Involuntary Entrepreneurship – Evidence from Thai Urban Data*

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Abstract

We structurally estimate an equilibrium heterogeneous-agent model of occupational choice between entrepreneurship and wage work, which explicitly allows for 'involuntary' entrepreneurship (running a business out of necessity). Involuntary entrepreneurs would earn higher income as workers but cannot obtain a wage job because of labor market frictions. Using Thai urban data, we estimate the share of involuntary entrepreneurs as 19% of all businesses. The involuntary entrepreneurs earn much lower income (85% less on average) than the rest of the entrepreneurs and are more likely among low-wealth and low-schooling households. We quantify the misallocations in occupational choice and investment in the data, implied by the estimated labor and credit market frictions. Our results imply 17% excess (involuntary) entrepreneurs because of labor market frictions and 1% less entrepreneurs because of credit frictions, both relative to the first best. Counterfactual policy evaluations show that involuntary entrepreneurship can only be reduced by directly targeting labor market frictions, e.g., by active labor market policies, with attention paid to their equilibrium effect on wages.

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1 Introduction

Ever since Smith, Knight and Schumpeter, entrepreneurship, or running an own business, has been viewed as an engine of innovation and progress. Many taxation and regulatory policies explicitly target small businesses and startups. At the same time, self-employment is widespread in the developing world, accounting for up to 80% of total employment in some countries (ILO, 2020). This apparent contradiction is explained by the observation that not all entrepreneurs are alike (e.g., Banerjee and Duflo 2007, 2011; Djankov et al., 2006). Some people start businesses on their own volition, sometimes quitting a job to do so. Others are self-employed out of necessity, as their only option to earn income and survive. Clearly, the policy implications differ for these two categories – while some business owners would benefit from tax rebates, others need social safety nets or job skills and qualifications.

We structurally estimate an equilibrium heterogeneous-agents occupational choice model which explicitly allows for involuntary (necessity) entrepreneurship and its coexistence with voluntary entrepreneurship. The agents differ in initial wealth, labor market skills and entrepreneurial ability, and choose between running an own business or wage work based on the income they can earn. However, an agent's occupational choice may be constrained, because of labor market frictions restricting access to wage work, forcing the agent to run a business out of necessity.[1] We call such business owners, who would prefer wage work but cannot access it, involuntary entrepreneurs.

Our model extends and nests classical occupational choice models in which entrepreneurship is chosen over wage work if and only if an agent's income from running a business is larger than the agent's income from wage work (e.g., Evans and Jovanovic, 1989; Banerjee and Newman, 1993; Piketty, 1997). As is common in this literature and well-documented in developing country settings, we allow for credit market frictions – the agents can only borrow up to a fraction of their wealth (represented by a parameter we estimate) to invest in their business. We modify and augment this basic setting by allowing the possibility that, because of labor market frictions the magnitude of which we estimate, an agent may not have access to a wage job.[2]

We allow the probability of no access to the wage sector to depend on agents' labor market skills, proxied by schooling or other observable characteristics. In addition, the probability depends on an endogenous search effort choice – the larger is the income differential between wage work and running a business, the larger is the supplied wage job search effort. The labor market friction can be motivated by search, matching or information frictions, or could exist because of low human capital, lack of formal qualifications, the need for connections, and other barriers to finding paid work. We incorporate equilibrium effects by allowing the labor market wage to endogenously adjust as a result of the agents' occupational choices. Our structural approach uses household-level data on occupations and income to reveal whether the labor market friction is significant or negligible and disentangles its interaction with the credit market friction to quantify the resulting misallocations in occupational choice and capital investment. We also estimate the rate of involuntary entrepreneurship and its distribution over observables (initial wealth, years of schooling).

[1] Unemployment is ruled out as a viable choice, e.g., because of lack of safety net policies. Subsistence agriculture is not applicable for the urban setting we study.

[2] In Section 6 we also consider a specification with fixed cost to access the wage occupation or, equivalently, non-pecuniary benefits of running an own business, see also Hamilton (2000) or Hurst and Pugsley (2011).

We use data from the 2005 Townsend Thai Project Household Survey – Urban Area (NORC, 2008) on households in urban and semi-urban areas in six provinces in Thailand. The data include detailed current and retrospective information about the households' assets, income and businesses, in addition to demographic and occupation variables. About 66% of the households in our sample answered "yes" to the question "Does any household member have on own business?", which we use as our baseline definition of business households.[3] Most businesses are small, with 86% reporting that they did not hire any paid worker in the 12 months prior to the survey. About 60% of the business owners are traders (e.g. food vendors); 33% run a service business (tailor, laundry, restaurant, repair ship, taxi, etc.). Among the non-business households, 93% earn the majority of their gross annual income from wages.

We estimate the model using the simulated method of moments (SMM), by matching actual and simulated data on occupational choice and income in different stratifications by household initial wealth and schooling. We treat entrepreneurial ability as unobserved heterogeneity, potentially correlated with initial wealth and schooling. At our baseline estimates, 19% of the business households in our sample are classified as involuntary entrepreneurs. That is, about a fifth of all households running a business are subject to binding labor market constraints. The estimated rate of involuntary entrepreneurship varies in the agents' observable characteristics, from as high as 43% to as low as 4%. Specifically, involuntary entrepreneurship is decreasing in the principal earner's schooling and in initial wealth. An estimated 40% of all involuntary entrepreneurs are among the households with initial wealth and schooling both below the median. At our SMM estimates, the voluntary entrepreneurs earn significantly higher yearly income on average (519,000 Baht) compared to the involuntary entrepreneurs (75,000 Baht), and the wage workers (165,000 Baht).[4] The credit constraint is more likely to bind for the voluntary entrepreneurs (41%) than for involuntary entrepreneurs (17%).

Our results regarding involuntary entrepreneurship are robust to using alternative definitions for business ownership, labor market characteristics, and different specifications of the labor market constraint (see Section 6). We also assess the impact of other observables by estimating the model on different sub-samples, stratified by gender or age of the principal earner. We find that the estimated rate of involuntary entrepreneurship is significantly higher in the female principal earner sample (18% of all businesses) vs. 11.4% in the male principal earner sample. The credit and labor market constraints are also estimated as more severe in the female principal earner sample.

In terms of quantifying the misallocations in occupational choice and investment from the market frictions, simulations using our baseline estimates imply 16.8% excess (involuntary) entrepreneurs arising from the labor market friction, and 1.1% fewer entrepreneurs because of the credit market friction, relative to the first best. Only 61% of the first-best capital level is invested in the estimated model economy; 2.7% of this total is used by involuntary entrepreneurs. We also quantify the incidence and main sources of occupational and investment misallocations across households with different observables. The entrepreneurship rate is in excess of its first-best level among households with low schooling, because of the labor market friction, and lower than the first-best for those with high schooling and low initial wealth, because of the credit friction (see Fig. 3). There is significant underinvestment among all business households with low initial wealth. Holding initial

[3] In robustness analysis (Section 6) we also consider an alternative definition based on the major source of income.

[4] The 2005 exchange rate is about 40 Thai Baht per 1 USD.

wealth constant, the investment of voluntary entrepreneurs is more constrained relative to the first best, than the investment of involuntary entrepreneurs.

We evaluate four policy counterfactuals using the estimated model. We first consider eliminating the labor market friction. This lowers the fraction of entrepreneurs in the economy by 10 percentage points (as only voluntary entrepreneurs remain) and reduces the equilibrium wage by 9% (as more agents enter wage labor), see Table 11.[5] The overall estimated impact on agents' income is minor (increase by 0.1% on average), however, this masks important distributional and compositional changes before vs. after the policy. For ex-post workers, the elimination of the labor constraint results in 13.8% lower average income, both because of the lower wage and because of many low-skill ex-ante involuntary entrepreneurs entering wage work; while the average income of the ex-post entrepreneurs goes up by 15% on average.

We assess the effect of relaxing credit constraints via two counterfactuals. First, we double the parameter that determines the maximum business investment as fraction of initial wealth from the estimated 35% to 70%. This can be interpreted as improvement in enforcement or property rights. Second, we mimic an actual microcredit program in Thailand (the Million Baht village program) by allowing all agents to access a microfinance loan for business investment. Reducing the credit constraint enables larger investment, which makes running a business more profitable, however, the impact of this on involuntary entrepreneurship is limited by the labor market friction. In both credit market counterfactuals, we find that relaxing the credit constraint has only a minor effect on involuntary entrepreneurship (a decrease from the baseline estimate of 19.1% to 18.9% or 18.6%, see Tables 11 and 12). Consequently, these policies have a small effect on the equilibrium wage. The policies do, however, significantly impact incomes (average increases by 3.5% and 2.2%), by enabling ex-ante constrained entrepreneurs to invest more, with the largest income gains among relatively poor ex-ante voluntary entrepreneurs. Involuntary entrepreneurs and workers register minor income gains.[6] Doubling the agents' ability to invest as fraction of initial wealth benefits households with intermediate wealth the most (see Fig. 5). The microfinance policy, on the other hand, yields income gains monotonically decreasing in initial wealth, as poor households experience a large increase in their ability to borrow (see Fig. 6).

We also evaluate a 10% increase in the demand for wage labor, e.g., to reflect the impact of urban industry growth. This counterfactual increases the equilibrium wage by 7% and average income by 1.4% while lowering the entrepreneurship rate from 65% to 62.9%. While in theory a higher wage may reduce involuntary entrepreneurship by eliciting higher job search effort, we find that this effect is dominated by the labor constraint (more agents want a wage job but are unable to secure it) and hence involuntary entrepreneurship increases from 19.1% to 19.7%.

Our misallocation and counterfactual analysis is predicated on the (standard for this literature) assumption that agents are income maximizers and hence entrepreneurs earning less than their potential wage income is a sign of inefficiency. If, instead, some agents engaged in entrepreneurship because of unobserved non-pecuniary reasons, then the interpretation of some of our results would change. We address this further in Section 6.3.

Related literature

The observation that entrepreneurs are heterogeneous is well-documented, however, it is difficult to distin-

[5]Without the equilibrium wage decrease, average income would have gone up by 2% instead (see Table 11).

[6]By construction this counterfactual cannot decrease one's income since we assume that the interest rate is not affected by relaxing the credit constraint locally.

guish ‘voluntary’from ‘involuntary’businesses in actual occupation data and quantify the resulting misallocations.[7] Most of the empirical literature adopts ex-ante criteria, based on data availability, to distinguish across different types of entrepreneurs. For example, some authors differentiate between own-account entrepreneurs vs. employers (de Mel et al., 2010; Earle and Sakova, 2000; Schoar, 2010), others between persons who started a business after voluntarily quitting a job vs. after losing their job (Block and Wagner, 2010; Fonseca, 2019), between informal vs. formal businesses (La Porta and Schleifer, 2014), between incorporated vs. unincorporated businesses (Levine and Rubinstein, 2017), or between businesses that existed before vs. those that were started after a microcredit intervention (Banerjee et al., 2019).[8] Instead of using such proxies, we define voluntary vs. involuntary entrepreneurs in a structural way, as an endogenous outcome of the interaction between income-maximization and credit and labor market constraints, for given observable characteristics.

