship rate for the three different scenarios, as described above. Misallocation in entrepreneurship is given by the difference between predicted entrepreneurship rate for the first-best scenario and each of the three scenarios. Warmer colors represent larger rate of entrepreneurship in the three scenarios relative to the first-best scenario and colder colors represent smaller values.

First, in Figure 8a, we predict 27.2 percentage points higher total entrepreneurship rate with the SMM estimates at baseline than at first-best scenario, consistent with the findings of Karaivanov and Yindok (2022). A majority of entrepreneurs in the sample are involuntary entrepreneurs and hence, this highlights the important role of both imperfect credit and labor markets in determining occupational choices. These results are also comparable with the evidence of labor rationing by Breza et al. (2021), who find that at least 24% of the lean self-employment in India occurs due to labor market frictions. Second, we find that misallocation in entrepreneurial choice is higher in bottom tercile of schooling and in top tercile of wealth than rest of the distribution. While the agents with lower years of schooling may be facing binding labor market frictions, those with higher wealth levels may be facing both binding credit and labor market frictions. Third, misallocation is largest for those in top tercile of schooling and wealth.

In Figure 8b, when we compare first-best scenario with a scenario comprising of perfect labor markets but with credit market frictions, misallocation in entrepreneurial choice, as seen in the previous figure, reduces from 27% excess entrepreneurship rate to 5.7%. Given the high prevalence of involuntary entrepreneurship due to binding labor market frictions, this result is not surprising. We also find that misallocation in top tercile of wealth does not decrease significantly, reflecting binding credit constraints. However, misallocation for lower levels of schooling reduces significantly due to perfect labor markets.

In Figure 8c, when we compare first-best scenario with a scenario comprising only of labor market frictions, misallocation in occupational choice reduces by a lesser margin compared to when there is only credit market friction (reduces only to 15.3%). While misallocation does not reduce much for lower levels of schooling, it reduces a lot for those in top tercile of wealth.

Overall, we find excess entrepreneurship in the presence of credit and labor market frictions as compared to first-best scenario. This misallocation at extensive margin reduces significantly when we relax labor market frictions than when we relax credit market frictions. Hence, making more jobs available or reducing search frictions in local labor markets would be a significant policy tool to enable agents to choose their preferred occupations, compared to relaxing credit market frictions.

Misallocation in capital investments: Next, we investigate misallocation in capital investments for the three different scenarios in Figure 9. Misallocation in capital investments is given by log of the ratio of capital investments in the first-best scenario to capital investments in the three scenarios, as predicted by the model. Warmer colors represent more capital investments in the first-best scenario relative to the three scenarios and colder colors represent lower values. In Figure 9a, when we compare first-best scenario with SMM estimates, we find that, on average, entrepreneurs are investing marginally higher levels of capital than in first-best scenario. Those agents with lower levels of wealth and higher levels of schooling invest less capital than in the first-best scenario. Misallocation in capital investments is highest for entrepreneurs in bottom tercile of wealth and top tercile of schooling. When there are no labor markets frictions (Figure 9b), entrepreneurs still invest marginally higher levels of capital than in first-best scenario, but by a smaller magnitude than with SMM estimates. When there are no credit market frictions (Figure 9c), misallocation in capital is lower i.e., they invest closer to optimal levels of capital than when there are no labor market frictions.

Misallocation in enterprise size: We now explore misallocation in enterprise size i.e., labor hired, for the three different scenarios in Figure 10. Misallocation in labor investments is given by log of ratio of labor demand estimated in the model in first-best scenario to labor investments in the three scenarios, as predicted by the model. Warmer colors represent more capital investments in the first-best scenario relative to the three scenarios and colder colors represent lower values. In Figure 10a, when we compare labor investments in first-best scenario with SMM estimates, we find that, on average, agents are hiring more labor than optimal amount of labor in the first-best scenario. Misallocation in enterprise size is the lowest when we relax credit market frictions (Figure 10c relative to when we relax labor market frictions (Figure 10b). However, this may be specific to the Indian context where labor markets are less imperfect i.e., η is very small.

5.5 Treatment effects of Microfinance

In Table 5, we investigate model-implied impacts of microfinance on entrepreneurship rate, incomes, proportion of credit and labor constrained entrepreneurs and credit and labor investments. These treatment effects are estimated on the model sample compiled from the pooled first endline survey sample for Hyderabad and includes both experimentally identified treatment and control groups. We also analyze the case of crowding-in effects of microfinance as an extension of the model. Column (1) shows statistics for when there is no access to microfinance. Column (2) shows model-implied treatment effects of microfinance and Column (4) refers to impacts of microfinance when we model its crowding-in effects. Columns (3) and (5) are percent changes in statistics for without and with the crowding-in effects of microfinance, respectively.

The total entrepreneurship rate is at 32.7% without microfinance. With microfinance, entrepreneurship rate decreases by 5.2% and the proportion of wage workers increases to 69% (Column (3)). The decline in entrepreneurship rate is due to a decline in involuntary entrepreneurs of 10.6% compared to an increase in voluntary entrepreneurship rate of 8.4%. Microfinance leads businesses to face lower credit constraints and hence, increase their business investments including hiring more labor. As more wage jobs become available, some agents with less binding labor market constraints and/or higher labor market qualifications switch to wage jobs leading to a decline in involuntary entrepreneurship. Lower credit constraints also causes entrepreneurial income to increase and hence, some agents who were earlier constrained and had lower expected income from businesses switch to voluntarily starting a business. Factoring in crowding effects of microfinance, entrepreneurship rate declines further by 7.5% (Column (5)). The proportion of wage workers increases to 69.8%.

The mean incomes rise for both entrepreneurs and wage workers. The incomes gains is larger among entrepreneurs than among wage workers: 31.7% compared to 23.0%. The increase in mean wage income is driven by 23.2% increase in equilibrium wage. With the crowding-in effects, we see further income gains for both entrepreneurs and wage workers and equilibrium wage rises by 30.0%. The gains in entrepreneurial income is largely driven by voluntary entrepreneurs than by involuntary entrepreneurs. In fact, incomes of voluntary entrepreneurs increases by 25.4% relative to 17.7% of those of involuntary entrepreneurs.

As credit constraint relaxes with access to microfinance, both the model-predicted amount of mean capital and labor inputs increases. Microfinance leads to more increase in capital investments than labor inputs: 93% for capital compared to 2.14% for labor. With the crowding-in effect of microfinance, mean capital rises further by 155% and labor investments by 3.5%. The business investment gains are concentrated among agents in bottom and top tercile of wealth. Before microfinance, 29.4% of the model sample are credit-constrained and labor-constrained entrepreneurs. Microfinance leads to a reduction in the proportion of credit- and labor-constrained entrepreneurs by 13%. Crowding-in effects of microfinance implies a further reduction by 16.7% but the gains are concentrated among those in bottom tercile of schooling.

We further explore the distributional impacts of microfinance, across terciles of schooling and wealth, in Appendix D.2. Overall, microfinance leads to an increase in entrepreneurship in bottom tercile of wealth and a small decline in bottom tercile of schooling. The agents in bottom and middle tercile of wealth gain the most in terms of entrepreneurial income while the gains in wage income is uniformly distributed. The business investment gains are concentrated among agents in bottom and top tercile of wealth. These heterogeneous impacts of microfinance correspond to the heterogeneous results documented in the literature: Karaivanov and Yindok (2022) show that the poorest households in at the 10^{th} income percentile benefit the most (up to 40%) from microfinance. The income gains are uniformly distributed by years of schooling. Buera et al. (2020) also find that in partial equilibrium, the poor and those with low labor productivity and marginal entrepreneurial productivity gain the most while in general equilibrium, wealthy agents gain the most. Banerjee et al. (2020) find substantial heterogeneity in impact among the Million Baht program in Thailand benefited high productivity households the most. Banerjee et al. (2015) find where the gains of microfinance are concentrated in the right tail of the distributions.

5.6 Empirical validation of results

The results from structural estimation provide evidence of misallocation in occupations given by the predicted rate of entrepreneurship in the presence of credit and labor market frictions. The prevalence of entrepreneurship especially involuntary entrepreneurs is higher using SMM parameter estimates than in the first-best scenario where there are no labor or credit market frictions. We leverage the model-predicted entrepreneur type and the randomized access to microfinance to further investigate and validate the causal and heterogeneous effects of microfinance across voluntary and involuntary entrepreneurs. Given that the RCTs only influence the credit market parameter, we assume that treatment and control groups are exposed to similar labor market conditions. Following Banerjee et al. (2015), all regressions described in this section include the following control variables measured at baseline: area population, area total businesses, average expenditure per capita, share of household heads who are literate, and share of adults who are literate.[31] We cluster standard errors at area level.

Treatment effects of microfinance: In Panel A of Table 6, we present the impacts of microfinance on occupation transitions (based on Equation (10)). On average, we do not find evidence of an increase in entrepreneurship or new business entry or exit or increase in share of wage workers. The lack of evidence on increase in entrepreneurship with microfinance may correspond to decline in entrepreneurship as implied by the model. In Panel B, we investigate how these results vary for involuntary entrepreneurs. In these regressions, we use the model-implied predicted probability of involuntary entrepreneurship for the sample. Consistent with model results, as the probability of being an involuntary entrepreneur increases by 1%, the probability of becoming an entrepreneur is 41.1 p.p. smaller for treatment group as compared to control group. Similarly, the likelihood of being a wage worker is 27.2 p.p higher for treatment group as compared to control group (by 31%). These results are statistically significant at 5 and 10 percent level, respectively. Further, we report $\beta_1 + \beta_3$, which represents total change in expected outcome for treated households from a marginal increase in probability of being an involuntary entrepreneur, as described in Equation (11). We find that a 1% increase in probability of being an involuntary entrepreneur corresponds to a 28.5 p.p (by 68%) lower likelihood of being an entrepreneur, statistically significant at 10% level.

We now explore the impact of microfinance on access to credit (Columns (1) to (4)), business performance (Columns (5) to (8) and household assets and income (Columns (9) to (11)) in Table 7. In Panel A, similar to Banerjee et al. (2015), we find evidence of credit take-up among treated group. However, we do not find evidence of crowding-in effects on other loans. In addition, we do not find evidence that these effects differ for involuntary entrepreneurs (Panel B). This difference might be driven by a change in composition of the sample imposed by structural estimation. Further, the left-out group includes agents who either have a higher likelihood of being a voluntary entrepreneurs or a wage worker apart from having a lower predicted probability of being an involuntary entrepreneur.[32]

Further, in Panel A, we find that, on average, microfinance leads to an increase of 883

[31] The treatment and control groups are balanced across all observable characteristics.

[32] We run two alternative specifications to account for sample composition. On the one hand, we restrict the sample to observed entrepreneurs in the data, using both the continuous measure of model-predicted involuntary entrepreneurship and a dummy indicator for that probability being greater than the 75^th percentile. On the other hand, we implement a triple difference-in-differences specification on wage workers. Overall, the direction of the estimates stay consistent across different specifications, although these estimates become less precise.

INR in enterprise revenue (by 19%) and 2,831 INR in assets (by 20%) compared to control group. But in contrast to the structural results, wage income reduces by 665 INR (10%) compared to control group. In Panel B, we analyze differential impacts of microfinance for involuntary entrepreneurs. We find evidence that, as probability of involuntary entrepreneurship increases by 1%, treated households earn 5,805 INR less than control households i.e., 126% lower at endline. This result is statistically significant at 10% level. We also find that treated households earn 4,576 INR more from wage jobs (by 71%) as compared to control households as probability of involuntary entrepreneurship increases by 1%. This result is statistically significant at 10% level and consistent with the model-implied treatment effects on wage income. There is no evidence of heterogeneous treatment effects of microfinance for involuntary entrepreneurs on the remaining outcomes. Nonetheless, the direction of these coefficients suggest that involuntary entrepreneurs, on average, earn lower profits and have smaller businesses. Turning to the overall impact measured by $\beta_1 + \beta_3$, we find that for the treated group, a 1% increase in predicted probability of being an involuntary entrepreneur decreases revenue by 3,558 INR (by 78 %) and this result is statistically significant at 10% level. However, for treated group, a 1% increase in probability of being an involuntary entrepreneur increases wage income by 2,851 INR (by 44%). This effect is statistically significant at 5% level. These results are consistent with findings from Bosnia and Herzegovina where we find that involuntary entrepreneurs earn significantly lower revenue and profits and less likely to be take up wage job.

Characteristics of involuntary entrepreneurs: Using experimental survey data, we explore further dimensions of the characteristics of involuntary entrepreneurs estimated by the structural analysis. To do so, we define an involuntary entrepreneur as follows: an agent whose probability of involuntary entrepreneurship as predicted by the model is greater than the 75^{th} percentile of the distribution.[33] This yields a total of 582 involuntary entrepreneurs, similar to the model-predicted share of involuntary entrepreneurs (23.5% as shown in Table 5).

Table 8 describes characteristics of involuntary entrepreneurs for the model sample.

[33] The left-out group consists of agents for whom predicted probability of involuntary entrepreneurship is lower than or equal to 75^{th} percentile. They also include wage workers and voluntary entrepreneurs. Using the median threshold for predicted probability of involuntary entrepreneurship to classify entrepreneurs yields 40 involuntary entrepreneurs in the data, which will lead to imprecise conclusions. This is explained by the skewed distribution of predicted probability of involuntary entrepreneurship in Figure D.2. The mean predicted probability of involuntary entrepreneurship is 0.23 and median is 0.22. We run two alternative specifications: a) restricting the sample to include only entrepreneurs as observed in the data, and b) using continuous measure of model-predicted probability of involuntary entrepreneurship. We find that the results from these specifications are similar to baseline results. Further, we find that that the involuntary entrepreneurs invest less in businesses in agriculture sector and earn less profits.

In Panel A, we compare key household characteristics and find that, on average, "involuntary entrepreneurs" are older, have larger households and lower educational qualifications. They are also more likely to be females and entrepreneurs. In Panel B, we find that these entrepreneurs work more hours in their businesses and borrow more. Consistent with these results, (de Mel et al., 2009) find that own-account workers are female, resemble wage workers and experience low returns to capital. In addition, findings by Gindling and Newhouse (2014); Falco and Haywood (2016); Karaivanov and Yindok (2022) suggest that entrepreneurs with low returns to capital usually have lower educational qualifications and possess lower wealth.

Additionally, when we compare the model sample across terciles of schooling (results not shown), we find that, on average, those in bottom tercile are older, have larger households and more loans. They are also more likely to be females and entrepreneurs. When we compare across terciles of wealth (results not shown), we find that, on average, those in top tercile of wealth earn higher income and are less likely to be wage workers. The ones in bottom tercile of wealth hire less employees (both family and non-family), spend less hours working in the business, earn less revenue and profits and have fewer outstanding loans than those with higher wealth levels.

5.7 Counterfactual policy analysis

The extent of misallocation at extensive and intensive margin and the treatment effects of microfinance leads us to explore how different credit and labor market policies would affect welfare outcomes. We explore impacts of different policies by varying credit and labor market friction parameters i.e. λ and η, respectively (Testable predictions 3 and 4). For example, relaxed credit markets through large loan sizes or efficient targeting of borrowers could be parameterized as larger values of λ and relaxed local labor market policies such as improved availability of wage jobs through public works programs could be parameterized as smaller values of η. These analyses also help us understand sensitivity of target moments to these two key parameters. We explore the following welfare outcomes: entrepreneurship rate (total, involuntary and voluntary) and prevalence of wage workers and mean incomes for entrepreneur types and wage workers.

Change in λ: In Figure 11, we vary credit market friction parameter, λ, from 0 (i.e., missing credit market) to 10 (i.e., relatively relaxed credit market). In Figure 11a, as λ increases, proportion of involuntary entrepreneurs declines marginally and proportion of voluntary entrepreneurs remains stable. As access to credit market improves, labor demand from businesses and equilibrium wage increases and hence, proportion of wage workers also increases marginally. With respect to incomes, in Figure 11b, voluntary entrepreneurs gain the most as access to credit market improves while entrepreneurial income among involuntary entrepreneurs remains stable.

Change in η: In Figure 12, we vary labor market friction parameter from 0 (i.e., perfect labor market) to 50 (i.e., very imperfect labor market). We find, in Figure 12a, that as η increases i.e., labor market gets more imperfect, involuntary entrepreneurship rate increases and proportion of wage workers decreases significantly. When the labor market is perfect, involuntary entrepreneurship reduces to zero i.e., there are available jobs and every agent who prefers wage work finds a wage job. In Figure 12b, as labor market relaxes (i.e, η decreases), total entrepreneurial income increases significantly driven by an increase in income for voluntary entrepreneurs. As η decreases, more wage jobs are available and hence, involuntary entrepreneurs switch to preferred wage jobs. An increase in labor supply leads to a decline in equilibrium wage and hence, wage incomes reduce.

6 Robustness and sensitivity analysis

In Table 9, we check for robustness of our SMM parameter estimates as well as key statistics using alternative model specifications or data definitions. In Column (1), we present the SMM parameter estimates, criterion function and key statistics based on baseline SMM parameter estimates. In Column (2), we estimate the credit market friction parameter, λ, as an additional parameter using SMM, instead of calibrating it. This checks for validity of the calibrated value and also checks for the impact of including additional dimensions on the estimated parameters. In Column (3), we winsorize household assets and incomes at top 1 percentile instead of top 5 percentile. In Column (4), we use an alternative definition of credit market friction. In the model, we assume that agents can invest only up to a fraction λ of the total assets into their businesses (i.e., $k \leq \lambda z$. Instead, we now assume that agents can invest all of their assets plus borrow additional amount from various formal and informal sources. That is, an agent can invest a proportion of up to $1 + \lambda$ of the total assets ($k \leq (1 + \lambda)z$). In Column (5), we estimate fixed cost (F) to starting a business as an additional parameter using SMM. In Column (6), we use an alternative definition of an entrepreneur - an agent is an entrepreneur if she owns a business and does not earn any income from wage jobs. That is, owning a business is her only occupation. This helps us check for the assumption that there are no start up costs to business.

Overall, the model fit is poorer than baseline SMM estimates for different specifications and definitions of the parameters. The key parameter for labor market friction remains within

95% confidence intervals except when we factor in fixed cost to starting a business and use an alternative entrepreneur definition. The correlation between entrepreneurial productivity and schooling also becomes strongly negative and is not within 95% confidence intervals. We describe results from each of the robustness checks in detail in Appendix E.

7 Concluding Remarks

An individual's decision to be an entrepreneur by choice or out of necessity in the presence of credit and labor market frictions is typically not observed empirically. Constrained occupational choices thus made has impacts on business investments, returns and profits. In this paper, we build on the heterogeneous agents model of occupational choices, developed by Karaivanov and Yindok (2022), to classify entrepreneurs as involuntary and voluntary types. An involuntary entrepreneur prefers to be a wage worker but due to both credit and labor market frictions chooses to be an entrepreneur out of necessity. While a voluntary entrepreneur always chooses to be an entrepreneur but could face credit market frictions, affecting his business investments and returns. We further model entrepreneurs to also be potential employers by specifying a more general production function (Buera, 2009; Lucas, 1978) and allow for crowding-in effects of microfinance (Banerjee et al., 2015). Using data from two microfinance RCTs in Bosnia and Herzegovina and India - Augsburg et al. (2015) and Banerjee et al. (2015), respectively, we structurally estimate the model using the Simulated Method of Moments. The structural methods are used to investigate and quantify the impacts of microfinance at both extensive and intensive margin in the presence of credit and labor market frictions. The exogenous variation in access to microfinance lends internal validity to the results and the contextual differences provide external validity. We further validate these results using reduced form methods.

We estimate that a majority of entrepreneurs in the sample are involuntary entrepreneurs, consistent with the evidence of labor rationing in low-middle income countries by Breza et al. (2021) and Karaivanov and Yindok (2022). Apart from this misallocation at extensive margin, we also find significant misallocation at intensive margin for both capital and labor investments in businesses. Overall, in the sample, there exists too many entrepreneurs than in the first-best scenario where there is no labor or credit market friction. However, while some agents invest too much capital, most of the agents invest too little capital or labor in their businesses. These findings are consistent with the literature on misallocation in capital investments in poorer countries (Hsieh & Klenow, 2014; Foster & Rosenzweig, 2017; Restuccia & Rogerson, 2008). We simulate and quantify the impacts of microfinance and find that relaxing credit constraints has a larger positive impact on incomes for voluntary entrepreneurs than for involuntary ones due to an increase in capital and labor investments in businesses. However, microfinance does not have substantial impact on misallocation at extensive margin i.e., it does not affect the prevalence of involuntary entrepreneurs significantly relative to relaxing labor market frictions. Using the model-predicted expected probability of being an involuntary entrepreneur, we validate these results by estimating reduced form treatment effects of microfinance.

These findings suggest that microfinance may not be a panacea and that relaxation of both labor market frictions and credit market constraints are necessary to reduce allocative inefficiencies of resources at both extensive and intensive margins (Bandiera et al., 2020; Buera et al., 2020). Public work programs (Imbert & Papp, 2015; Muralidharan et al., 2021), adult education, skills or vocational training (Chakravorty et al., 2021), targeting of credit lending to high-return borrowers (Hussam et al., 2021) are some of the key labor market policies to help individuals choose their preferred occupation and increase entrepreneurial productivity and returns.

Our study benefits from combining both structural and reduced form methods. However, there are areas that could be better explored in future research. First, our analysis relies on the assumption that initial wealth and schooling are orthogonal to each other. Banerjee and Newman (1993) refer to the implausibility of this assumption and show that correlation between schooling and wealth yields poverty traps. Second, we rely on experimental datasets that were not necessarily intended to study enterprise activity in greater detail and hence, are prone to measurement errors. Third, for simplicity, we assume that all microfinance loans are used for business activity and make no distinction between consumption and business loans. Buera et al. (2020) make this distinction and find that while the poor gain the most from consumption dimension of microfinance, the marginally productive gain the most from both consumption and business dimensions of microfinance. Fourth, while risk neutrality may be a valid assumption in the model given the weak correlation between wealth and entrepreneurial productivity, we will explore relaxing this assumption in future research. In future, we will further explore the external validity of the results using other microfinance RCTs from Morocco, Mexico and Mongolia (Angelucci et al., 2015; Attanasio et al., 2015; Crépon et al., 2015). We will also explore the impact of specific labor market policies relative to microfinance and complimentary effects of credit and labor market policies as future extensions to this research.