By incorporating labor market frictions our paper differs from a large literature on occupational choice under credit constraints (Banerjee and Newman 1993; Piketty 1997; Aghion and Bolton 1997; Evans and Jovanovic 1989; Lloyd-Ellis and Bernhardt 2000; Paulson et al. 2006; Karaivanov 2012; Buera 2009; Nguimkeu 2014, among others).[9] A key assumption in these papers is that agents can freely choose, out of all possible options, the occupation which would yield maximum expected income, with credit market imperfections shaping the agents’choices.[10]

Our paper also complements recent research documenting the importance of labor market frictions in developing countries. For example, Poschke (2019) calibrates a search and matching model with firm heterogeneity and finds that labor market frictions (the cost of hiring workers and match efficiency) are important in explaining the variation in unemployment and self-employment across eight countries and may push searchers into low-productivity own-account work. We differ in having a less detailed job search model and focus on quantifying and disentangling the effects of both credit and labor market frictions on voluntary and involuntary entrepreneurship. The finding that labor market frictions are consequential in developing countries is also echoed in the RCT literature on active labor market policies (e.g., Abebe et al. 2020; Bassi and Nansamba 2018; Banerjee and Chiplunkar 2018; Beam 2016).[11]

[7] Self-identified data on involuntary entrepreneurship is rare, the exception being the Global Entrepreneurship Monitor (GEM) survey which finds that in 2005 on average 17% of the respondents in high-income countries and 33% of the respondents in low or middle-income countries chose the second option in the question: “Are you in this start-up/firm to take advantage of a business opportunity or because you have no better choices for work?”(Minniti et al., 2005; Poschke, 2013). The GEM 2012-15 numbers for Thailand and the USA are 17-18% and 14-21% respectively.

[8] De Mel et al. (2010) find that in Sri Lanka, most own-account entrepreneurs are more similar to wage workers than to firm owners who employ workers. Block and Wagner (2010) estimate a 16% earnings premium in Germany for those who start a business after voluntarily leaving a job; Fonseca (2019) finds that those who start a business in Canada after losing their job hire 26% fewer workers and are 30% more likely to exit.

[9] Buera et al. (2020) include a brief analysis of ‘forced entrepreneurs’ in an extension, however, their focus is on the impact of microfinance in a dynamic occupational choice model without such entrepreneurs.

[10] Yindok (2019) estimates the Evans and Jovanovic (1989) model and explains the large observed increase in business ownership in rural Thailand during the 1997 Asian crisis as caused by a decline in the outside option, e.g., reduced access to urban jobs. Unlike this paper, Yindok does not model labor market frictions and treats all new post-crisis entrepreneurs as voluntary.

[11] Abebe et al. (2020) show that job application workshops and transport subsidies have large positive effect on the job-finding rate of young job-seekers in Ethiopia. Bassi and Nansamba (2018) find that certifying workers’ work ethic and interpersonal skills improves labor market outcomes in Uganda. Banerjee and Chiplunkar (2018) document substantial matching frictions, especially among young educated workers in India. Beam (2016) finds that attending a job fair increases formal employment by 10 percentage points, with a matched reduction in self-employment. See also McKenzie (2017) and Blattman and Dercon (2016) for critiques.

2 Model

Consider a large number of risk-neutral households ('agents') with strictly increasing preferences over income. The agents differ in their initial endowment, $z \geq 0$, hereafter, 'initial wealth'. The agents also differ in two productive characteristics: $x \in [1, \bar{x}]$ interpreted as 'labor market skills' (qualifications, schooling); and $\theta \in [\theta_{\min}, \bar{\theta}]$ interpreted as entrepreneurial ability.

There are two occupations (technologies). The first occupation, E is an 'entrepreneurship' or business occupation, which uses capital investment $k > 0$ and yields (expected) output θk^{α} where $\alpha \in (0, 1)$.[12] The second occupation, W ('wage work') does not use capital and yields income wx^{γ} where x^{γ} denotes the efficiency units of labor supplied by an agent with labor market skills (e.g., years of schooling) x, and where w is the labor market wage, endogenously determined in equilibrium. The parameter $\gamma \geq 0$ governs the sensitivity of labor income to the skill level x.

2.1 Credit market and investment

Assume that the agents have access to a financial intermediary through which they can save or borrow at a fixed gross interest rate $r \geq 1$. The credit market is imperfect – because of a limited enforcement problem the maximum amount of capital k that an agent can invest is λz, where $\lambda > 0$ is a parameter capturing the tightness of the credit constraint.[13] A sufficiently large value of λ corresponds to a perfect credit market while $\lambda = 0$ corresponds to a missing credit market (saving only). The parameter λ can also reflect the liquidity or ability to collateralize household wealth (e.g., land, household durables and agricultural assets in our empirical application). A λ estimate less than 1 is interpreted as households not able to fully use their wealth to finance their businesses.

The agents employed in the E occupation (entrepreneurs) earn business income $\theta k^{\alpha} - rk$, where k is their chosen investment. If an entrepreneur has a sufficiently large initial wealth z, the credit constraint $k \leq \lambda z$ does not bind and the agent optimally invests the first-best (unconstrained) amount of capital $k_u(\theta)$,

$$k_u(\theta) \equiv \arg\max_k \theta k^{\alpha} - rk = (\frac{\theta\alpha}{r})^{\frac{1}{1-\alpha}} \tag{1}$$

Note that $k_u(\theta)$ is increasing in θ – higher-ability entrepreneurs would like to invest more and $k_u(\theta)$ does not depend on the entrepreneur's initial wealth z. Intuitively, if there were no credit constraints or if if $k_u(\theta) \leq \lambda z$, the business is capitalized at the efficient level equalizing marginal product with marginal cost, regardless of the owner's wealth. Otherwise, if an entrepreneur has relatively low initial wealth, so that $\lambda z < k_u(\theta)$, she is credit-constrained and invests the maximum possible amount λz (since at $k = \lambda z$ the marginal product of capital exceeds the marginal cost). The credit market constraint causes underinvestment. For given initial wealth z, the credit constraint is more likely to bind for higher-ability entrepreneurs.

Call $\tilde{\theta}(z) \equiv \frac{r}{\alpha}(\lambda z)^{1-\alpha}$ the threshold level of θ at which $k_u(\theta) = \lambda z$, i.e., $\tilde{\theta}(z)$ is the highest entrepreneurial

[12] Output can be assumed explicitly stochastic as in Evans and Jovanovic (1989) but, because we assume risk neutrality, what matters is expected output. Therefore, without loss of generality, we interpret all revenue and income variables in our model as expected values over stochastic technology or other shocks.

[13] The upper bound λz can be micro-founded in a limited enforcement model, see for example Paulson et al. (2006).

ability θ at which the agent is financially not constrained and able to invest $k_u(\theta)$. The entrepreneur's income is therefore:

$$y^E(\theta, z) \equiv \begin{cases} (1-\alpha)\theta^{\frac{1}{1-\alpha}}(\frac{\alpha}{r})^{\frac{\alpha}{1-\alpha}} & \text{if} \quad \theta \leq \tilde{\theta}(z) \ \ \text{(unconstrained)} \\ \theta(\lambda z)^\alpha - r\lambda z & \text{if} \quad \theta > \tilde{\theta}(z) \ \ \text{(constrained)} \end{cases} \tag{2}$$

2.2 Labor market and job search

For now we treat the labor market wage w as given. We discuss its endogenous determination in Section 2.4. An agent with labor market skills x employed in the W occupation (worker) earns labor income

$$y^W(x, w) \equiv wx^\gamma \tag{3}$$

In classical occupational choice models, e.g., Evans and Jovanovic (1989), the agents always select the occupation, E or W which yields the higher expected income, $\max\{y^E, y^W\}$. We extend this setting by assuming that the market for occupation W is subject to a friction. Specifically, assume that, for given wage w and agent characteristics $\psi \equiv (\theta, z, x)$, the agent has no access to occupation W with some probability $p \in [0, 1]$.

We model the probability of an agent having no access to the wage occupation (constrained occupational choice) as endogenous and depending on the agent's labor market skills, x and an action, e interpreted as job search effort. Formally, the agent chooses the effort level e^* solving:

$$e^* = \arg\max_e \ (1 - p(e, x)) \max\{y^E(\theta, z), y^W(x, w)\} + p(e, x)y^E(\theta, z) - c(e) \tag{4}$$

where $p(e, x)$ corresponds to the probability of not having access to occupation W and is assumed decreasing in the agent's effort e and in labor market skills x, with $p(0, x) = 1$. For example, agents with lower skills x may find it harder to find wage work as government or private sector jobs may require diplomas, qualifications, certificates, etc. The values $y^W(x, w)$ and $y^E(\theta, z)$ are the agent's potential incomes, respectively as worker or entrepreneur, defined in (3) and (2) and $c(e)$ is the cost of effort, assumed to be strictly increasing in e with $c(0) = 0$.

The economic interpretation of (4) is that agents for whom $y^W > y^E$, i.e., who prefer a wage job W, put effort in searching for such job, with their optimal effort level $e^* > 0$ increasing in the income differential $y^W - y^E$. In general, the chosen e^* also depends on the agent's characteristics ψ and the wage w. On the other hand, agents for whom entrepreneurship yields higher income, those for whom $y^E \geq y^W$, would optimally put no effort in trying to secure a wage job, i.e., for them $e^* = 0$.

For given wage w and agent characteristics $\psi \equiv (\theta, z, x)$, denote

$$p^*(\psi, w) \equiv p(e^*, x), \tag{5}$$

that is, with the endogenous probability $p^*(\psi, w)$ the agent is *constrained* to only the entrepreneurial occupation E.[14]

$$\textit{occupational choice set } = \begin{cases} \{E\} & \text{with probability } p^*(\psi, w) \\ \{E, W\} & \text{with probability } 1 - p^*(\psi, w) \end{cases} \tag{6}$$

Evans and Jovanovic (1989) and other classical occupational choice papers assume $p^*(\psi, w) = 0$ for all agents; that is, one's income-maximizing occupation is always accessible. In contrast, we introduce a labor market friction – a match between an agent who prefers a wage job and an employer only occurs with probability less than 1. In Section 6.3 we also consider an alternative specification for the friction, with a fixed cost of entering occupation W.

In the empirical application we use the functional forms:

$$p(e, x) = 1 - \frac{xe}{\eta + xe} \text{ and } c(e) = e \tag{7}$$

where the parameter $\eta \geq 0$ captures the severity of the labor market friction for given labor market skills x. The special case $\eta = 0$ corresponds to a frictionless labor market ($p^*(\psi, w) = 0$), that is, all agents can always freely select both occupations. Figure A1 in the Appendix displays the estimated probability of no access to the wage occupation, $p^*(\psi, w)$ at the baseline SMM estimates where we proxy x with years of schooling.

2.3 Occupational choice and involuntary entrepreneurship

For given wage w and agent characteristics $\psi = (x, z, \theta)$, with probability $p^*(\psi, w)$ the agent is constrained and only has access to the entrepreneurial occupation E, see (6). If $y^W(x, w) > y^E(\theta, z)$ for that agent (i.e., the agent prefers wage work but it is not accessible), we call the agent *involuntary entrepreneur*. In contrast, if $y^E(\theta, z) \geq y^W(x, w)$, we call the agent *voluntary entrepreneur*.

The labor market friction severity η and labor market skills x jointly affect an agent's probability of involuntary entrepreneurship. On the one hand, the labor market constraint is more likely to bind for agents with low x through the direct effect of η and x on $p(e, x)$. On the other hand, agents with low x have lower wage income y^W which can make wage work less attractive. The overall impact of the labor market friction on involuntary entrepreneurship thus depends on the relative size of these two effects.