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Figures and Tables

Figures

Figure 1: Probability of not finding a wage job by schooling

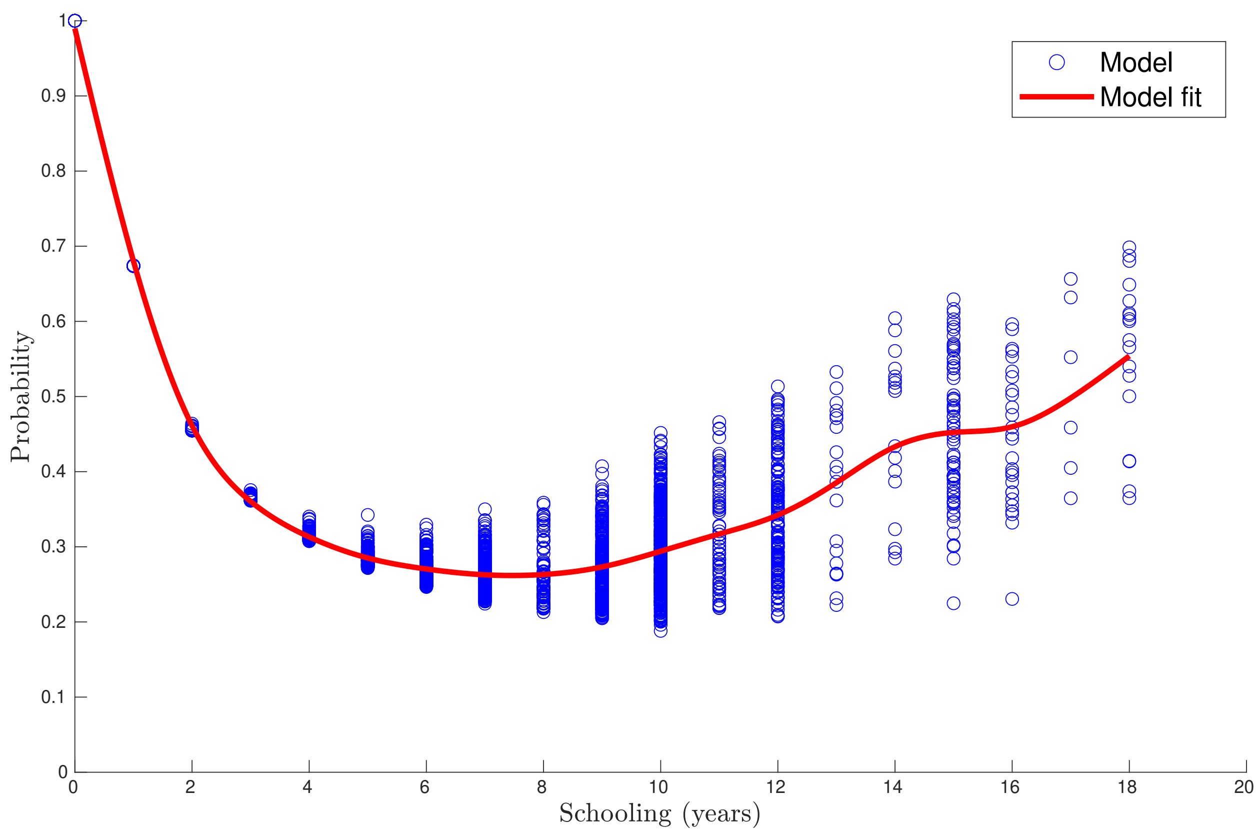
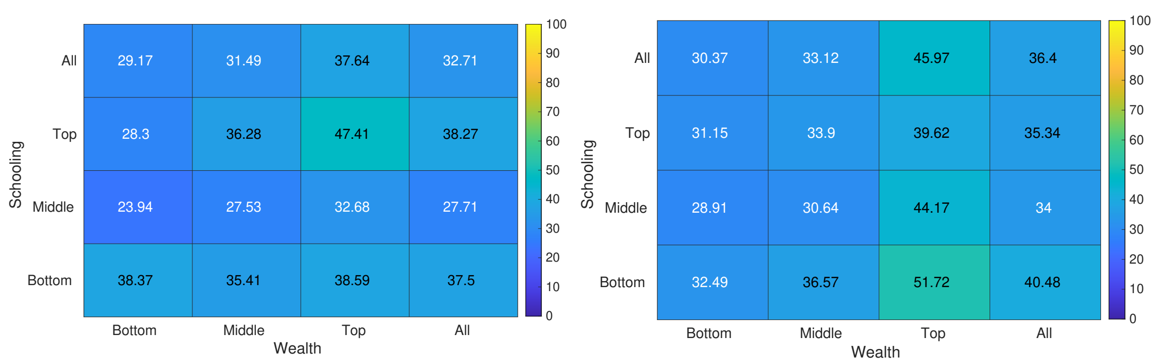
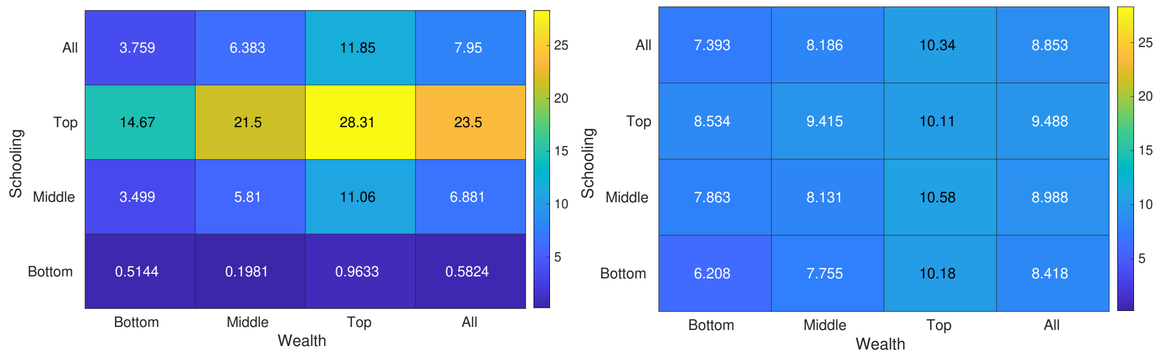


Figure 2: Distribution of entrepreneurs between model and data



(a) Distribution of entrepreneurs (from Model) (b) Distribution of entrepreneurs (from Data)

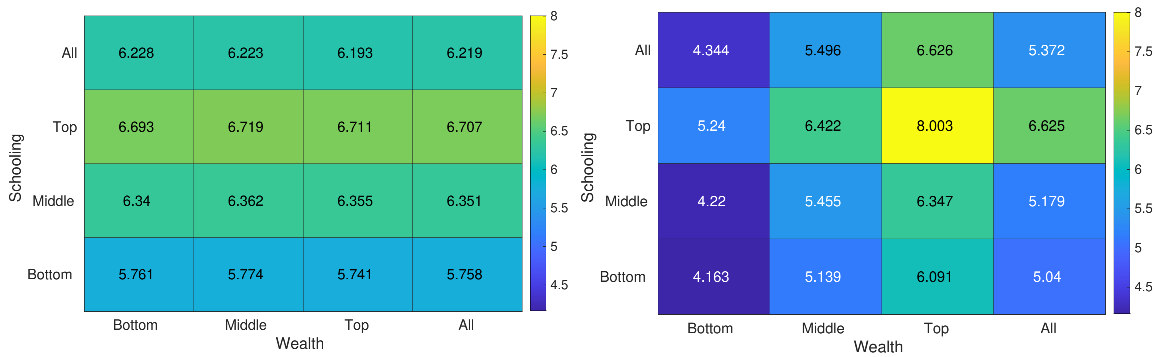
Figure 3: Distribution of mean entrepreneurial income between model and data



(a) Mean entrepreneurial income (from Model) (b) Mean entrepreneurial income (from Data)

Note: Incomes are expressed in thousands INR.

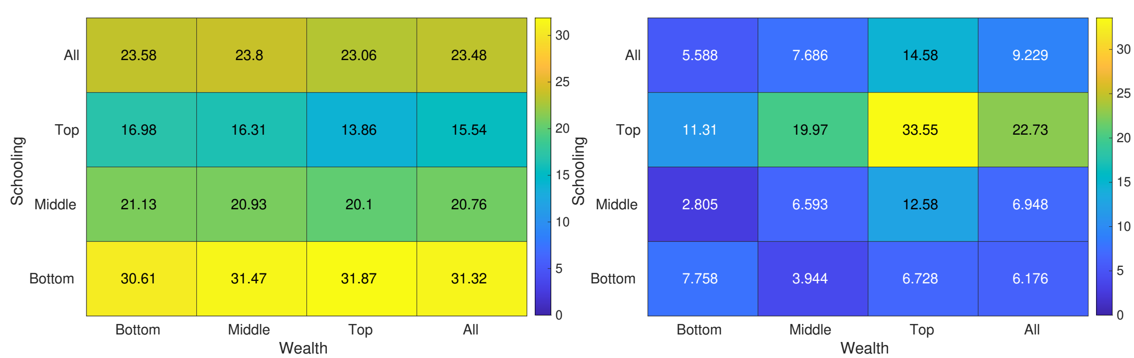
Figure 4: Distribution of mean wage income between model and data



(a) Mean wage income (from Model) (b) Mean wage income (from Data)

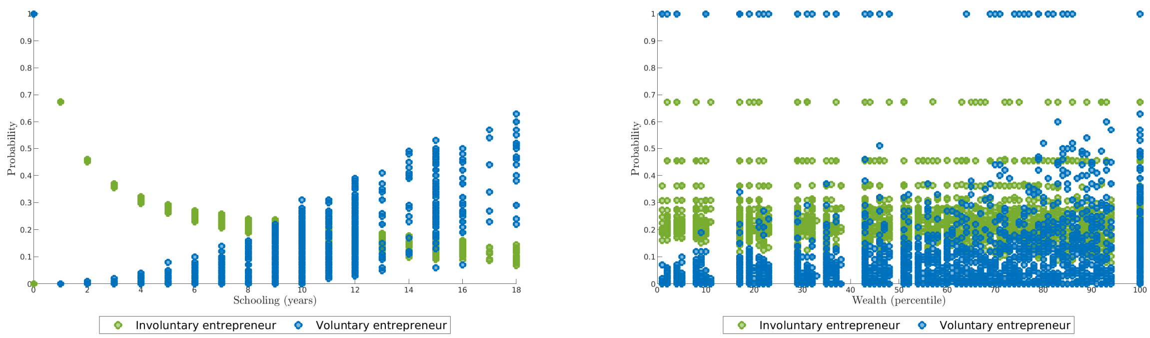
Note: Incomes are expressed in thousands INR.