For an agent with characteristics $\psi \equiv (\theta, z, x)$ and wage w, the income differential between entrepreneurship and wage work is

$$\Delta(\psi, w) \equiv y^E(\theta, z) - y^W(x, w).$$

where $y^E(\theta, z)$ and $y^W(x, w)$ are defined in (2) and (3). Denote by $\mathbf{1}_E$ the indicator function such that $\mathbf{1}_E = 1$ if the agent is entrepreneur and $\mathbf{1}_E = 0$ otherwise. Write the event $\{\mathbf{1}_E = 1\}$ as

$$\{\mathbf{1}_E = 1\} = \{\mathbf{1}_E = 1 | \Delta(\psi, w) \geq 0\} \cup \{\mathbf{1}_E = 1 | \Delta(\psi, w) < 0\}$$

Note that *Prob*$(\mathbf{1}_E = 1 | \Delta(\psi, w) \geq 0) = 1$, since any agent who earns higher income by being entrepreneur ($\Delta(\psi, w) \geq 0$) would choose occupation E which is always available. The second term, *Prob*$(\mathbf{1}_E =$

[14]The lack of access to W could be interpreted as a result of a shock occuring with probability $P(\psi, w)$, similar to Buera et al. (2014).

$1|\Delta(\psi, w) < 0) = p^*(\psi, w)$ is the probability with which an agent with characteristics ψ is cannot obtain their preferred (higher-income) occupation W and hence also takes occupation E.

This implies that the probability, $P_E(\psi, w)$ that an agent with attributes $\psi = (x, z, \theta)$ is an entrepreneur equals:

$$P_E(\psi, w) \equiv \mathbf{1}_{\Delta(\psi,w)\geq 0} + p^*(\psi, w)\mathbf{1}_{\Delta(\psi,w)<0}. \tag{8}$$

The first term, $\mathbf{1}_{\Delta(\psi,w)\geq 0}$ corresponds to the case of a voluntary entrepreneur who selects occupation E based on income maximization, as typically assumed in the literature. The second term,

$$P_I(\psi, w) \equiv p^*(\psi, w)\mathbf{1}_{\Delta(\psi,w)<0}$$

is the additional probability of entrepreneurship, relative to the income-maximization model, which call the rate of involuntary entrepreneurship.

We follow the previous literature and assume that entrepreneurial ability θ is known by the agents but is unobservable to the econometrician. That is, we treat θ as unobserved heterogeneity in the empirical application, with a parametric distribution $F(\theta)$ which we estimate. Specifically, as in Paulson et al. (2006) and others, assume that θ is log-normally distributed:

$$\ln \theta = \delta_0 + \delta_1 \ln z + \delta_2 \ln(1 + x) + \varepsilon \tag{9}$$

$$\text{where } \varepsilon | z, x \sim N(0, \sigma)$$

The interpretation is that entrepreneurial ability may be correlated with initial wealth z and the observable labor market characteristics x (in the baseline estimation we proxy x by the years of schooling of the household's principal earner) but we also allow a stochastic ability component or shock, ε. The parameters $\delta_0, \delta_1, \delta_2$ and σ are estimated jointly with the structural parameters (see Section 4).

In contrast to entrepreneurial ability θ, the agents' initial wealth z and the labor characteristics x are treated as observable in both the model and the data. Hence, for given distribution of θ, observables z and x and parameter values, the model implies a probability with which an agent is an entrepreneur (E) or a worker (W). Specifically, we compute the predicted probability of entrepreneurship $P_E(x, z, w)$ and involuntary entrepreneurship $P_I(x, z, w)$, as functions of the wage w, the observables x and z and the model parameters ϕ by by integrating out the unobservable heterogeneity θ:

$$\begin{aligned} P_E(x, z, w) &= \int_\theta P_E(\psi, w) dF(\theta) \\ P_I(x, z, w) &= \int_\theta P_I(\psi, w) dF(\theta) \end{aligned} \tag{10}$$

We use standard Monte Carlo techniques to numerically compute the integrals. In Section 4 we use these predicted probabilities to estimate the structural parameters of the model using data on occupations and incomes of Thai households. Note that, for any observables z and x, the structural model is used to compute/estimate the rate of involuntary entrepreneurship, which is not directly observed in the data. Table 1 summarizes all possible occupational outcomes, calling $\Delta \equiv \Delta(\psi, w)$ to simplify the notation:

Table 1: Occupational outcomes

involuntary entrepreneur $Prob(\Delta < 0, \mathbf{1}_E = 1) = P_I(x, z, w)$	worker $Prob(\Delta < 0, \mathbf{1}_E = 0) = 1 - P_E(x, z, w)$
voluntary entrepreneur $Prob(\Delta \geq 0, \mathbf{1}_E = 1) = Prob(\Delta \geq 0)$	n.a. (impossible) $Prob(\Delta \geq 0, \mathbf{1}_E = 0) = 0$

2.4 Labor market equilibrium

Finally, we explain how the equilibrium wage w is determined. Suppose that there exists a competitive industry (aggregate firm) in which all agents in occupation W are employed, at market wage w per efficiency unit of labor. This 'third party' employer assumption is justified by the fact that in our data the vast majority of businesses (86%) do not hire paid workers. Similarly to Restuccia and Rogerson (2008) and others, assume a Cobb-Douglas aggregate production function $AL^\beta K^\zeta$ with $A, \beta, \zeta > 0$, $0 < \beta < 1$ and where L is the total amount of efficiency units of labor used. For simplicity normalize the aggregate firm capital stock to $K = 1$. This yields labor market demand:

$$L^d(w) = (\frac{A\beta}{w})^{\frac{1}{1-\beta}}.$$

The equilibrium wage w^* is the value equalizing labor demand, $L^d(w)$ with the total labor supply in efficiency units, $L^s(w)$ of all agents in occupation W,

$$L^s(w) = \int\int_{x,z} (1 - P_E(x, z, w))x^\gamma g(x, z)dxdz$$

where $g(x, z)$ is the pdf of the observables x and z. In the empirical application the double integral is replaced by the sum $\sum_{i=1}^N (1 - P_E(x_i, z_i, w))x_i^\gamma$ over all agents $i = 1, ..N$ with characteristics x_i and z_i in the data.

3 Data and reduced form analysis

We use data from the Townsend Thai Project's 2005 Urban Annual Survey.[15] Our main outcome of interest is household business ownership. We measure business ownership in the data by whether a household reports that they own at least one business at the time of the survey. That is, we construct a binary variable equal to one if a household reports owning a business and equal to zero otherwise. The corresponding variable in the model is $\mathbf{1}_E$. We also consider an alternative definition of business ownership, based on the major source of income, in Section 6.

Initial household wealth (z in the model) is measured as the total value, in 2005 Thai Baht, of land holdings, household durables and agricultural assets owned by a household *five years prior to* the survey. The reason for back-dating is to avoid possible simultaneity between occupational status and current wealth. Recall that in

[15] Full details are available at `cier.uchicago.edu`.

the model initial wealth z affects the investment potential of a household. We are therefore assuming that pre-existing (year 2000) measure of wealth is free of reverse causality. We allow initial wealth z to be correlated with entrepreneurial ability θ and therefore we capture, in reduced form, the possibility that more talented agents may save more in anticipation of becoming business owners.

We proxy the model variable x interpreted as education, qualifications or other characteristics determining a person's wage labor market income by the years of schooling of the principal earner in the household.[16] To identify the principal earner we use data on individual occupations and work type within the households. For business households, the principal earner is defined as the member whose occupation and worker type matches the reported business type (for households running more than one business, the principal earner is defined as the owner of the largest business in terms of assets). For non-business households, the principal earner is defined as the wage-earning member (for households with multiple wage-earners, the principal earner is the member earning the highest monthly wage income). We also consider alternative definitions of x in the robustness Section 6.

We also use data on the households' annual gross earned income, defined as total household income excluding remittances, government transfers and interest income. The model analogs are gross business revenue, $R^E(\theta) \equiv \theta k^\alpha$ and labor earnings, $y^W(x,w) = wx^\gamma$ for the business and non-business households respectively. As discussed in Section 2, we can think of these variables as expected values averaging over possible stochastic shocks within the one-year time horizon in the data.

The data sample used in the estimation is constructed as follows. We exclude all households in the top percentile of the initial wealth distribution, all households with zero initial wealth or with zero gross income, and all households in which the principal earner could not be identified.[17] Table 2 shows that 66.1% of the households in our sample report running a business. Among the business owners, about 60% are traders (e.g., vendors of prepared food) and 33% run a business involving services (tailor, laundry, restaurant, repair shop, taxi, etc.) Most businesses are small and/or family-run: 86% of the businesses in our sample did not hire any paid workers in the prior 12 months; only 5 businesses (0.3% of all) hired more than 10 workers. Among the non-business households, 93% earn the majority of their annual income from wages.

From the income data (Table 2), we also see that running a business and wage work are by far the two major sources of income for households. More than half of all households derive the majority of their annual gross income from running a business and nearly 42% of all households do so from wages. Only a small fraction (2.9%) derive the major part of their income from farming (rice, other crops, and livestock-raising).

Table 3 presents summary statistics of the main data variables. Business households have statistically significantly larger mean wealth and annual gross income than non-business households. The annual gross income of business households also has much larger standard deviation than that of non-business households. The principal earners in non-business households have more years of schooling, are younger, and are more likely to be male, compared to the principal earners in business households. There is no statistically significant difference in household size between the two types.

Table 4 reports the estimates from a probit regression of business ownership (a binary variable equal to one

[16]We set $x = 1 + s$ where s is years of schooling in the data.

[17]Because of data limitations we were not able to identify a principal earner for about 15% of all surveyed households.

Table 2 – Occupation and Major source of income

A. Self-reported business ownership	number	percent
yes	786	66.1
no	403	33.9
total	1,189	100

B. Major source of annual gross income	number	percent
business	632	53.2
wage	496	41.7
farming	34	2.9
other	27	2.2
total	1,189	100

Notes: The sample excludes households in the top 1% of the wealth distribution, households with zero wealth or zero income, and where a principal earner could not be identified.

Table 3 – Summary statistics

	business	non-business	all
wealth 5 years ago ('000 Baht), mean*	620.5	469.4	569.3
standard deviation	(814.8)	(682.3)	(775.5)
median	*335.1*	*235.1*	*305.0*
annual gross income ('000 Baht), mean*	513.6	164.7	395.3
standard deviation	(1313)	(132.5)	(1075)
median	*276.8*	*126.0*	*200.8*
years schooling of principal earner, mean*	7.3	9.8	8.1
standard deviation	(4.0)	(4.7)	(4.5)
age of principal earner, mean*	49.4	41.2	46.6
standard deviation	(11.0)	(13.1)	(12.3)
male (gender of principal earner), mean*	0.45	0.59	0.50
standard deviation	(0.50)	(0.49)	(0.50)
household size, mean	4.28	4.35	4.30
standard deviation	(1.90)	(1.83)	(1.87)
sample size	786	403	1189
sample proportion	66.1%	33.9%	100%

Notes: The sample excludes the top percentile of the wealth distribution, households with zero income or wealth, and where a principal earner could not be identified. Mean and standard deviations (in parentheses) are reported for all variables, median (in italics) is reported for all monetary values. Wealth and income are measured in thousands of 2005 Thai baht. *denotes that the difference-in-means test between business and non-business is statistically significant at the 1% significance level.

if a household reports owning a business) on initial wealth (five years prior to the survey), years of schooling, and household characteristics. The results indicate that both the household's initial wealth and the principal earner's schooling are correlated with business ownership in a statistically significant way. Larger initial wealth is associated with a higher rate of entrepreneurship, consistent with the credit constraint assumption. On the other hand, more schooling is associated with a *lower* observed rate of entrepreneurship, consistent with our assumptions about the labor market friction (the function $p(e, x)$). Households with female or older principal earners and those with larger size are more likely to be business owners. We view these results as a validation of our key modeling assumptions regarding the role of initial wealth and schooling in determining the rate of business ownership. We consider the effects of age and gender in robustness checks with sub-samples of the data (see Section 6 and Table 13).