Figure 5: Model fit: Voluntary and involuntary entrepreneurship rate by schooling and wealth



(a) Involuntary entrepreneurs (b) Voluntary entrepreneurs

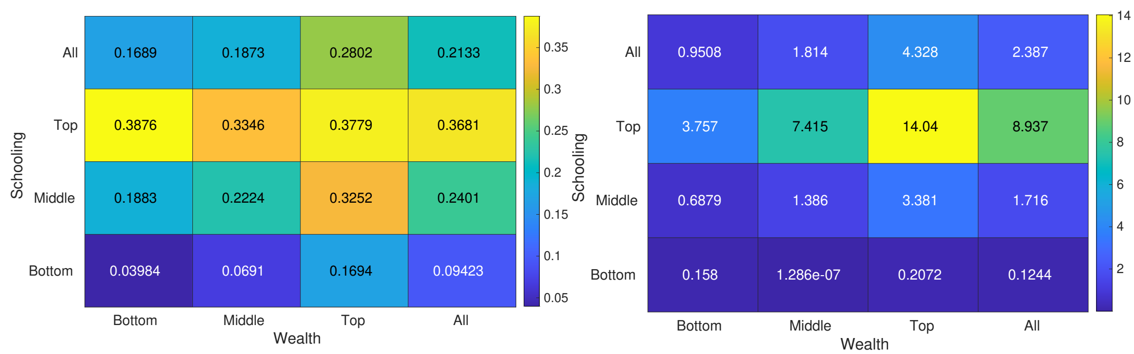
Figure 6: Model fit: Voluntary and involuntary entrepreneurship rate by schooling and wealth



(a) By schooling

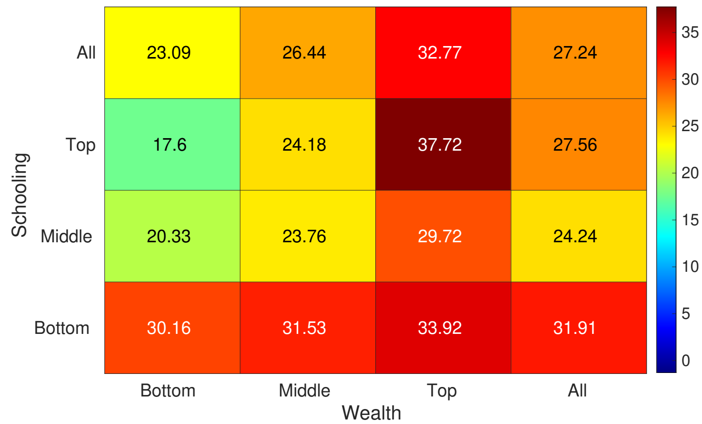
(b) By wealth

Figure 7: Model fit: Income by schooling and wealth for involuntary and voluntary entrepreneurs

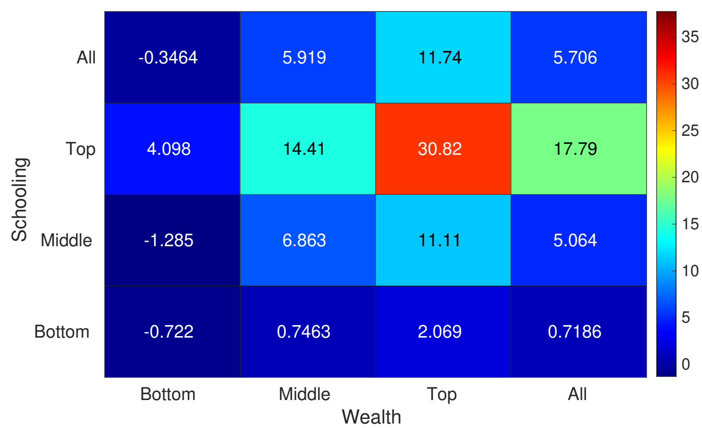


Note: Incomes are expressed in thousands INR.

Figure 8: Misallocation in entrepreneurship rate



(a) First-best vs. SMM estimates

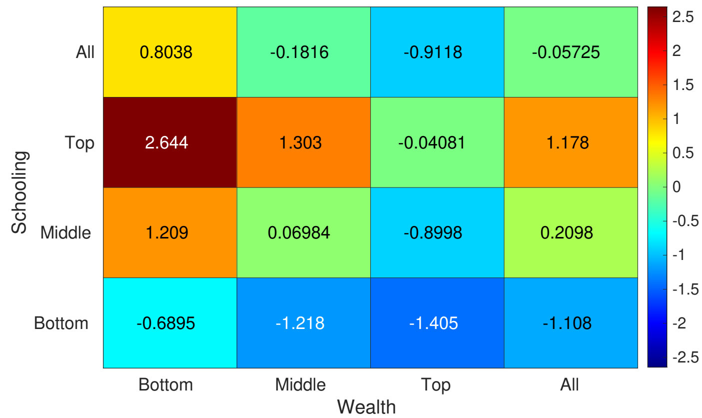


(b) First-best vs. credit market friction only

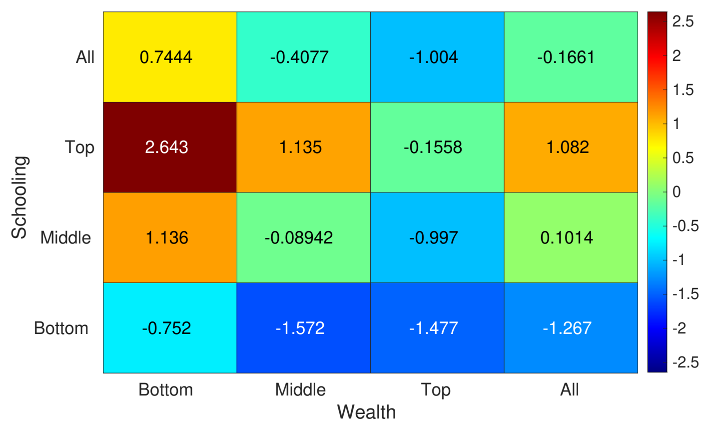
(c) First-best vs. labor market friction only

Note: Figure 8a compares the difference between predicted entrepreneurship rate for the first-best scenario (i.e., absence of both credit and labor market friction, $\lambda = 10^8$ and $\eta = 0$) and at SMM estimates. Figure 8b compares the difference between predicted entrepreneurship rate for the first-best scenario and when there is only credit market friction (i.e., $\eta = 0$ and $\lambda =$ SMM estimate). Figure 8c compares the difference between predicted entrepreneurship rate for the first-best scenario and when there is only labor market friction (i.e., $\eta =$ SMM estimate and $\lambda = 10^8$).

Figure 9: Misallocation in capital investments



(a) First-best vs. SMM estimates



(b) First-best vs. credit market friction only

(c) First-best vs. labor market friction only

Note: Figure 9a compares log of the ratio of predicted capital investments in the first-best scenario (i.e., absence of both credit and labor market friction, $\lambda = 10^8$ and $\eta = 0$) with the predicted capital investments made at SMM estimates. Figure 9b compares log of the ratio of predicted capital investments for the first-best scenario with the predicted capital investments made when there is only credit market friction (i.e., $\eta = 0$ and $\lambda =$ SMM estimate). Figure 9c compares log of the ratio of predicted capital investments for the first-best scenario with the predicted capital investments made when there is only labor market friction (i.e., $\eta =$ SMM estimate and $\lambda = 10^8$).

Figure 10: Misallocation in enterprise size

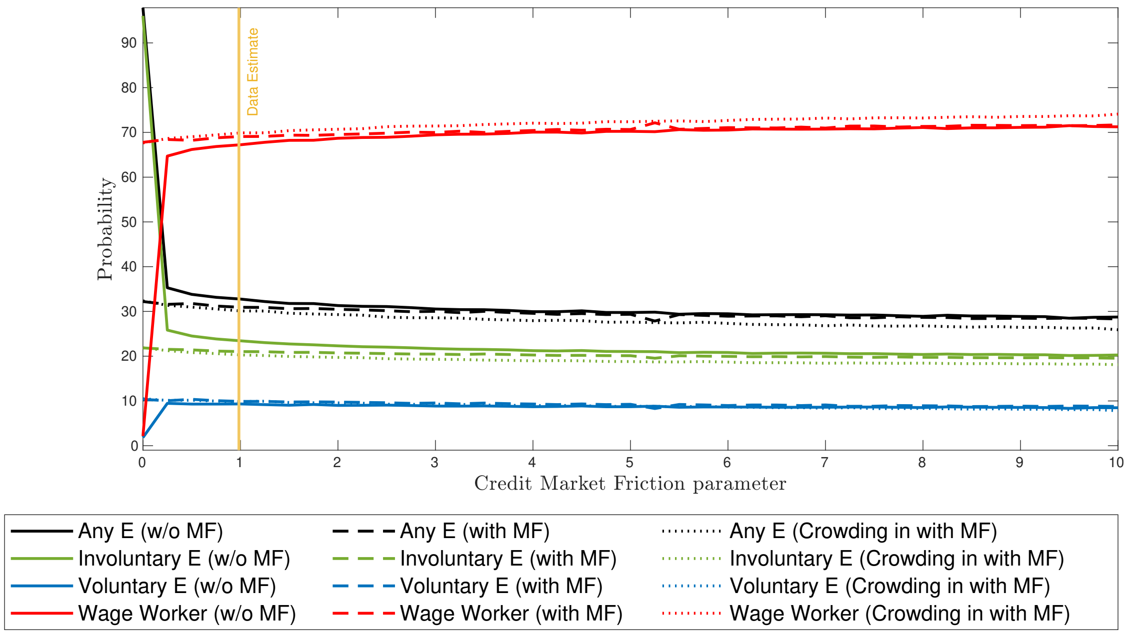
(a) First-best vs. SMM estimates

(b) First-best vs. credit market friction only

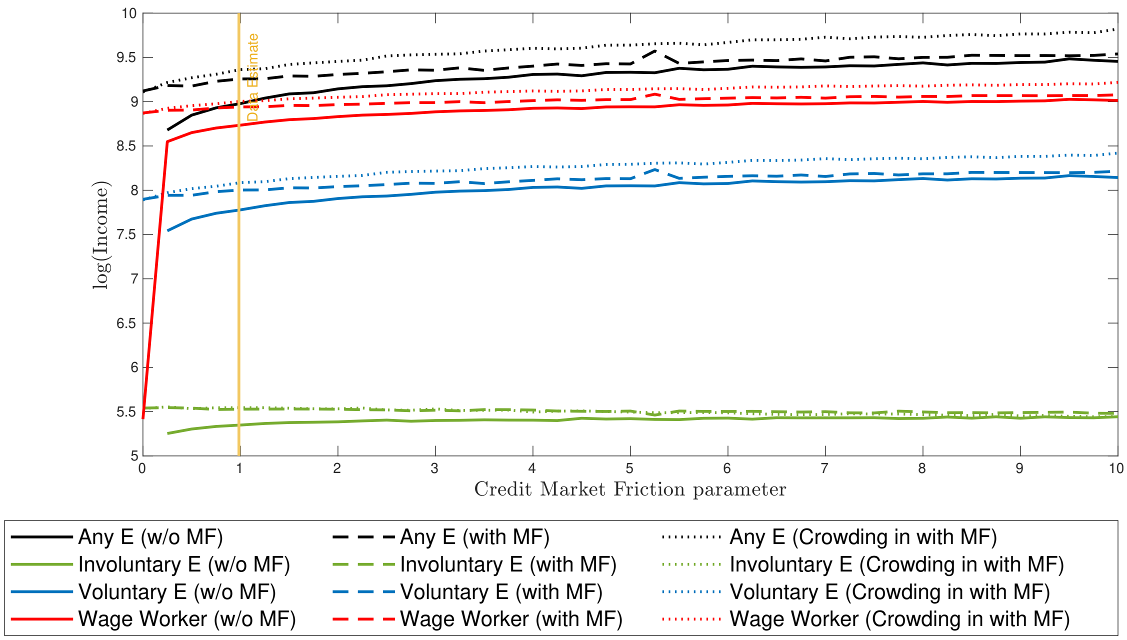
(c) First-best vs. labor market friction only

Note: Figure 9a compares log of the ratio of predicted labor investments in the first-best scenario (i.e., absence of both credit and labor market friction, $\lambda = 10^8$ and $\eta = 0$) with the predicted labor investments made at SMM estimates. Figure 9b compares log of the ratio of predicted labor investments for the first-best scenario with the predicted labor investments made when there is only credit market friction (i.e., $\eta = 0$ and $\lambda =$ SMM estimate). Figure 9c compares log of the ratio of predicted labor investments for the first-best scenario with the predicted labor investments made when there is only labor market friction (i.e., $\eta =$ SMM estimate and $\lambda = 10^8$).

Figure 11: Changes in credit market friction parameter



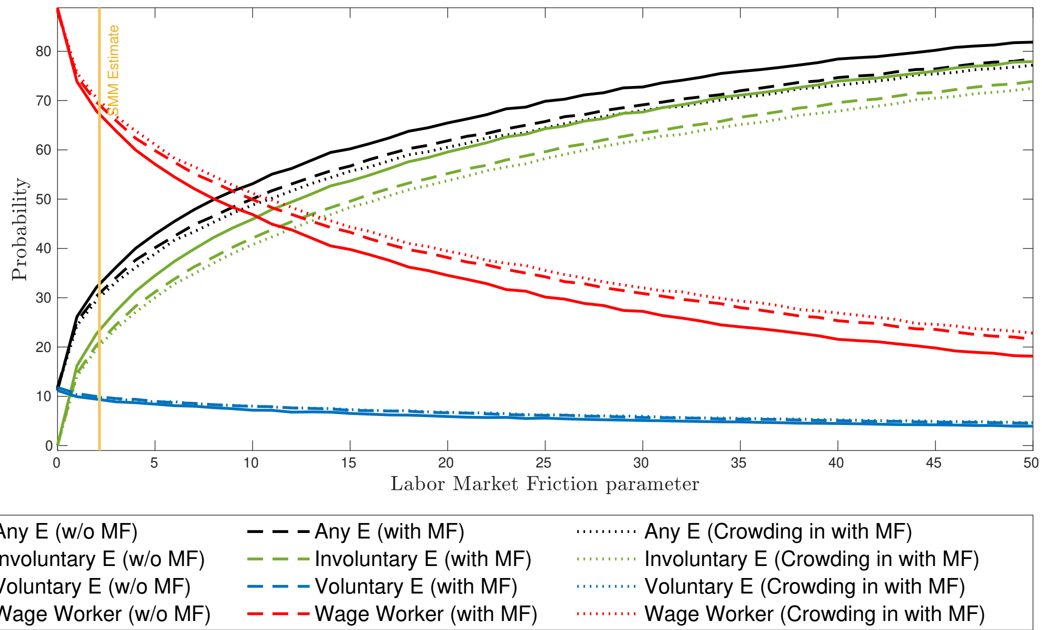
(a) Entrepreneurship rate



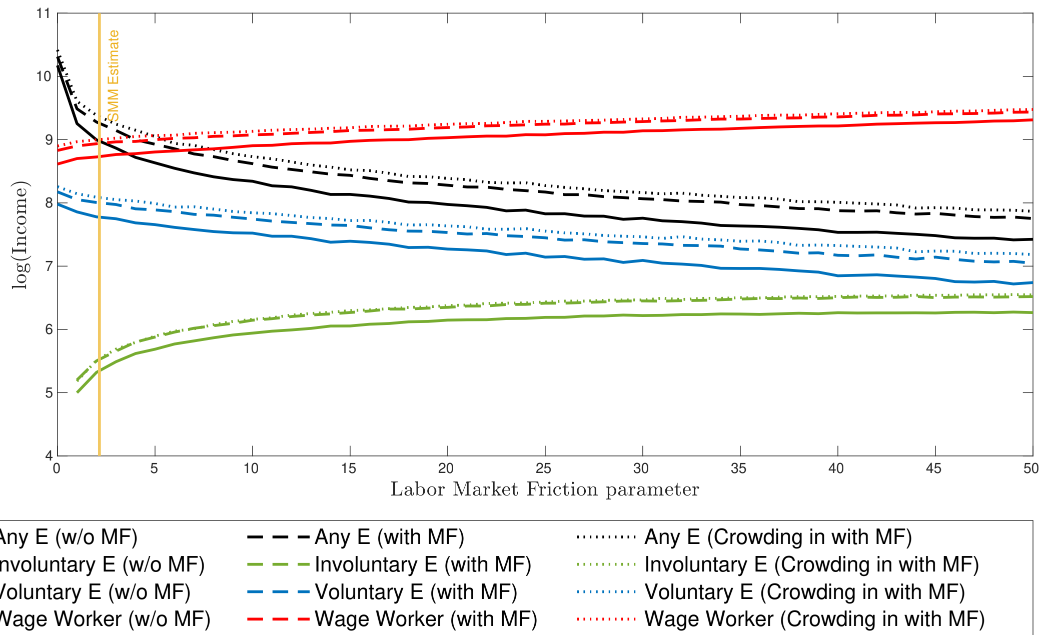
(b) Entrepreneurial and wage incomes

Note: In Figure 11 shows how prevalence of involuntary and voluntary entrepreneurs and wage workers (top panel) and log of entrepreneurial and wage incomes (bottom panel) change with credit market friction parameter (λ). $\lambda = 0$ reflects missing credit market and $\lambda = 10$ reflects a relatively relaxed credit market.

Figure 12: Changes in labor market friction parameter



(a) Entrepreneurship rate



(b) Entrepreneurial and wage incomes

Note: In Figure 12 shows how prevalence of involuntary and voluntary entrepreneurs and wage workers (top panel) and entrepreneurial and wage incomes (bottom panel) change with labor market friction parameter (η). $\eta = 0$ reflects perfect labor market and $\eta = 50$ reflects a relatively imperfect labor market.

Tables

Table 1: Parameters and definitions

Parameter	Definition
α	Share of payments going to the variable factors that are paid to the capital
ϕ	Business technology parameter
	Elasticity of business revenue with respect to capital, $\frac{\ln R^E}{\ln k}$
ν	Span of control parameter, $\frac{\ln R^E}{\ln \theta}$
BE	Total factor productivity (Entrepreneur)
F	Fixed cost of starting a business
λ	Credit market constraint parameter
γ	Wage technology parameter
	Elasticity of non-business income with respect to schooling, $\frac{\ln R^W}{\ln s}$
η	Labor market constraint parameter
δ_0	Conditional mean of log entrepreneurial productivity
δ_1	Elasticity of entrepreneurial productivity with respect to assets, $\frac{\ln \theta}{\ln z}$
δ_2	Elasticity of entrepreneurial productivity with respect to schooling, $\frac{\ln \theta}{\ln s}$
σ	Standard deviation of log entrepreneurial productivity
r	Net interest rate
ψ	Elasticity of non-business income with respect to labor
BW	Total factor productivity parameter (Third Party Employer)

Table 2: Target moments

	Target Moments
1	Proportion of entrepreneurs
2	Proportion of entrepreneurs, with s in the bottom tercile
3	Proportion of entrepreneurs, with s in the top tercile
4	Proportion of entrepreneurs, with z in the bottom tercile
5	Proportion of entrepreneurs, with z in the top tercile
6	Proportion of entrepreneurs, with s and z in the bottom tercile
7	Proportion of entrepreneurs, with s and z in the top tercile
8	Mean business revenue, entrepreneurs, R^E
9	Mean wage earnings, wage workers, R^W

Table 3: Model fit: Parameter estimates

	Estimate	Standard error	95% Lower bound	95% Upper bound
Calibrated parameters				
α	0.21			
ν	0.36			
ϕ	0.27			
λ	0.98			
γ	0.14			
r	0.03			
ψ	0.48			
F	0.00			
Estimated parameters				
η	2.15	0.76	0.66	3.64
δ_0	-17.50	7.11	-31.44	-3.57
δ_1	0.00	3.28	-6.42	6.42
δ_2	5.26	4.15	-2.87	13.39
σ	2.63	1.52	-0.34	5.60
BE	13.24	28.22	-42.06	68.54
BW	3.08	2.80	-2.40	8.56

Note: The parameters in the top panel are calibrated based on literature and study dataset and the parameters in the lower panel are estimated using SMM. The standard errors are estimated using bootstrapping methods. Incomes are expressed in thousands INR.

Table 4: Model fit: Target Moments

	Simulated Moments	Data moments	% Deviation
Entrepreneurs (%)	32.71	36.40	-10.14
Entrepreneurs, bottom s tercile (%)	37.50	40.48	-7.36
Entrepreneurs, top s tercile (%)	38.27	35.34	8.30
Entrepreneurs, bottom z tercile (%)	29.17	30.37	-3.96
Entrepreneurs, top z tercile (%)	37.64	45.97	-18.11
Entrepreneurs, bottom s & z tercile (%)	38.37	32.49	18.09
Entrepreneurs, top s & z tercile (%)	47.41	39.62	19.64
Mean entrepreneurial income	7.95	8.85	-10.20
Mean wage income	6.22	5.37	15.75
Criterion Value			0.16
Hansen J-statistic			0.32

Note: The simulated moments are estimated using SMM. Column (3) shows the percent deviation between targeted simulated moments and data moments. Incomes are expressed in thousands INR.

Table 5: Model implied treatment effects: Key variables

	w/o MF	w/ MF (I)	Δ(%)	w/ MF (II)	Δ(%)
Entrepreneurs (E) (%)	32.71	31.00	-5.23	30.25	-7.52
Involuntary E (%)	23.48	21.00	-10.58	20.36	-13.30
Voluntary E (%)	9.23	10.00	8.37	9.89	7.18
Wage Worker (%)	67.29	69.00	2.54	69.75	3.66
Mean income, E	7.95	10.47	31.66	11.47	44.24
Mean income, involuntary E	0.21	0.25	17.68	0.26	20.46
Mean income, voluntary E	2.39	2.99	25.40	3.21	34.55
Mean income, wage worker	6.22	7.65	23.00	8.07	29.84
Equilibrium wage	4.74	5.84	23.16	6.17	30.03
Capital constrained E (%)	29.38	25.46	-13.34	24.45	-16.77
Labor constrained E (%)	29.38	25.46	-13.34	24.45	-16.77
Capital investments	5.41	10.49	93.80	13.80	155.00
Labor investments	0.88	0.90	2.40	0.91	3.50

Note: Column (1) refers to estimates before the introduction of microfinance (MF); Column (2) refers to estimates after the introduction of MF; Column (3) is the percent deviation between Column (1) and (2); Column (4) refers to crowding-in effects of MF and Column (5) is the percent deviation between Column (1) and (4). E stands for entrepreneurs. Incomes and equilibrium wage are expressed in thousands INR.

Table 6: Microfinance treatment effects on Entrepreneurship at the extensive margin

	(1)	(2)	(3)	(4)
VARIABLES	Entrepreneur	New business entry	Business exit	Wage worker
Panel A: Treatment effect				
Treated	0.030	-0.007	0.007	-0.013
	(0.0305)	(0.0132)	(0.0109)	(0.0175)
P-value	0.3260	0.5937	0.5431	0.4583
Control mean	0.4151	0.1375	0.0526	0.8659
Control S.D.	0.4929	0.3445	0.2234	0.3409
Observations	2,328	2,328	2,328	2,328
Panel B: Heterogeneous treatment effect				
Treated	0.126**	0.018	-0.027	-0.077**
	(0.0539)	(0.0367)	(0.0299)	(0.0360)
IVE	0.436***	0.072	0.020	-0.171*
	(0.145)	(0.114)	(0.0841)	(0.102)
Treat*IVE	-0.411**	-0.108	0.143	0.272*
	(0.201)	(0.151)	(0.125)	(0.139)
P[(Treat*IVE)=0]	0.0429	0.4732	0.2536	0.0528
Treat + Treat*IVE	-0.2851	-0.0901	0.1157	0.1949
P[(Treat + Treat*IVE)=0]	0.0678	0.6917	0.4715	0.1053
Control mean	0.4151	0.1375	0.0526	0.8659
Control S.D.	0.4929	0.3445	0.2234	0.3409
Observations	2,328	2,328	2,328	2,328

Note: "IVE" is the probability of involuntary entrepreneurship as predicted by the model. In this table, we present impact of microfinance on entrepreneurship as observed in the data (Column (1)); new business entries at endline (Column (2)); business exits at endline (Column (3)); and wage workers i.e., households that have at least one wage job (Column (4)). P[(Treat + IVE+ Treat*IVE)=0] is the *p-value* of the joint test on Treat, IVE and Treat*IVE. P[(Treat*IVE)=0] is the *p-value* on Treat*IVE. Standard errors are clustered at area level. * p<0.1; ** p<0.05; *** p<0.001