Table 4 – Determinants of household business ownership

Dependent variable: business ownership	
initial wealth (mln Baht)	0.140***
	(0.059)
schooling of principal earner	-0.062***
	(0.010)
age of principal earner	0.025***
	(0.004)
male (gender of principal earner)	-0.401***
	(0.082)
household size	0.041**
	(0.023)
province fixed effects	included
sample size	1189

Notes: Probit regression including province fixed effects. The dependent variable is an indicator for whether a household reports owning a business in 2005. Standard errors are in parentheses. P-value significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4 Structural Estimation

Our data is a sample of N households, $i = 1, ..., N$ with observations on their initial wealth, z_i, years of schooling of the principal earner, x_i and occupational status E_i (with $E_i = 1$ if the household runs a business and zero otherwise), as defined in Section 3. We estimate the structural parameters (technology, credit and labor market frictions) and the distributional parameters of entrepreneurial ability θ via the simulated method of moments (SMM) by matching a set of entrepreneurship rates and income moments in the model to their data counterparts, at the observed x_i and z_i.

We estimate nine model parameters: α – the elasticity of business output (revenue) with respect to investment; γ – the elasticity of wage income with respect to x; λ – the parameter governing the credit constraint tightness; η – the parameter governing the labor market constraint tightness; A – the demand scale (TFP) parameter in the wage sector; δ_0 – the conditional mean of log entrepreneurial talent; δ_1 and δ_2 – the elasticities of log talent with respect to initial wealth and schooling and σ – the standard deviation of log-talent. Call the vector of all estimated parameters $\phi \equiv (\alpha, \lambda, \gamma, \eta, A, \delta_0, \delta_1, \delta_2, \sigma)$. We calibrate the gross interest rate r to 1.06, which corresponds to the median rate of interest on household loans in the Thai data. The production function parameter β in the wage sector is set equal to 0.5 in our baseline specification[18] but in Section 6 we

[18]The parameter β is related to the labor share and the overall returns to scale in labor and capital, $\beta + \zeta$ in the production function

also do robustness checks using $\beta = 1/3$ and $\beta = 2/3$ which show that our main results are not very sensitive to β.

4.1 Targeted moments and computation

The model parameters are estimated by minimizing the percentage deviation between simulated moments from the model and their respective data analogs. Specifically, given parameters ϕ, denote the moment values in the model by $h_j(x, z, \phi)$ for $j = 1, ..., J$ and their respective data analogs by h_j^d. The list and definitions of all moments we use is provided in Table A in the Appendix. Define the percentage deviation of the model-simulated moment from its data analog as

$$q_j(x, z, \phi) \equiv \frac{h_j(x, z, \phi) - h_j^d}{h_j^d}, \quad j = 1, ...J$$

Construct $\mathbf{q}(x, z, \phi)$ as the $J \times 1$ vector of percentage deviations $q_j(x, z, \phi)$. We estimate the model by SMM, minimizing the quadratic criterion $\mathbf{q}(x, z, \phi)'\mathbf{q}(x, z, \phi)$ over the parameters ϕ. We use an optimization routine robust to local extrema, initialized at the results from an extensive grid search over the parameter space.[19]

In our baseline specification we match eleven moments by choice of the nine parameters ϕ. The first seven targeted moments ($j = 1, ...7$) correspond to the expected rate (probability) of entrepreneurship in different stratifications $s \in \{x_s \in X, z_s \in Z\}$ for (sub-)sets of the observables x and z.

1. percent entrepreneurs, overall
2. percent entrepreneurs, schooling x in the bottom tercile
3. percent entrepreneurs, wealth z in the bottom tercile
4. percent entrepreneurs, schooling x in the top tercile
5. percent entrepreneurs, wealth z in the top tercile
6. percent entrepreneurs, z and x in the bottom terciles
7. percent entrepreneurs, z and x in the top terciles

We chose these moments to fit the occupational choice distribution in the data over the observables. Since the distribution of observables is fixed, other residual moments are also automatically matched. For example, moment 5 and moment 7 can be used to match the entrepreneurship rate for z in the top tercile and x in the bottom or medium tercile; moments 3 and 6 can be used to match the entrepreneurship rate for z in the bottom tercile and x in the medium or top terciles, etc.

Targeting the entrepreneurship rate among the richer households (top z tercile) with schooling x in the top tercile (moment 7) and any x (moment 5) are informative of the labor constraint parameter η. In the model, high-z and high-x households are least likely to be constrained in both the credit market and the labor market. Thus, matching the occupational choice and income of the high-wealth and low-schooling households (which can be inferred from moments 5 and 7) is informative about the labor constraint parameter η since

$AL^\beta K^\zeta$ (see Section 2.4). For example, Bosworth (2005) reports a value of .56 for the labor share in Thailand. Restuccia and Rogerson (2008) set the overall returns to scale at .85 which, assuming labor share of $2/3$ yields $\beta = .57$.

[19] We first perform an extensive grid search, over more than 20,000 parameter configurations. We then use Matlab's global optimization routine *particleswarm* initialized with the 20 best-fitting parameter vectors from the grid search.

their occupational choice does not depend directly on λ, but is likely to be affected by η. Similarly, the rate of entrepreneurship among poorer households (with z in the bottom tercile) for different x levels (bottom tercile vs. the rest) is informative of the credit constraint parameter λ. The impact of the two constraints can be disentangled by comparing the probability of entrepreneurship between low-wealth and low-schooling households (likely affected by both constraints) vs. low-wealth and high-schooling households (likely affected by only the credit constraint) vs. high-wealth and low-schooling households (likely affected by the labor constraint). We analyze further the role of the market friction parameters λ and η for the model fit with the data in Section 4.3 and Table B in the Appendix.

The remaining four targeted moments, labeled $j = 8, .., 11$ correspond to the average gross business revenue and wage earnings, in the whole sample or stratified by initial wealth and schooling.[20]

8. average output (gross revenue) of entrepreneurs, $R^E = \theta k^\alpha$
9. average labor earnings of workers, $y^W = wx^\gamma$
10. average output of entrepreneurs with wealth z below the median
11. average output of entrepreneurs with schooling x below the median

We chose these moments since matching earnings in each occupation is important for identifying the business technology and wage earnings parameters α and γ. Because of the fixed distribution of observables, this also implies matching other moments (e.g., average output of entrepreneurs with wealth above the median). All moments are defined in Appendix Table A. The data analogs are obtained using the households' observed occupation, E_i and observed gross income, R_i^E or y_i^W for the business and non-business households in the data, respectively. See Section 4.3. for further discussion on the chosen moments and their relationship with the model parameters.

4.2 Results

Table 5 reports the SMM parameter estimates. The entrepreneurial technology parameter, α is estimated as 0.21, implying that a 10 percent increase in investment k would lead to an approximately 2% percent increase in the income of an unconstrained entrepreneur. The labor earnings parameter γ determines how schooling affects the wage income of a household – the estimate implies that an increase in years of schooling from 4 to 5 would raise labor income by 20% on average. The credit market friction parameter λ is estimated as 0.35, which indicates relatively strict credit or collateral constraints and implies a maximum investment of 107,000 Baht for a household with the median initial wealth z (305,000 Baht). For comparison, the median business assets in the data are 19,700 Baht (6.5% of median initial wealth). The credit friction parameter estimate however has a large standard error since in some bootstrap simulations its estimated value was significantly larger.

The labor market friction parameter η is estimated at 25.3, also with a large standard error. At the modal years of schooling $x = 4$, the estimate implies a 40% average probability that an agent is subject to the labor market constraint (see also Figure A1 in the Appendix). Entrepreneurial skill θ is estimated as weakly positively correlated with both initial wealth and years of schooling (the estimates of δ_1 and δ_2 are positive,

[20] We exclude interest income as we focus on the model implications for business or wage earnings. The results including interest income are very similar and available from the authors.

Table 5 – SMM estimates

Parameter		**estimate**	**standard error**
business technology parameter	α	0.21	0.06
non-business technology parameter	γ	0.83	0.20
credit market friction parameter	λ	0.35	1.03
labor market friction parameter	η	25.3	16.4
labor demand scale parameter	A	2,537	526
entrepreneurial skill θ – constant	δ_0	3.33	0.46
skill θ, elasticity in initial wealth	δ_1	0.15	0.04
skill θ, elasticity in schooling	δ_2	0.13	0.17
skill θ, standard deviation	σ	0.98	0.10

Note: the standard errors are computed by bootstrapping; we calibrate $r = 1.06$ and $\beta = .5$.

although δ_2 is not statistically significantly different from zero).

In Table 6 we report simulation results from the model, computed at the SMM estimates. We draw 100 random values from the distribution of the entrepreneurial ability shock ε, for each household $i = 1, ...N$. We then average, first over ε for each i, and then over the respective household occupation.

Table 6 – Model results at the SMM estimates

Statistic	Value
entrepreneurs, % of all agents	65.0
involuntary entrepreneurs, % of all entrepreneurs	19.1
voluntary entrepreneurs, % of all entrepreneurs	80.9
equilibrium wage, w^*	23.5
average income, all	339.5
average income, entrepreneurs y^E	433.8
average income, voluntary entrepreneurs	518.7
average income, involuntary entrepreneurs	74.6
average income, workers y^W	164.6
credit constrained, % of all entrepreneurs	36.5
credit constrained, % of voluntary entrepreneurs	41.2
credit constrained, % of involuntary entrepreneurs	16.8

Note: the reported income values are averages of $y^E(\theta, z)$ or $y^W(x, w)$ over the respective agents.

The estimated proportion of involuntary entrepreneurs among all business owners is 19.1%. This estimate is within the range reported in the GEM surveys discussed earlier. The remainder 80.9% of business owners are classified by the model as voluntary entrepreneurs.

The equilibrium wage w^* at the SMM estimates is 23.5. This value is consistent with an auxiliary non-linear least squares (NLLS) regression of observed wage earnings y^W on years of schooling, x with the functional form $y^W = bx^\gamma$ which yields a b estimate of 23.54 (remember, in the model $y^W = w^* x^\gamma$). The same NLLS regression yields γ estimate of 0.82 which is also very close to our SMM estimate 0.83 in Table 5.

We also compute average income by occupation by integrating $y^E(\theta, z)$ over the ability shock ε for the entrepreneurs and then averaging the incomes y^E and y^W across all households of each type (using the x_i and z_i, $i = 1, ...N$ from the data). Table 6 shows that voluntary entrepreneurs earn on average about seven times higher income than involuntary entrepreneurs (519 vs. 75 thousand Baht). The involuntary entrepreneurs earn on average about two times less than wage workers (75 vs. 165 thousand Baht). These results reflect both differences in entrepreneurial ability θ and in labor market characteristics x. The agents with the highest estimated propensity of being involuntary entrepreneurs have both low θ and low x.