Table 7: Microfinance treatment effects

	Access to credit				**Business performance**				**Household assets and income**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Treatment loan	Other loans	Treatment loan size	Other loans size	Revenue	Expenses	Profits	Labor	Total income	Assets	Wage income
Panel A: Treatment effect											
Treated	0.071***	-0.006	6,026	819	0.883*	0.442	0.920	-0.044	0.335	2.831*	-0.665**
	(0.0259)	(0.0205)	(4,960)	(2,319)	(0.4907)	(0.3479)	(0.9458)	(0.0721)	(0.4206)	(1.5602)	(0.2866)
Constant	0.057	0.815***	55,447*	10,945	4.357*	3.284*	-5.282	-0.256	3.360	24.790***	-0.450
	(0.1193)	(0.1136)	(28,477)	(12,587)	(2.3963)	(1.7056)	(5.7174)	(0.3503)	(2.0304)	(7.3663)	(1.5604)
P-value	0.007	0.7816	0.2272	0.7244	0.0749	0.2070	0.3330	0.5406	0.4271	0.0726	0.0223
Control mean	0.1188	0.7258	76,978.1561	34,536.2186	4.579	2.9350	1.0932	0.2275	9.2301	14.1462	6.4852
Control S.D.	0.3234	0.4463	88,645.2633	49,589.5677	8.9211	6.6099	19.4544	2.1270	8.6356	25.6689	6.54217
Observations	2,328	2,328	2,328	2,328	2,328	2,328	2,321	2,328	2,328	2,328	2,328
Panel B: Heterogeneous treatment effect											
Treated	0.067	0.017	8,992	1,490	2.247**	1.147	0.941	0.003	0.317	3.709	-1.725***
	(0.0420)	(0.0512)	(12,162)	(6,455)	(0.9756)	(0.7133)	(1.5747)	(0.1296)	(0.8330)	(3.6535)	(0.6326)
IVE	0.083	0.223	-15,756	-6,305	4.297*	2.527*	-5.367	0.218	-4.128**	-4.697	-8.968***
	(0.1033)	(0.1492)	(29,306)	(16,588)	(2.2372)	(1.4526)	(6.6402)	(0.4118)	(1.7423)	(9.4139)	(1.9383)
Treated*IVE	0.016	-0.098	-12,332	-2,756	-5.805*	-3.004	-0.023	-0.200	0.124	-3.651	4.576*
	(0.1386)	(0.1927)	(43,756)	(24,810)	(3.4458)	(2.6478)	(7.8783)	(0.4363)	(2.9374)	(13.0879)	(2.4055)
P[(Treat*IVE)=0]	0.906	0.612	0.778	0.912	0.095	0.259	0.998	0.648	0.966	0.781	0.060
Treat + Treat*IVE	0.083	-0.081	-3340.472	-1265.544	-3.558	-1.857	0.918	-0.197	0.442	0.058	2.851
P[(Treat + Treat*IVE)=0]	0.026	0.828	0.475	0.933	0.063	0.240	0.507	0.729	0.707	0.1967	0.014
Control mean	0.119	0.726	76,978.156	34,536.219	4.579	2.935	1.093	0.228	9.230	14.146	6.486
Control S.D.	0.324	0.446	88,645.263	49,589.568	8.921	6.610	19.454	2.127	8.636	25.669	6.542
Observations	2,328	2,328	2,328	2,328	2,328	2,328	2,321	2,328	2,328	2,328	2,328

Note: "IVE" is the probability of involuntary entrepreneurship as predicted by the model. In this table, we present impact of microfinance on take-up of treatment loan (from Spandana MFI) (Column (1)); take-up of loans other than treatment loans (Column (2)); treatment loan size (Column (3)); loan size of other loans (Column (4)); annual gross revenue from business (Column(5)); total annual expenditure on business (Column (6)); profits from businesses (Column (7)); number of employees working in business (Column(8)); total household income (Column(9)); total assets owned by the households (Column (10)); and gross wage earnings (Column (11)). P[(Treat + IVE + Treat*IVE)=0] is the *p-value* of the joint test on Treat, IVE and Treat*IVE. P[(Treat*IVE)=0] is the *p-value* on Treat*IVE. Standard errors are clustered at area level. Monetary variables are in thousands INR and winsorized at top 5 percentile. * p<0.1; ** p<0.05; *** p<0.001

Table 8: Characteristics of Involuntary Entrepreneurs

	(1) Mean	(2) S.D	(3) Difference
Panel A: Household characteristics			
Age	43	10.28	3.49***
Male	0.92	0.28	-0.06***
Married	0.92	0.26	-0.02***
Household size	6	2.35	0.53***
Years of schooling	3.7	1.38	-5.46***
Land value	8	21.72	0.98
Durable assets value	5.7	7.44	-0.03
Total assets value	16	28.44	0.81
Entrepreneur	0.41	0.49	0.06***
Wage worker	0.81	0.39	0.00
Household income	6.6	5.78	-0.39
Household wage income	4.1	5.27	-0.55***
N involuntary	582		
N Non-involuntary	1746		
Panel B: Business characteristics			
Number of employees	0.26	0.93	0.02
Hours worked in business	113	80.16	8.54***
Any outstanding loan	0.92	0.27	0.04***
Enterprise revenue	8.8	7.31	0.40
Enterprise expenditures	5.6	5.53	0.14
Wage expenditures	0.00	0.00	0.00
Enterprise profits	7.1	64.93	-0.01
Agriculture	0.21	0.41	-0.00
Services	0.23	0.42	0.01
Trade	0.07	0.26	0.01
N involuntary	237		
N Non-involuntary	593		

Note: Table shows the difference in means for household and business-related characteristics for "involuntary entrepreneurs" at baseline. An agent is classified as "involuntary entrepreneur" if her predicted probability of involuntary entrepreneurship is greater than 75^{th} percentile of the distribution. Column (1) presents mean value for "involuntary entrepreneurs". Column (2) presents standard deviation of mean estimates. Column (3) is the difference in means between "involuntary entrepreneurs" and the rest of the sample. We cluster standard errors at area level for these difference-in-means regressions. Monetary variables are in thousands INR and winsorized at top 5 percentile. * p<0.1; ** p<0.05; *** p<0.001

Table 9: Model fit: Robustness and sensitivity analysis

	(1)	(2)	(3)	(4)	(5)	(6)
η	2.15	3.32	3.33	3.31	49.96	0.31
δ_0	-17.50	-7.81	-7.29	-7.99	-7.94	-7.75
δ_1	0.00	-0.31	-0.27	0.18	-0.24	-5.45
δ_2	5.26	-7.99	-7.98	-8.00	-8.00	-9.19
σ	2.63	1.12	1.59	0.57	0.10	0.16
BE	13.24	266.86	226.58	213.75	295.57	25.81
BW	3.08	2.99	2.13	2.70	1.47	9.76
λ	0.98	0.89	0.98	0.98	0.98	0.89
F	0.00	0.00	0.00	0.00	73.74	0.00
Criterion Function	0.16	0.77	0.84	0.76	0.65	2.74
Entrepreneurs (E) (%)	32.71	32.32	30.90	32.24	32.38	15.00
Involuntary E (%)	23.48	29.90	28.52	29.74	30.60	13.02
Voluntary E (%)	9.23	2.42	2.38	2.50	1.78	1.98
Wage Worker (%)	67.29	67.68	69.10	67.76	67.62	85.00
Mean income, E	7.95	8.63	10.21	8.66	8.50	11.38
Mean income, involuntary E	0.21	0.04	0.04	0.04	0.11	0.00
Mean income, voluntary E	2.39	2.75	3.11	2.76	2.65	1.71
Mean income, wage worker	6.22	5.60	6.21	5.60	5.57	2.73
Equilibrium wage	4.75	4.23	4.69	4.23	4.21	2.08

Note: Column (1) refers to baseline SMM estimates (same as Table 3); Column (2) refers to estimates after estimating λ as a parameter using SMM instead of calibrating it using study dataset; Column (3) presents SMM estimates when data especially households assets and income is winsorized at top 1 percentile instead of top 5 percentile as in Column (1); Column (4) refers using an alternative credit constraint specification, using $1+\lambda$ instead of λ as in Column (1); Column (5) estimates fixed cost to starting a business using SMM which is assumed to be 0 in Column (1) and Column (6) uses an alternative definition for an entrepreneur where she does not earn any wage income and owns business as her sole occupation. E stands for entrepreneurs. Fixed cost of starting a business (F), incomes and equilibrium wage are expressed in thousands INR.

Appendix

A Model

A.1 Properties of entrepreneur's production function

The properties of $f(\theta, k)$ are:

- $f(\theta, k)$ is strictly increasing in θ and k;
- $f(\theta, k)$ is homogeneous of degree 1;
- $f(\theta, k)$ is strictly concave in k;
- $f_\theta(\theta, k) > 0$; $f_k(\theta, k) > 0$; $f_{kk}(\theta, k) < 0$ for $\theta, k > 0$;
- Inada conditions are assumed to hold: $\lim_{k\to 0} f_k(\theta, k) = \infty$; $\lim_{k\to\infty} f_k(\theta, k) = 0$ for $\theta, k > 0$.

High entrepreneurial productivity is associated with a higher marginal product of capital: $f_{\theta k}(\theta, k) > 0$ for $\theta, k > 0$. Also, $f(0, k) = 0$ and $\lim_{\theta\to\infty} f(\theta, k) = \infty$ for $\theta, k > 0$. If $z < k$ then an agent is a net borrower and if $z > k$ then she is a net saver. The agent is assumed to also put her own labor in the business activity. Given the general production function, $\tilde{f}(\theta, k, n)$, one can solve for it by first maximizing output with respect to labor. The optimal amount of labor, n^*, is given by:

$$n^* = \left(\frac{\theta^\nu(1-\nu)(1-\alpha)k^{\alpha(1-\nu)}}{w}\right)^{\frac{1}{\nu+\alpha(1-\nu)}}$$

A.2 Threshold level of entrepreneurial productivity and wealth

Given $k_u(\theta)$, there is a threshold level of entrepreneurial productivity above which entrepreneurs would be capital constrained. The threshold level of entrepreneurial productivity is given by:

$$\tilde{\theta}(z) = \left(\frac{r(\lambda z)^{(1-\phi)}}{A\phi}\right)^{\frac{1}{1-\phi}} \tag{12}$$

Hence, the threshold level of assets $\tilde{z}(\theta)$ is given by:

$$\tilde{z}(\theta) = \frac{1}{\lambda}\left(\frac{\phi A\theta^{1-\phi}}{r}\right)^{\frac{1}{1-\phi}} \tag{13}$$

A.3 Optimal effort choice

The optimal effort choice (e^*) exerted by an agent given her characteristics and labor market frictions can be derived by minimizing the following optimization problem:

$$e^*(s, \theta, z, w) \equiv \arg\max_{e} \; p(e, s)y^W(s, w) + (1 - p(e, s))y^E(\theta, z) - c(e)$$

This has the following implications:

- If the income differential ($y^W - y^E$) is large, then an agent will exert more effort, lowering the probability of not finding a wage job or probability of being constrained in the labor market, $P(s, \theta, z, w)$.
- If $y^W \geq y^E$, then an agent chooses $e^* > 0$.
- if $y^W \leq y^E$, then an agent chooses $e^* = 0$.

B Data

B.1 Overview of RCTs

In this section, we briefly summarize the two RCTs used for this paper (also presented in Table B.1).

Banerjee et al. (2015): This is a cluster RCT conducted in 104 neighborhoods (slums or *bastis*) in urban Hyderabad (India) in collaboration with Spandana, one of the largest and fastest growing MFI in India in 2008. The eligibility for the study was based on the client being female, between 18 and 59 years of age, resident of the neighborhood for the last one year, had some valid identification and residential proof and owned the house they lived in. The clients were eligible under a group lending program with first loan of INR 10,000 ($200 at prevailing exchange rate) and subsequent loans up to INR 20,000 at 24% Annual Percentage Rate (APR). The experiment was conducted between 2005 and 2010 with baseline in 2005-06, first endline in 2007-08 and second endline in 2009-10.[34] A total of 6,863 households were surveyed at the endline.

The authors find that there was an 8.4 p.p. increase in take up microfinance. There was an increase in self-employment but the results are not statistically significant. While business investments and profits increased, they do not find a significant increase in consumption (expenditures on durable goods increased by INR 19.7, that on "temptation goods" (such as alcohol, tobacco, gambling, etc.) declined by INR 8.8). There was also an increase in labor supply among household heads and spouses. These impacts did not persist for two years even though the amount of borrowing from the MFI had increased.

Augsburg et al. (2015): This RCT was implemented in Bosnia and Herzegovina between 2008 and 2010 in collaboration with a large microfinance institution (MFI), right after the financial crisis of 2008. Individual-liability microcredit loans were randomly offered to a subset of the population that were originally rejected by the MFI as they failed to meet the credit requirements ("marginal applicants"). The loan amount ranged from 300 to 3,000 BAM (US$184 to 1,840 at prevailing exchange rate) at 22% APR. The study sampled a total of 1,196 marginal applicants (men and women), including both treatment and control groups, across baseline and endline in both urban and rural areas.

The study found that microfinance raised the levels of business activity (ownership and inventories) and self-employment: treated households had a 6 percentage points (p.p.)

[34] Since the sampling frame for the baseline survey was not considered rigorous enough, the authors did not purposely re-survey the households from baseline in the two endline surveys. Baseline survey was solely used for the purpose of stratification. Impact analysis was conducted only on the endline data.

higher likelihood of owning a business and 8 p.p lower likelihood of earning wage income. Even though there was a positive impact on business profits, there is no evidence for increase in household income. The effect on business profits was driven the those at the top of the distribution of profits. The treatment households also consumed 648 BAM less than the control group. Households with prior business ownership complemented the loan with their own savings to make lumpy business investments, while poorer households complemented the loan with reduced consumption.

Table B.1: Summary of RCTs in Microfinance used for the study

	Augsburg et al. (2015)	**Banerjee et al. (2015, 2019)**
Country	Bosnia and Herzegovina	India
Year	2008-10	2005-10
Duration (months)	14	40
Urban/Rural	Both	Urban
Randomization level	Individual	Community
Eligibility criteria	Marginal applicants	Female; Aged 18 - 59 years; Resided in the same area for at least 1 year; Valid ID and residential proof; At least 80% of women in a group must own their home
Target Women	No	Yes
Treatments	Individual lending	Group lending
Loan size	BAM 300 - 3,000 (US$ 184 - 1,840)	INR 10,000 - 20,000 (US$ 200 - 400)
Collateral	Yes	No
Interest rate (APR)	22%	24%
Surveys	Baseline; Endline	Baseline; Endline 1; Endline 2
Sampling frame	Marginal applicants	Households with at least 1 woman age 18–55 of stable residence
Sample size	1,196	6,863
Pre-existing access to MFI		No access to any other MFI at baseline but high MFI coverage by endline

Note: BAM = Bosnia and Herzegovina convertible mark; INR = Indian Rupees; APR = Annual Percentage Rate

B.2 Key variables and their definitions

The definitions of key variables used for model estimation are presented in Table B.2.

Table B.2: Description of key variables across two RCTs

	Augsburg et al. (2015)	**Banerjee et al. (2015, 2019)**
Model sample (baseline)	683	2,478[a]
Agent	Household head	Woman aged 18 to 55 years
Entrepreneur[b], $\mathbf{1_E}$	Agent owns a business	Household owns a business
Initial assets[c], z	House, land, apartment, household durables, livestock, and other asset items of value greater than 2,500 BAM	House, land, apartment, household durables, livestock
Schooling, s	Years of schooling of the household head[d]	Years of schooling of the household head
Wage income, R_W	Household gross wage income from agricultural work, shop/market work, bank/financial services, manufacturing/industry, tourism, government and from other private business (does not include pensions, social security and other benefits from government schemes)	Gross earnings from wage work, excluding pensions, social security and other benefits
Entrepreneurial income, R_E	Main and secondary business revenues	Gross earnings from sale of goods and services, rental of business assets, and others

Note: [a]First endline survey

[b]In the data, we observe several households reporting that they own a business and are also employed in a wage job.

[c]The datasets differ in asset categories measured and hence, we use total value of assets possessed by the household across all datasets. We do not just include business-related assets as it leads to a significantly small sample size.

[d]Agents reporting receiving vocational training are imputed with 10-13 years of schooling per Bosnia and Herzegovina's Vocational Education and Training Reform guidelines (ETF, 2011). Agents reporting having completed grade 10 of vocational and technical school are imputed with 10 years of schooling, those who completed grade 11 of vocational and technical school are imputed with 11 years of schooling, those who completed grade 12 of vocational and technical school are imputed with 12 years of schooling, and those who completed grade 13 of vocational and technical school are imputed with 13 years of schooling.

C Simulated Method of Moments (SMM) Approach

SMM involves minimizing percentage deviation between simulated targeted moments from the model and sample moments calculated using data. Let $\mathbf{m^d}$ be a vector of J empirical moments estimated using data and $\mathbf{m^x}$ be a vector of corresponding moments estimated using simulated data where $x = 1, .., X$ is number of simulations, where $X = 100$. The percentage deviation between simulated and data moments to estimate a set of parameters (Θ), $e_J(s, z, \Theta)$, determined by the joint distribution of schooling (s) and wealth (z) is:

$$e_j(s, z, \Theta) \equiv \frac{\frac{1}{X}\sum_{x=1}^{X} m_j^x(s, z, \Theta) - m_j^d}{m_j^d}, j = 1, ..., J$$

Hence, the set of parameters, Θ, that solve this minimization problem is as follows:

$$\Theta_{SMM} = \arg\min_{\Theta}\ e_J(s, z, \Theta)' W^{-1} e_J(s, z, \Theta)$$

where W^{-1} is the weighting matrix. We use identity matrix, with dimension J, as the weighting matrix to provide consistent estimates of the parameters. The identity matrix applies same weight to all targeted moments. We use percent deviation, instead of absolute deviation, between simulated and data moments to scale the moments appropriately. For the model to be identified, the number of moments (J) should be greater than or equal to the number of parameters to be estimated (N_Θ) i.e., $J \geq N_\Theta$. We calibrate some parameters and estimate the remaining parameters using SMM to ensure efficiency and also reduces the total number of target moment conditions needed. The identification of target moment conditions is an important step to identify the model and estimating the true model parameters.

Target Moments: We now define target moment conditions, outlined in Table 2. For an agent i, years of schooling and initial asset levels are distributed as $s_i \in S$ and $z_i \in Z$. The probability of being an entrepreneur, given s, z and equilibrium wage (w^*) is given by Equation (7). These predicted entrepreneurship rate is then compared against the observed entrepreneurship rate i.e., agents choosing entrepreneurship as occupation i.e., E in the data given the characteristics $s_i \in S$ and $z_i \in Z$. Hence, the predicted probability of entrepreneurship across s and z is given by:

$$m_j^s(s, z, \Theta) = \frac{\sum_{i=1}^{N} 1_{\{s_i \in S, z_i \in Z\}} P_E(s_i, z_i, w^*)}{\sum_{i=1}^{N} 1_{\{s_i \in S, z_i \in Z\}}}, j = 1, .., 7$$

The predicted mean expected entrepreneurial revenue is given by:

$$m_8^s(s, z, \Theta) = \frac{\sum_{i=1}^{N} E(R^E | \mathbf{1}_E = 1, s_i, z_i, \Theta)}{\sum_{i=1}^{N} P_E(s_i, z_i, w^*)}$$

The predicted mean wage earnings is given by:

$$m_9^s(s, z, \Theta) = \frac{\sum_{i=1}^{N} (R^W | \mathbf{1}_E = 0, s_i, z_i)}{\sum_{i=1}^{N} P_W(s_i, z_i, w^*)}$$

Given the distribution of observable characteristics s and z, residual moments for entrepreneurship rate in middle tercile of s and middle tercile of z are also automatically matched. Targeting total proportion of entrepreneurs (in moment condition 1) automatically matches proportion of wage workers. When we target entrepreneurship rate in top tercile of z and in top tercile of s and z (moment conditions 5 and 7, respectively), it provides us with residual entrepreneurship rate for high z but lower s and is informative of labor market friction parameter, η. Agents with high s and z (moment condition 7) are not affected by either η or λ but their occupational choice depend on equilibrium wage. Agents with low s but high z may not be affected by λ but will be affected by η. Similarly, agents in bottom tercile of s and z (moment condition 6), will be affected by both η and λ. The last two target moment conditions, mean business revenue and mean wage earnings, are informative of Total Factor Productivity (TFP) for entrepreneur and third party employer, respectively.

Estimation: We use hybrid global optimization routine of simulated annealing and pattern search to find global minima and estimate true parameters. Simulated annealing searches for the best solution by first generating a random solution and then exploring the nearby parameter space. This algorithm is less time consuming than an exhaustive grid search, less likely to generate local minima solutions, returns a global solution and is suitable for highly non-linear problems. The pattern search algorithm uses patterns which are a set of vectors to determine which points to search at each iteration to approach the optimal point using a method called "polling". Combining both of these algorithms ensures that the optimization routine returns more exact global minima. Standard errors for the parameters are estimated by bootstrapping 100 times. We also conduct Hansen's J-test for over-identification.[35]

[35] J-test statistic, ξ_T, where T is number of replications i.e., 10 and $\xi_T \sim \chi^2(J - N_\Theta)$, is given by:

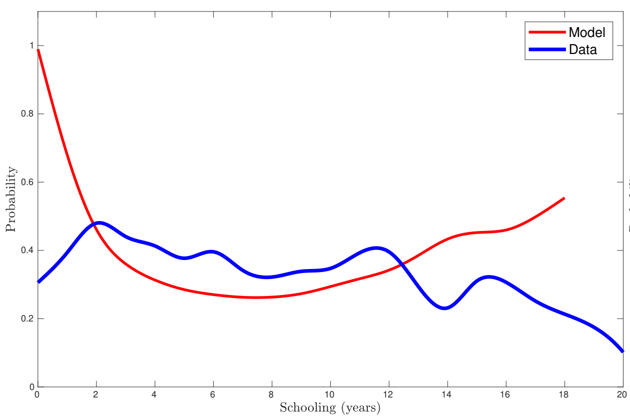
$$\xi_T = \Big(\frac{T}{1+T}\Big)\Big[\Big(m^d - \frac{\sum_{t=1}^{T} m_t^s}{T}\Big) W^{-1} \Big(m^d - \frac{\sum_{t=1}^{T} m_t^s}{T}\Big)\Big]$$

D Results

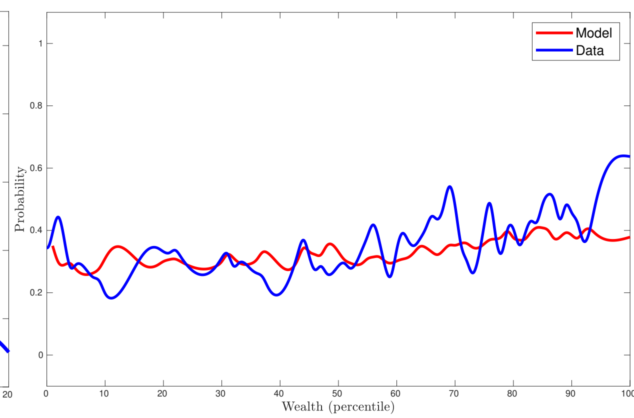
D.1 Model fit

We further investigate the model fit by schooling in Figure D.1a and by initial wealth in Figure D.1b. In these figures, we plot smoothing spline fit for the model and compare against smoothing spline fit for the data. First, according to the model, entrepreneurship rate decreases as schooling increases but at higher levels of schooling, entrepreneurship increases again, as reflected by the positive value of δ_2. Second, the model overestimates entrepreneurship rate for both lower and higher levels of schooling. Third, there is no strong evidence of positive or negative relationship between initial wealth and entrepreneurship rate, as reflected by weak correlation between entrepreneurial productivity and initial wealth. Fourth, the model overestimates entrepreneurship rate for lower percentiles of wealth but underestimates for higher percentiles of wealth.