Approximately 37% of all entrepreneurs are estimated to be credit constrained – that is, they invest λz which is less than their unconstrained optimum $k_u(\theta)$. The fraction of credit-constrained agents is relatively large among the voluntary entrepreneurs (41%), while much lower (17%) among the involuntary entrepreneurs. The reason is that voluntary entrepreneurs have higher entrepreneurial ability θ on average, and hence larger unconstrained capital requirement. Indeed, the estimated log entrepreneurial skill, $\ln \theta$ is 5.2 on average for the voluntary entrepreneurs versus 3.7 on average for the involuntary entrepreneurs and 3.6 for the wage workers. This implies that, compared to the voluntary entrepreneurs, involuntary entrepreneurs are estimated to be about 78% less entrepreneurially skilled (lower θ) on average; wage workers are about 80% less entrepreneurially skilled.

Table 7 breaks down the distribution of involuntary and voluntary entrepreneurs at the SMM estimates by initial wealth, z and years of schooling, x (both taken from the data). The majority of involuntary entrepreneurs (62%) are estimated to have schooling below the median (6 years) and, in addition, 58% have wealth below the median (Table 7, part A). There are two reasons for these results. First, the labor market friction forcing agents into involuntary entrepreneurship is more restrictive for lower schooling x. Second, having lower wealth z makes it more likely that a person would be credit constrained if they chose to start a business, and hence more likely to prefer the wage occupation, all else equal. Indeed, in the simulation results (not reported in the table) 62% of all credit-constrained involuntary entrepreneurs have both wealth and schooling below the median and none of the credit-constrained involuntary entrepreneurs have wealth above the median.

Table 7 further shows that the majority (55%) of voluntary entrepreneurs have wealth above the median. Intuitively, larger wealth makes it less probable that an entrepreneur would be credit constrained and prefer the wage occupation. The distribution of voluntary entrepreneurs with schooling below vs. above the median is 58% vs. 42%. The smallest fraction of voluntary entrepreneurs (15%) is estimated among the households with wealth below the median and schooling above the median. Intuitively, those agents are most likely to be credit constrained and to have larger potential wage income.

The model results using the SMM estimates and the observed household characteristics in the data also allow us to answer (probabilistically) the question: "What type of businesses are the most or the least likely to be involuntary?" Among the business households with estimated high probability of involuntary entrepreneurship (the top quintile), 35% are traders and 29% run a restaurant or noodle/other shop in the data.[21] Furthermore, the businesses with high estimated rate of involuntary entrepreneurship (the top quintile) have median assets equal to 9,600 Thai Baht, and on average hire 0.13 paid workers, compared to the businesses with low esti-

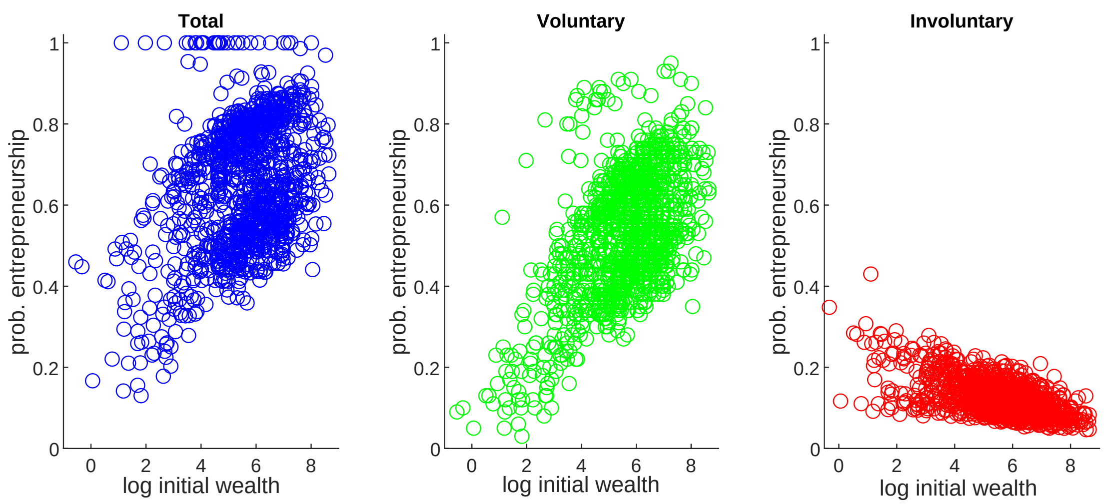
[21] In contrast, among the businesses with estimated low probability of involuntary entrepreneurship 43% are in the 'other' category, including copy shop, furniture maker, livestock raiser, rental, tailor and shops that sell electric appliances, ceramics and computers.

Table 7 – Distribution of entrepreneurs

A. Involuntary entrepreneurs, % with			
	wealth $z \leq$ median	wealth $z >$ median	total
schooling $x \leq$ median	40	23	62
schooling $x >$ median	18	19	38
total	58	42	
B. Voluntary entrepreneurs, % with			
	wealth $z \leq$ median	wealth $z >$ median	total
schooling $x \leq$ median	30	28	58
schooling $x >$ median	15	27	42
total	45	55	

mated probability of involuntary entrepreneurship (the bottom quintile) which have median assets 40,600 Baht and on average hire 0.84 paid workers.

Figure 1. Probability of entrepreneurship



The relationship between ex-ante wealth and entrepreneurship has been an important research area, with positive correlation often interpreted as evidence of credit constraints (Evans and Jovanovic, 1989; Paulson et al., 2006 among many others). Our model contributes to this research by explicitly modeling involuntary entrepreneurship arising because of labor market frictions. Figure 1 further clarifies how our setting differs from the standard income-maximization occupational choice model such as Evans and Jovanovic (1989). The left panel of the Figure shows the overall relationship between initial wealth and the estimated rate of entrepreneurship – it is positive overall but there is a lot of variation. In contrast, the relationship between initial wealth and *voluntary* entrepreneurship is strongly positive with much less dispersion (the middle panel). We conclude that the positive relationship between initial wealth and entrepreneurship symptomatic of credit constraints can be weakened by a negative relationship (as we estimate) between initial wealth and *involuntary* entrepreneurship (the right panel). This further emphasizes the importance of accounting for and quantifying both credit and labor market frictions in the data.

4.3 Model fit

In Table 8 we assess the fit between the data and the model evaluated at the SMM estimates. We report the fit for the 11 targeted moments computed by minimizing the SMM criterion function over the nine parameters ϕ. The seven occupational choice moments based on the entrepreneurship rate in different stratifications (1-7) are all within 5% deviation of their data analogs. The four income moments (8-11) are matched even closer, to within 0.3% of their data analogs.

Table 8 – Model fit: targeted moments

	moment	model	data	% deviation
1.	% entrepreneurs	65.0	66.1	-1.7
2.	% entrepreneurs, x in bottom tercile	79.2	79.5	-0.4
3.	% entrepreneurs, z in bottom tercile	59.2	58.9	0.4
4.	% entrepreneurs, x in top tercile	50.6	52.1	-2.8
5.	% entrepreneurs, z in top tercile	69.2	71.9	-3.9
6.	% entrepreneurs, z and x in bottom terciles	74.2	72.5	2.4
7.	% entrepreneurs, z and x in top terciles	57.0	54.3	4.9
8.	average output, entrepreneurs, R^E	512.3	513.6	-0.3
9.	average earnings, workers, y^W	164.6	164.7	-0.0
10.	average output – entr., z below median	350.2	350.3	-0.0
11.	average output – entr., x below median	386.4	385.7	0.2
criterion value (sum of squared deviations)				$5.6(10^{-3})$

Note: output/earnings levels are in thousand Baht.

In Tables 9A and 9B we further assess the model fit by stratifying over the observables, initial wealth z and schooling x. In Table 9A we compare the model-predicted with the actual fraction of entrepreneurs across the wealth and schooling distribution terciles. The model matches well the observed fraction of entrepreneurs in each of the nine tercile cells (the largest deviations, of about 10%, are observed for medium schooling and medium or high wealth). The fit by z tercile (the last row) or by x tercile (the last column) is very close, within 2% model vs. data. We conclude that our targets (moments 1 to 7 in Section 4.1) fit well the rate of entrepreneurship in the data, conditional on the observables (at least at the tercile level of aggregation).

In Table 9B we compare the average estimated vs. actual business output (revenue), R^E stratifying over the observables. Consistent with our choice of moments we compare the income values for wealth or schooling below vs. above the median. The estimated model fits the data reasonably well overall and for each of x and z separately. The model results are a bit less close to the data (up to 12% deviation) in matching the business revenue for households with wealth and schooling both below or both above the median. The reason is that the estimated model over-predicts the dispersion of business revenue over wealth for schooling below the median

Table 9A. Estimated vs. actual fraction of entrepreneurs by initial wealth, z and years of schooling, x

Model (percent)				
	z_1	z_2	z_3	all z
x_1	16.0*	17.0	14.0	47.0*
x_2	9.0	9.2	9.2	27.4
x_3	4.9	8.7	12.0*	25.6*
all x	29.9*	34.9	35.2*	100

Data (percent)				
	z_1	z_2	z_3	all z
x_1	15.4	16.8	14.2	46.4
x_2	8.9	8.4	10.4	27.7
x_3	5.1	9.5	11.2	25.8
all x	29.4	34.7	35.8	100

Note: x_i denotes the i-th tercile of schooling (1=lowest, 3= highest); z_i denotes the i-th tercile of initial wealth; *targeted moment or equivalent.

(compare the x_L row in the model vs. data tables) and under-predicts the revenue dispersion over wealth for schooling above the median.

Table 9B. Estimated vs. actual average business output R^E by initial wealth z and years of schooling x

Model ('000 Baht)			
	z_L	z_H	all z
x_L	295	495	386*
x_H	462	797	667
all x	350*	640	512*

Data ('000 Baht)			
	z_L	z_H	all z
x_L	335	441	386
x_H	378	858	681
all x	350	651	514

Note: subscript L denotes values below the median, subscript H denotes values above the median; *targeted moment.

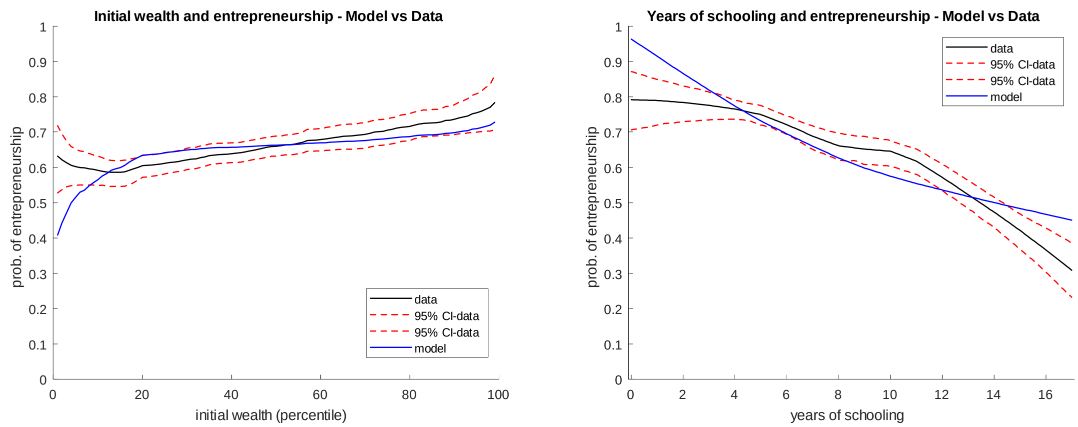
We next evaluate the model fit with the data going beyond the terciles and the median, by looking separately at initial wealth z and years of schooling x. On Figure 2 we plot lowess regression lines (model-simulated vs. actual data) and confidence intervals (the dashed lines). Since the initial wealth distribution is very skewed, we use a percentile scale for better visualization. The estimated model matches well the overall level and slope of the rate of entrepreneurship in the data, both with respect to initial wealth and schooling. We under-predict entrepreneurship for very low levels of wealth (the bottom 10%) and over-predict entrepreneurship for low and high levels of schooling. The under-prediction at low wealth is a common feature in the literature focusing on financial constraints. Here we get closer to the data by allowing for involuntary entrepreneurship.[22]

We further investigate the role of the market friction parameters, λ and η for the model's fit with the data in Appendix Table B. We hold all other parameters fixed at their SMM estimates and vary either the credit constraint parameter λ or the labor market friction parameter η to one half or two times its estimate, observing how the model fit changes. When varying λ (columns 3 and 4 in Table B), the following moments are the most sensitive: percent entrepreneurs with z in the bottom 1/3, average output of entrepreneurs, average output of entrepreneurs with z below median and average output of entrepreneurs with x below median. This suggests that targeting business output is important to pin down λ. Varying η (columns 5 and 6 in Table B) affects the fit of almost all targeted moments, with some occupational choice moments being especially sensitive:

[22] An alternative approach, by Lee (2016), explains the observation that many US households with zero or negative net worth start businesses by modeling unsecured credit with an interest rate premium (in addition to collateralized debt) and showing that this brings the rate of entrepreneurship at low wealth closer to the data.

percent entrepreneurs with z in the bottom 1/3, percent entrepreneurs with x in the bottom 1/3, and percent entrepreneurs with z and x in the bottom 1/3. These results are consistent with the earlier theoretical discussion on how λ and η shape the agents' occupational choices and incomes.

Figure 2. Rate of entrepreneurship, lowess fit

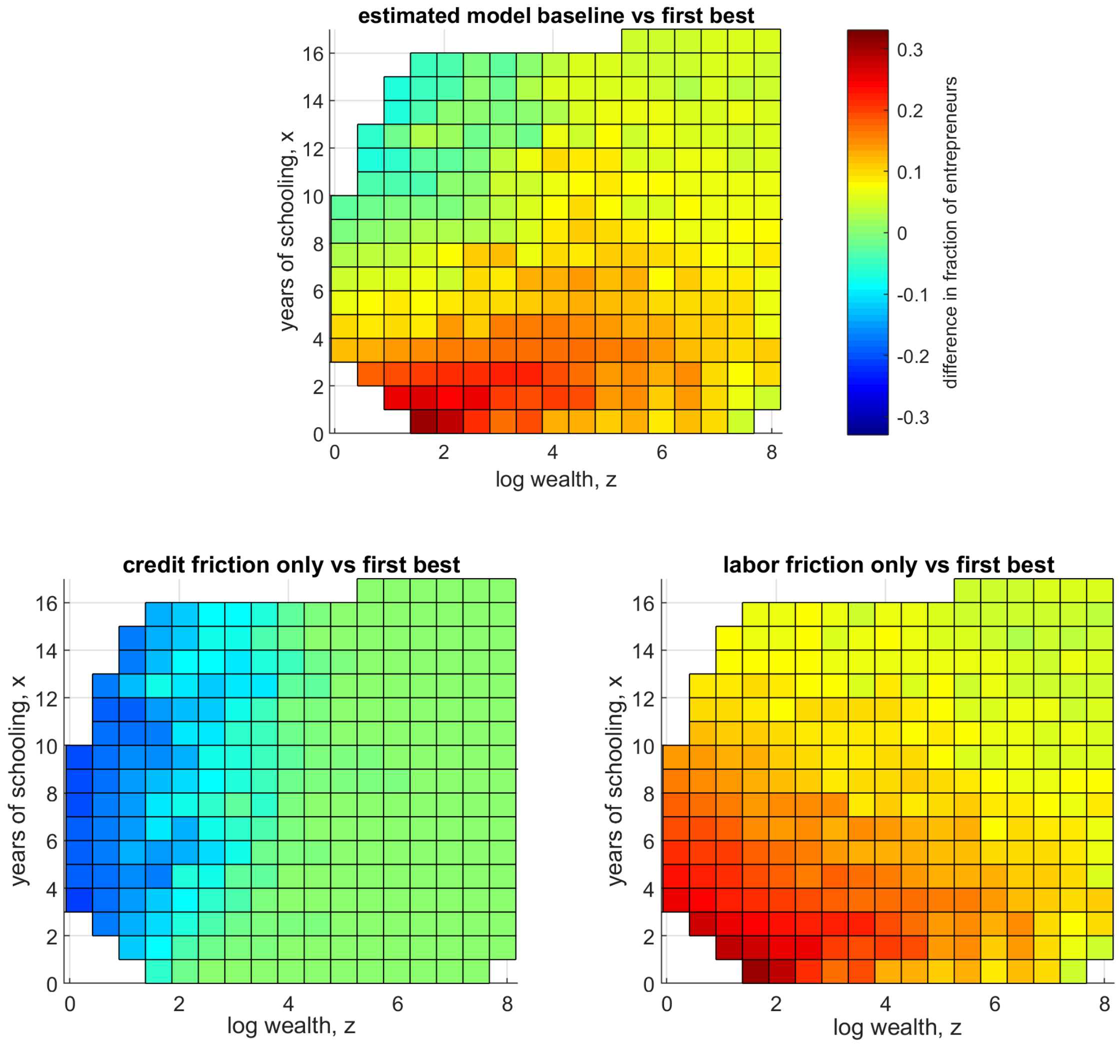


4.4 Market frictions and misallocations

We next use the model evaluated at the SMM estimates to quantify the misallocations and inefficiencies stemming from the labor market and credit market frictions, relative to the first best (unconstrained) benchmark. There are two main allocation decisions in the model. First, households differing in initial wealth z, entrepreneurial ability θ and labor market characteristics, x allocate across the two occupations. Second, capital k is allocated among the households who run businesses (voluntarily or involuntarily). The labor and credit market frictions can cause misallocations in both these dimensions. On the extensive margin (occupational choice), a household may end up in the suboptimal occupation. This can be expressed either as involuntary entrepreneurship, because of the labor market friction, or as a credit-constrained household engaging in wage work. On the intensive margin (capital investment), an entrepreneur may face a binding credit constraint and make inefficiently low investment k relative to the first-best level $k_u(\theta)$; also, any capital used by involuntary entrepreneurs is misallocated.

We first characterize the incidence of the misallocations across households with different observables – initial wealth z and schooling, x. We then disentangle the effects stemming from the labor market vs. the credit market frictions. In our model, the first best corresponds to setting $\eta = 0$, that is, no labor market / occupational choice friction, and setting $\lambda \to +\infty$ (10^8 is used in the computation), that is, no credit constraint. All other parameters are held fixed at their SMM estimates. Involuntary entrepreneurship arises in the model if both of the following hold: (i) a household does not have access to wage work, which we interpret as a labor market friction and (ii) household income is larger in the wage occupation. The labor market friction is important for (i), while the credit constraint affects (ii).

Figure 3. Misallocation in occupational choice



Note: warmer colors correspond to values larger than the first best; colder colors correspond to values smaller than the first best.

Figure 3, the top panel ("estimated model baseline vs. first best") plots the differences between the predicted probability of entrepreneurship in the estimated model (with both labor and credit frictions present, with the parameter values in Table 5) and in the first best ($\eta = 0$, $\lambda \to +\infty$), across the households with different initial wealth z and schooling x from the data. Warm colors (red, orange, yellow) show more predicted entrepreneurs relative to the first best, while cool colors (blue, cyan) show less entrepreneurs relative to the first best. Without misallocations, all differences between the model and the first best benchmark should be zero (depicted in green). We see, however, that the labor and credit frictions cause over-supply of entrepreneurs among some households and under-supply among others. Specifically, for low values of schooling, the model-predicted rate of entrepreneurship is higher (by up to 30 percentage points) than in the first best. This is because of involuntary entrepreneurship, as the labor market friction binds more likely for low schooling. These differences are largest for low wealth (the bottom left corner), where the involuntary entrepreneurship effect is amplified by a tighter credit constraint. In contrast, for households with high schooling but low wealth (the top left corner), the model predicts *less* entrepreneurship (by up to 10 percentage points) than there would be in the first best – this is because of the credit constraint. For high schooling and high wealth (the top right corner) the misallocation is nearly zero, since very few agents are constrained. The agent's occupational choices are also affected by the equilibrium wage w^*, which differs between the constrained economy and the first best (see Table 10). We analyze this equilibrium effect further in Section 5.

The bottom panels of Figure 3 disentangle the effects from the labor and credit constraints by decomposing the total difference in the rate of entrepreneurship between the estimated model and the first best. In the bottom left panel ("credit friction only vs. first best") we set $\eta = 0$ (no labor market friction) but keep the credit constraint parameter λ (and all other parameters) at its SMM estimate. As expected, the credit constraint alone results in a weakly lower rate of entrepreneurship throughout compared to the first best, since some capital-constrained agents do not find it worthwhile to run a business. This is most pronounced (by up to 26 percentage points) for low-wealth households but obviously has no effect on high-wealth households who invest the unconstrained amount. The magnitude of "missing" entrepreneurs because of the credit friction is slightly larger for higher levels of schooling x, since entrepreneurial ability θ is estimated as positively correlated with x.

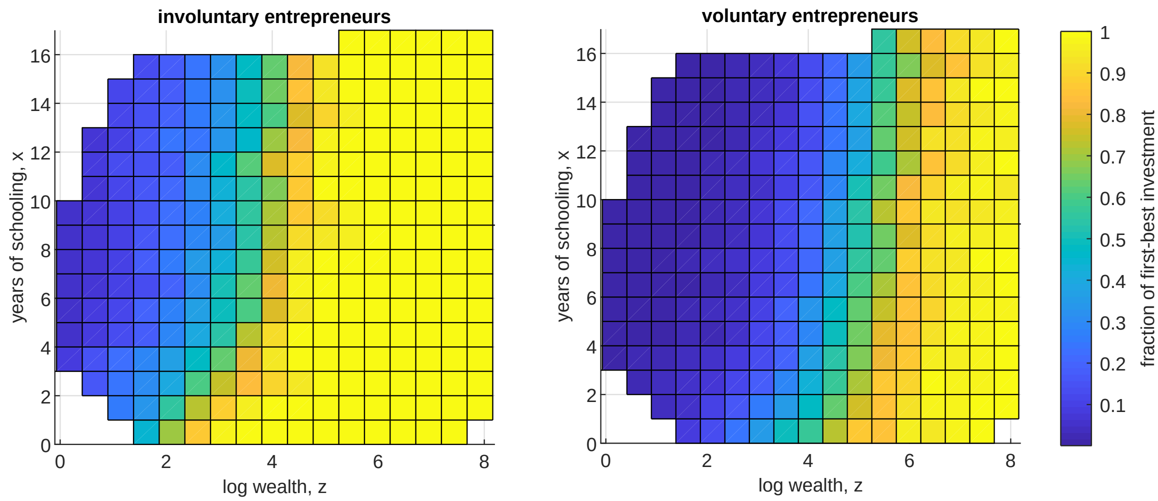
In the bottom right panel of Figure 3 ("labor friction only vs. first best"), we set $\lambda = 10^8$, which eliminates the credit constraint, but keep η and all other parameters at their SMM estimates. In contrast to the effect of the credit constraint discussed above, the direction of misallocation relative to the first best is now the opposite – the labor market friction results in an excess amount, by up to 30 percentage points, of (involuntary) entrepreneurs. The magnitude is the largest for households with low schooling and low wealth, both of which are estimated as positively correlated with low entrepreneurial talent.