Figure D.1: Model fit: Entrepreneurship rate by schooling and wealth



(a) Entrepreneurship rate by schooling



(b) Entrepreneurship rate by wealth

Note: In these figures, we plot smoothing spline fit for the model (in red) and compare against the smoothing spline fit for the data (in blue). The smoothing parameter for Figure D.1a is 0.089 and for Figure D.1b is 0.2.

D.2 Treatment effects of microfinance

In this section, we present impact of microfinance across terciles of schooling and initial wealth for entrepreneurship rate and incomes in Table D.3, capital and labor investments in Table D.4 and proportion of capital and labor constrained entrepreneurs in Table D.5.

Table D.3: Model implied treatment effects: Entrepreneurship rate and income

	w/o MF	w/ MF (I)	Δ(%)	w/ MF (II)	Δ(%)
Entrepreneurs (%)	32.71	31.00	-5.23	30.25	-7.52
bottom tercile z	29.17	30.31	3.93	29.84	2.31
middle tercile z	31.49	30.05	-4.57	29.35	-6.78
top tercile z	37.64	32.64	-13.29	31.55	-16.19
bottom tercile s	37.50	34.33	-8.46	33.54	-10.55
middle tercile s	27.71	26.57	-4.12	25.78	-6.95
top tercile s	38.27	37.84	-1.12	37.27	-2.61
Mean business income	7.95	10.47	31.66	11.47	44.24
bottom tercile z	3.76	8.40	123.40	8.17	117.32
middle tercile z	6.38	7.91	23.99	16.86	164.23
top tercile z	11.85	17.01	43.51	10.21	-13.82
bottom tercile s	0.58	0.53	-9.59	0.91	56.22
middle tercile s	6.88	9.05	31.57	10.97	59.39
top tercile s	23.50	35.68	51.81	33.05	40.63
Mean wage income	6.22	7.65	23.00	8.07	29.84
bottom tercile z	6.23	7.65	22.86	8.08	29.70
middle tercile z	6.22	7.65	22.89	8.07	29.61
top tercile z	6.19	7.64	23.37	8.07	30.27
bottom tercile s	5.76	7.08	23.01	7.47	29.80
middle tercile s	6.35	7.82	23.18	8.26	30.02
top tercile s	6.71	8.25	23.05	8.71	29.88

Note: Column (1) refers to estimates before the introduction of microfinance (MF); Column (2) refers to estimates after the introduction of MF; Column (3) is the percent deviation between Column (1) and (2); Column (4) refers to crowding-in effects of MF and Column (5) is the percent deviation between Column (1) and (4). Incomes are expressed in thousands INR.

Table D.4: Model implied treatment effects: Capital and labor investments

	w/o MF	w/ MF (I)	Δ(%)	w/ MF (II)	Δ(%)
Capital Investments	5.41	10.49	93.80	13.80	155.00
bottom tercile z	0.49	7.23	1361.58	11.87	2300.69
middle tercile z	2.11	8.36	296.04	11.77	457.38
top tercile z	0.49	7.23	1361.58	11.87	2300.69
bottom tercile s	1.61	2.47	53.63	3.63	125.37
middle tercile s	5.62	12.02	114.08	15.54	176.73
top tercile s	12.54	24.21	93.08	31.85	153.97
Labor investments	0.88	0.90	2.40	0.91	3.50
bottom tercile z	0.42	0.71	68.73	0.70	66.13
middle tercile z	0.71	0.71	1.17	1.27	79.37
top tercile z	0.42	0.71	68.73	0.70	66.13
bottom tercile s	0.10	0.08	-22.00	0.11	11.19
middle tercile s	0.72	0.73	2.35	0.82	15.00
top tercile s	2.90	3.52	21.24	3.05	5.14

Note: Column (1) refers to estimates before the introduction of microfinance (MF); Column (2) refers to estimates after the introduction of MF; Column (3) is the percent deviation between Column (1) and (2); Column (4) refers to crowding-in effects of MF and Column (5) is the percent deviation between Column (1) and (4).

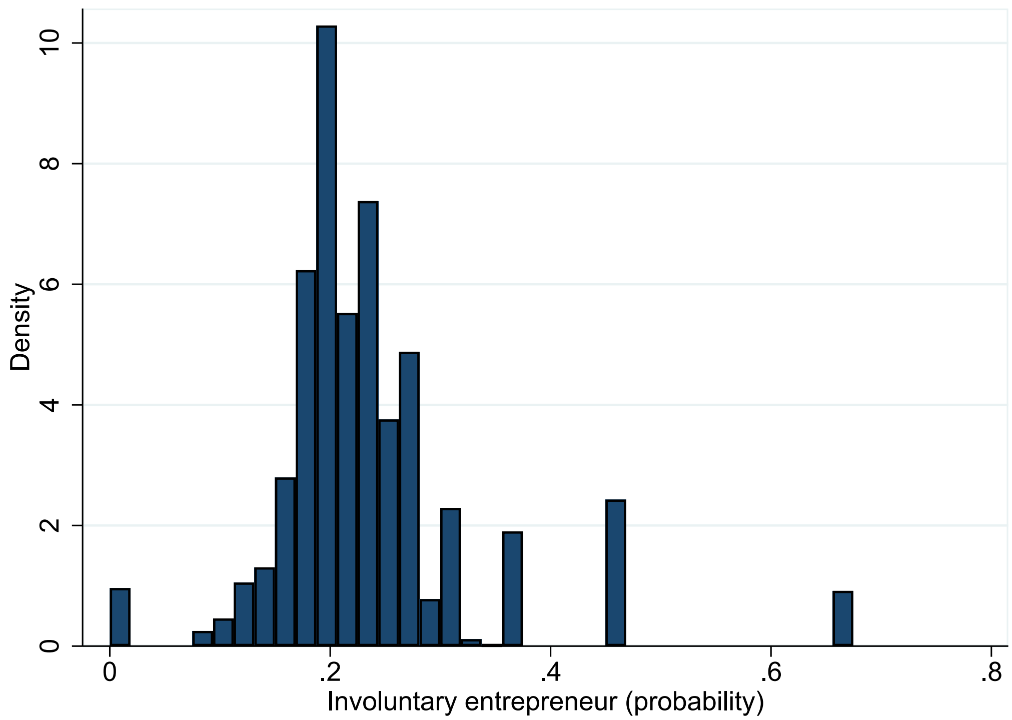
Table D.5: Model implied treatment effects: Capital and labor constrained entrepreneurs

	w/o MF	w/ MF (I)	Δ(%)	w/ MF (II)	Δ(%)
Credit constrained (%)	29.38	25.46	-13.34	24.45	-16.77
bottom tercile z	27.32	23.51	-13.97	24.83	-9.12
middle tercile z	29.29	26.58	-9.24	26.11	-10.84
top tercile z	33.41	26.15	-21.72	24.92	-25.41
bottom tercile s	27.65	17.78	-35.68	16.83	-39.13
middle tercile s	28.42	26.09	-8.21	26.83	-5.60
top tercile s	39.59	38.97	-1.58	38.07	-3.85
Labor constrained (%)	29.38	25.46	-13.34	24.45	-16.77
bottom tercile z	27.32	23.51	-13.97	24.83	-9.12
middle tercile z	29.29	26.58	-9.24	26.11	-10.84
top tercile z	33.41	26.15	-21.72	24.92	-25.41
bottom tercile s	27.65	17.78	-35.68	16.83	-39.13
middle tercile s	28.42	26.09	-8.21	26.83	-5.60
top tercile s	39.59	38.97	-1.58	38.07	-3.85

Note: Column (1) refers to estimates before the introduction of microfinance (MF); Column (2) refers to estimates after the introduction of MF; Column (3) is the percent deviation between Column (1) and (2); Column (4) refers to crowding-in effects of MF and Column (5) is the percent deviation between Column (1) and (4).

D.3 Distribution of model-predicted probability of involuntary entrepreneurship

Figure D.2: Distribution of model-predicted probability of involuntary entrepreneurship



E Robustness and sensitivity analysis

In this section, we describe robustness and sensitivity analysis checks as shown in Table 9 in detail.

Estimating λ: In Column (2), credit market friction parameter, λ, is estimated to be 0.89, similar to calibrated estimate of 0.98. However, the model fit declines from 0.16 to 0.77. The other key parameter of labor market friction parameter, η, is within 95% confidence intervals (shown in Table 3). In contrast to the baseline SMM estimates, correlation between entrepreneurial productivity and schooling becomes strongly negative. While correlation between entrepreneurial productivity and wealth remains weak. There is an increase in rate of involuntary entrepreneurs due to higher η. There is also a decline in voluntary entrepreneurship rate due to lower λ or relatively more credit constraints. The equilibrium wage is lower than baseline SMM estimates.

Winsorizing at top 1 percentile: The key parameter of η remains within 95% confidence intervals (Column (3)), when we winsorize assets and incomes at top 1 percentile. However, correlation between entrepreneurial productivity and schooling becomes strongly negative and the model fit is poorer than at baseline SMM estimates. The total entrepreneurship rate declines to 30.9%, mostly driven by a decline in voluntary entrepreneurship rate to 2.4% from 9.2%. This could be explained by both negative δ_1 and δ_2. The equilibrium wage declines marginally.

Alternative credit constraint specification: In Column (4), the key parameter of η remains within 95% confidence bounds. Correlation between entrepreneurial productivity and wealth remains weak and positive but correlation with schooling becomes strongly negative. The model fit declines. Even though the credit constraints relax further with this alternative credit constraint specification, we see a small decrease in entrepreneurship rate, mostly due to a decline in voluntary entrepreneurship rate. The equilibrium wage is lower than baseline SMM estimates and while the entrepreneurial income fits better.

Estimating F: In Column (5), the fixed cost to start a business is estimated to be 7,374 INR. However, the key parameter of η is now out of 95% confidence bounds and correlation between entrepreneurial productivity and wealth becomes weakly negative. Very high values of η implies severe labor market frictions and hence, higher rate of involuntary entrepreneurship. Entrepreneurship rate declines marginally and equilibrium wage falls. The model fit is poorer than at baseline SMM estimates.

Alternative entrepreneur definition: In Column (6), when we use an alternative definition of entrepreneur, the model sample reduces to 2,602. The labor market friction parameter η moves out of 95% confidence bounds. Both δ_1 and δ_2 become strongly negative. However, the model fit is very poor i.e., the criterion function is now 2.74. The model underestimates entrepreneurship rate significantly.