We next analyze the intensive margin, i.e., business investment. Figure 4 illustrates the level and the distribution over observed initial wealth and schooling, of investment in the estimated model relative to the unconstrained (first best) investment level. Specifically, we plot the ratio (integrated over θ) of actual investment k to the unconstrained level k_u for voluntary and involuntary entrepreneurs. For both types, underinvestment is most severe for low-wealth households, as expected. For the same wealth level, the degree of underinvestment for the voluntary entrepreneurs is, however, larger than that for the involuntary entrepreneurs. The reason is that the voluntary entrepreneurs have higher ability θ on average and hence larger investment needs $k_u(\theta)$.

We summarize the aggregate effects of each friction on the extensive and intensive margin, including the equilibrium effect from the wage w^*, in Table 10.[23] The results show that the major cause of excess entrepreneurship (19.1% involuntary entrepreneurs) is the labor market friction, which accounts for 18.7% of the total – compare columns (1) and (3) of Table 10. On the other hand, the fraction of missing voluntary entrepreneurs because of the credit constraint is estimated as 0.6% of all households (56% in column 4 minus 55.4% in column 2). Combined, these two effects imply a 9 percentage points higher entrepreneurship rate in the baseline estimated model with both frictions (column 1) and in the data (65%), relative to the estimated

[23] Eliminating the labor market friction, column (2), results in a substantial drop in the equilibrium wage w^*, from 23.5 to 21.4 thousand Baht. Intuitively, if occupational choice is unconstrained, more agents are able to access wage work and the increased labor supply lowers the wage. In contrast, in the setting with unconstrained credit in column (3), the impact on the equilibrium wage is very minor, as a small number of agents switch to entrepreneurship.

Figure 4. Investment relative to the first best



Note: warmer colors correspond to values larger than the first best; colder colors correspond to values smaller than the first best.

first-best entrepreneurship rate (56%) in column (4).

Table 10 – Aggregate effects of the market frictions

	(1) baseline	(2) credit friction only	(3) labor friction only	(4) first best
equilibrium wage, w^*	23.5	21.4	23.6	21.5
entrepreneurs, percent	65.0	55.4	65.4	56.0
of which involuntary	19.1	none	18.7	none
of which voluntary	80.9	all	81.3	all
investment by all entr.	61.2 (52.8)	59.6 (60.3)	101.7 (87.1)	100 (100)
investment by vol. entr.	58.5 (62.3)	59.6 (60.3)	98.7 (104)	100 (100)
investment by invol. entr.	2.7 (12.3)	0 (0)	3.0 (13.8)	0 (0)

We quantify the aggregate effects of the market frictions on capital investment in the bottom 3 lines in Table 10. The reported numbers include the compositional effects on the extensive margin and should be read together with Figure 4. We normalize total investment (capital used) in the first best and investment per entrepreneur in the first best to 100. Table 10, lines 5-7 report the percentage of total capital investment and investment per entrepreneur (in brackets), relative to the corresponding first-best levels. Column (1) shows that, in the estimated model with credit and labor market frictions, the entrepreneurs invest only about 61% of the first-best level on average (53% of the first-best per entrepreneur). Of this total, 2.7% is used by involuntary entrepreneurs – a capital misallocation. Removing the labor friction, in column (2), reduces total capital use to 59.6% of the first-best level, which measures the aggregate impact of the credit friction on investment. Alternatively, the labor friction alone (column 3) results in aggregate over-investment by 1.7% relative to the first best because of the capital use by involuntary entrepreneurs.

5 Counterfactuals and welfare analysis

5.1 Relaxing the labor or credit market constraints

We next analyze the effects of relaxing the labor and credit constraints on income. Since the households are assumed risk-neutral, all changes in household income can be interpreted as welfare effects. In addition, we characterize the equilibrium effects from the endogenous change in the market wage w^* (compared to holding the wage fixed) in the estimated model vs. the counterfactuals.

Table 11: Relaxing the labor and credit market frictions

	baseline (1)	**no labor friction**, $\eta = 0$ (2) *fixed wage*	(3) equil. wage	**relaxed credit**, $2\hat{\lambda}$ (4) *fixed wage*	(5) equil. wage
wage, w^*	23.47	*23.47*	21.39	*23.47*	23.54
A. entrepreneurs, %	65.0	*52.6*	55.4	*65.3*	65.2
of which involuntary	19.1	*0*	0	*18.9*	18.9
of which voluntary	80.9	*100*	100	*81.1*	81.1
B. income		income change		income change	
mean, all	339	*+2.0%*	+0.1%	*+3.5%*	+3.5%
10th percentile	186	*+4.7%*	+1.4%	*+7.5%*	+7.7%
30th percentile	266	*+3.2%*	+0.6%	*+4.9%*	+5.0%
median	327	*+2.0%*	+0.2%	*+3.4%*	+3.4%
70th percentile	392	*+1.5%*	+0%	*+3.1%*	+3.1%
90th percentile	506	*+1.2%*	-0.6%	*+2.5%*	+2.5%
mean, entrepreneurs	434	*+19.6%*	+15.1%	*+3.9%*	+4.0%
mean, voluntary	519	*+0.0%*	-3.8%	*+3.7%*	+3.9%
mean, involuntary	75	*n.a.*	n.a.	*+0.1%*	+0.5%
mean, workers	165	*-5.7%*	-13.8%	*+0.0%*	+0.3%

In the first counterfactual (Table 11, 'no labor friction'), we set the labor constraint parameter η in (7) to zero while keeping all other parameters at their SMM estimates. This eliminates involuntary entrepreneurship – all agents have unconstrained occupational choice, i.e., $p^*(\psi, w) = 0$ for all ψ. Agents' income is also affected, since previously involuntary entrepreneurs enter the wage occupation and there is also an equilibrium effect from the endogenous change in the wage. The latter effect is evaluated by comparing the 'fixed wage' (the values in italics) and 'equil. wage' columns in Table 11. For example, ex-ante voluntary entrepreneurs are not directly affected by the relaxation of the labor friction but their ex-post occupational choice may be affected by the new wage.

Table 11, part A shows that eliminating the labor market friction (setting $\eta = 0$) significantly reduces the overall rate of entrepreneurship in the economy from 65% to 55.4%. If the wage w was held fixed at its baseline estimated value of 23.47, then the fall in the entrepreneurship rate would have been even larger, to 52.6% (compare the columns 'fixed wage' vs. 'equil. wage'), however, this is partially offset by the decrease in w^*.

In Table 11, part B we report the mean, median and percentiles of household income (as defined in Table 6 and the surrounding discussion) and the resulting income changes from removing the labor friction (the numbers below ‘income change’). Relaxing the labor market friction results in a small increase in incomes throughout most of the income distribution (Table 11, column 3) – a 0.1% income increase on average as the equilibrium wage adjusts down to 21.4. This income increase would have been larger (+2% on average, see column 2) if the wage w were fixed, however, we see that a large part of the impact of removing the labor friction on income is offset by the lower equilibrium wage.

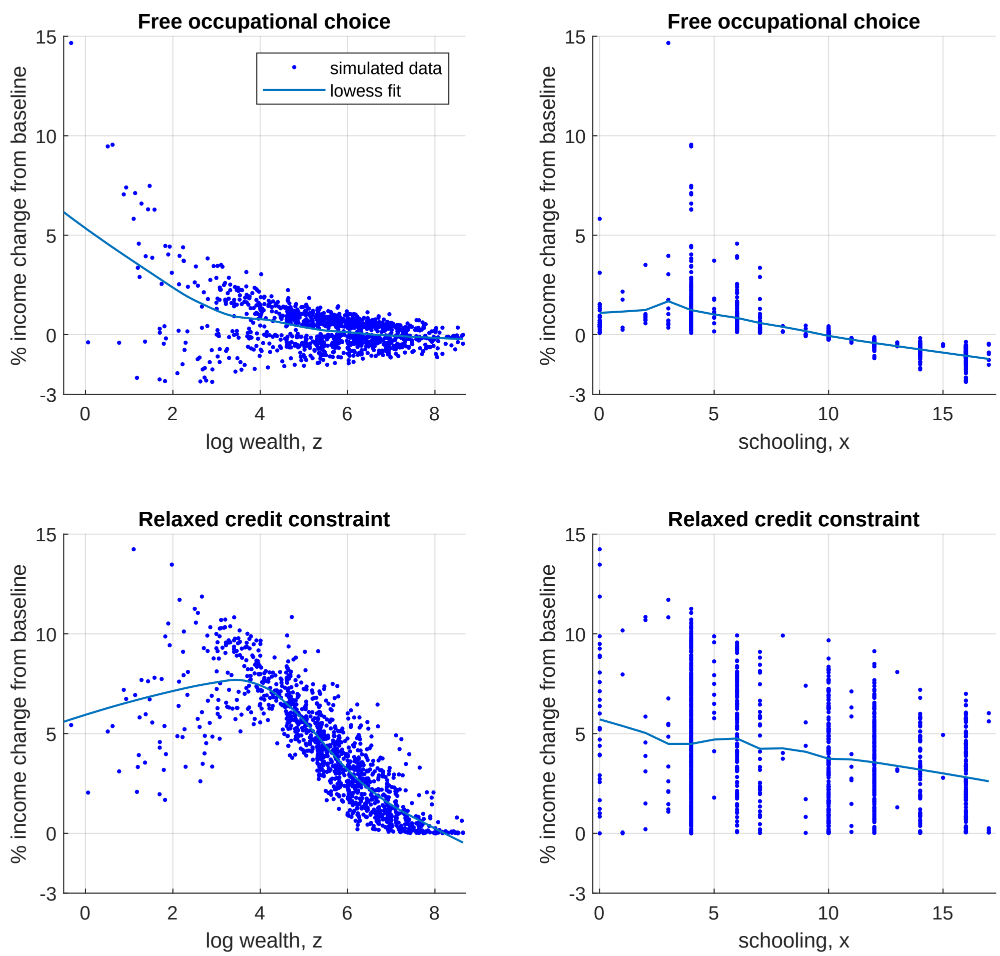
While the average impact on income in column (3) is minor, relaxing the labor constraint triggers important compositional changes within the income distribution. For example, some ex-ante involuntary entrepreneurs who can access wage work as the constraint is relaxed move to higher income percentiles. Removing the labor friction has strongest impact on the 10th income percentile level (1.4% increase) at which many households are likely to be involuntary entrepreneurs in the baseline. On the other hand, the 90-th income percentile level goes down by 0.6% when the equilibrium effects are factored in.

The mean income of all entrepreneurs when $\eta = 0$ (Table 11, column 3) is 15.1% higher compared to the column (1) baseline, a significant increase because of the exit of involuntary entrepreneurs. The average income of voluntary entrepreneurs, however, is 3.5% lower than in the baseline since some lower ability agents become entrepreneurs in the counterfactual because of the lower wage (compare columns 1, 2 and 3 in Table 11). The mean income of workers falls significantly, by 13.8%. The latter is partly a composition effect, as some ex-ante unproductive involuntary entrepreneurs become workers (compare with the ‘fixed wage’ column 2) and partly caused by the fall in the equilibrium wage. Finally, relaxing the labor constraint also affects the fraction of constrained entrepreneurs (those with $k = \lambda z$) – it increases from 51.3% in the baseline to 56.8% (not reported in the table). The reason is that, without a labor market constraint, all entrepreneurs are voluntary and have higher average ability θ.

The second counterfactual we study is relaxing the credit constraint, which we do by doubling the baseline estimated value of λ (from 0.35 to 0.7), keeping all other parameters at their SMM estimates (see Table 11, columns 4 and 5). Given the ample evidence for credit constraints in developing countries we consider doubling λ more informative than completely eliminating the credit constraint. Theoretically, credit market interventions may reduce involuntary entrepreneurship if ex-ante constrained agents can borrow more, earn higher income and hence prefer to run a business. This, however, can be offset by the labor market frictions. Table 11, part A indeed shows that relaxing the credit constraint has only minor effect on involuntary entrepreneurship (its rate falls from 19.1% to 18.9%) and entrepreneurship overall (an increases from 65.0% to 65.2%). This reinforces our conclusion that the labor market friction is the main cause of involuntary entrepreneurship.

The results in Table 11, part B (columns 4 and 5), on the other hand, show that relaxing the credit constraint can have significant impact on household income by mitigating the investment friction. Since the impact of relaxing the credit constraint on the equilibrium wage is estimated as minimal (compare columns 4 and 5 in Table 11), there are no strong offsetting equilibrium effects, as in the labor constraint relaxation counterfactual in columns 2 and 3. Specifically, the estimated increase in mean income from relaxing the credit constraint is 3.5%, which is significantly larger than the average income increase from relaxing the labor friction. Households at the 10th income percentile experience the largest income gains (+7.7%) as they can invest amounts closer to their first best. The voluntary entrepreneurs gain about the same as the average agent (+3.9%) since they are most likely to be credit constrained ex-ante. In contrast, the involuntary entrepreneurs and workers experience only minor income gains (0.5% and 0.3% respectively), the former since they are mostly constrained by ability, the latter because of the minor compositional shift in the economy towards entrepreneurship. Comparing the fraction of credit constrained entrepreneurs in the simulated data (not reported in the table), not surprisingly there is a large drop, from 36.5% to 22%. Among the voluntary entrepreneurs, the fraction of credit constrained falls from 41.1% to 24.9%, while the corresponding impact for involuntary entrepreneurs is a decrease from 16.8% to 9.5%.

Figure 5. Income gains from relaxing the labor and credit frictions



In Figure 5 we use model simulated data at the SMM estimates to further assess the impact of relaxing the labor and credit market constraints by conditioning on the observables, years of schooling x_i and initial wealth z_i. That is, we quantify the income effects for different types of households – e.g., low-wealth vs. high-wealth, low-schooling vs. high schooling. Since the income distribution percentiles shift endogenously as a result of the policy counterfactuals, ex-ante vs. ex-post, this assessment of the policy impact for fixed household characteristics helps clarify further the magnitude and incidence of income gains or losses.

Relaxing the labor friction (Figure 5, top panels) leads to large income gains (up to 10%) for some low-wealth individuals who can now access their income-maximizing occupation. For other agents, however, the decrease in the equilibrium wage causes an income loss of up to 3%.[24] On average, the income gains from eliminating the labor market friction decrease in initial wealth z, see the 'lowess fit' line. The income gains also mostly decrease in the years of schooling x, except for agents with very low x values. The reason is that households are less likely to be involuntary entrepreneurs for high z and x. In contrast, the income gains from relaxing the credit constraint (Figure 5, bottom panels) are non-monotonic in initial wealth and the agents with intermediate wealth levels gain the most. The reason is that these agents are most likely to be credit constrained entrepreneurs. The income gains from relaxing the credit constraint decline in schooling x on average, since households with larger x are more likely to have higher ability θ and hence are less likely to be investment constrained ex-ante.

5.2 Microfinance

We next consider a counterfactual of offering households to borrow and invest in their business up to an additional M Baht. This can be interpreted as a microfinance program,[25] with the requirement that the loan is used to buy or rent business capital at the current interest rate r. We analyze the effects of this policy on the rate of entrepreneurship and household incomes using the baseline SMM estimates. We set the maximum microfinance loan to $M = 20,000$ Baht, which is about 10% of the average gross income in the data. The chosen value for M is calibrated to equal the maximum loan size (applicable in 35% of all loans) in the Million Baht village program (Kaboski and Townsend, 2012).

Entrepreneurs choose investment k to solve

$$\max_k \theta k^\alpha - rk \quad \text{subject to} \quad k \leq \lambda z + M \quad \text{(MF)}$$

Clearly, all households who are initially not credit constrained are not affected by this policy while all constrained households have an incentive to participate (borrow).

Table 12 shows the impact of the microfinance program on occupational choice and household income. All reported values in the "microfinance" column include the equilibrium effects from the change in wage, although these effects are relatively minor. The overall entrepreneurship rate goes up by about half percentage point, from 65% to 65.5%. Within the larger number of businesses, the microcredit policy induces more voluntary entrepreneurship (+0.5%), while the rate of involuntary entrepreneurs falls from 19.1% to 18.6%. These results are consistent with the relatively small occupational choice effects from relaxing the credit constraint seen in Table 10.

Regarding the policy effects on household income, Table 12, part B shows that the microfinance policy raises average income by 2.2% and the gains are unevenly spread across the income distribution. The poorest households, at the 10-th income percentile, benefit the most from the availability of additional credit (10.5% increase post- vs. pre-policy), while richer households, those at the 90-th income percentile, benefit only slightly (+0.4%) as they are more likely to have been unconstrained ex-ante.

The mean income of entrepreneurs goes up by 2.1% for two reasons. First, the additional microfinance

[24] In contrast, if the wage were held fixed, all agents would experience income gains by construction.

[25] In our data a large fraction (over 80%) of households report being members of the Thai Million Baht village fund.

funds relax the credit friction and allow previously constrained entrepreneurs to earn larger business income. Second, there is a compositional shift from involuntary to voluntary entrepreneurs. The average worker's income goes up slightly (+0.1%) as some ex-ante constrained agents with low x exit wage work and since the equilibrium wage goes up slightly.

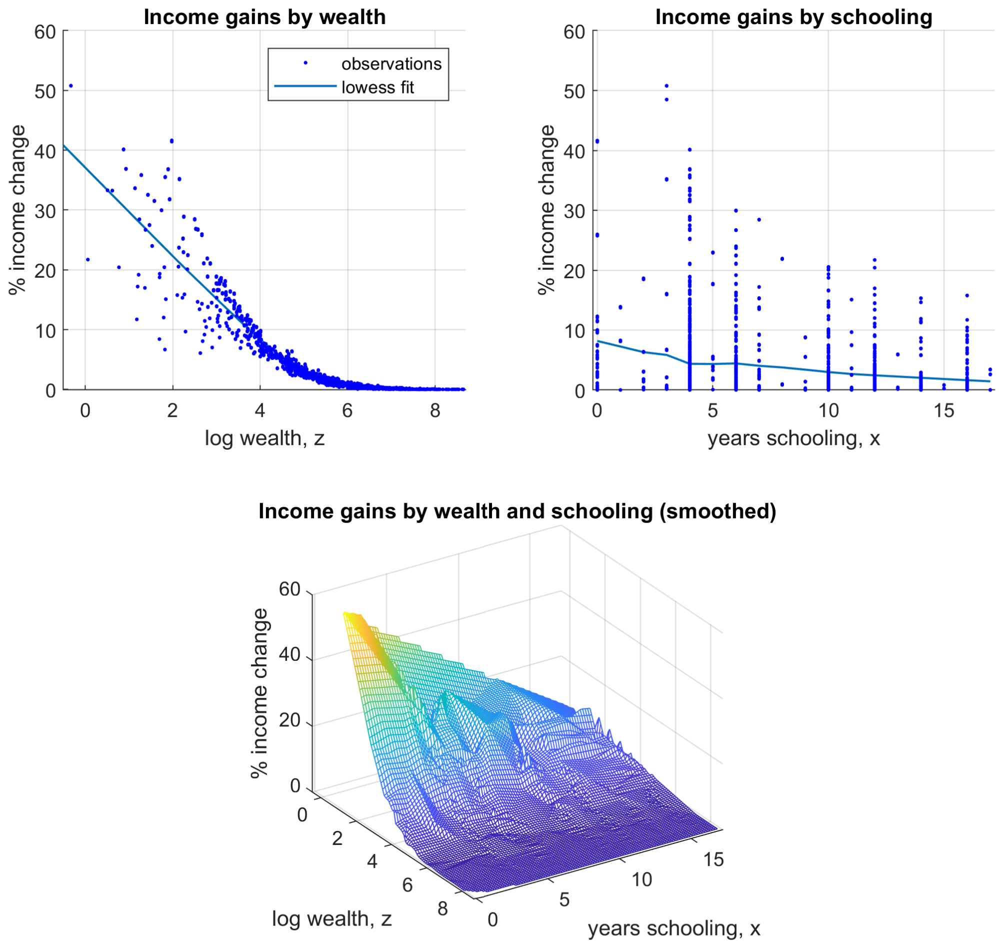
Table 12 – Policy evaluation

	(1) baseline	(2) microfinance	(3) increased labor demand
equilibrium wage, w^*	23.47	23.60	25.15
A. % entrepreneurs	65.0%	65.5%	62.9%
of which voluntary	80.9%	81.4%	80.3%
of which involuntary	19.1%	18.6%	19.7%
B. income		income change	income change
mean, all	339	+2.2%	+1.4%
10th percentile	186	+10.5%	+2.3%
30th percentile	266	+3.4%	+2.2%
median	327	+1.8%	+1.5%
70th percentile	392	+1.2%	+1.3%
90th percentile	506	+0.4%	+1.2%
mean, entrepreneurs	434	+2.1%	+2.3%
mean, voluntary entr.	519	+1.6%	+2.9%
mean, involuntary entr.	75	+0.6%	+4.4%
mean, workers	165	+0.1%	+6.6%

The income effects of the microfinance policy are further illustrated on Figure 6 where we stratify agents by initial wealth and years of schooling. The dots represent the estimated expected income change for each household with characteristics (z_i, x_i) from the data. The microfinance policy benefits poorer households significantly (some gain 40 percent or more relative to the baseline). The income gains are minor for wealthier households, since they are less likely to have been credit constrained ex-ante. The income gains are on average smaller (below 10%) and more evenly spread by years of schooling (the top right panel). Considering wealth and schooling jointly, the bottom panel of Figure 6 shows that the households who gain the most from the microcredit policy are those with the lowest wealth and schooling. Low-wealth agents with high schooling do not gain much, as they are more likely to be engaged in wage work. Only the involuntary entrepreneurs among them stand to gain from the access to microfinance.

The main difference between the results of the microfinance counterfactual (Table 11, column 2) and the counterfactual of relaxing the credit constraint by doubling the credit constraint parameter λ (Table 10, column 3) is that in the case of microfinance the income (welfare) gains are monotonically decreasing in household wealth – compare Figures 5 and 6. The reason is that under the microfinance policy poorer households (with low z) receive a relatively larger increment in their ability to borrow compared to wealthier households, as the maximum loan size M is held fixed. In contrast, when the credit constraint is relaxed by increasing λ (for example, interpreted as better enforcement or better property rights enabling posting more collateral) the effect is non-monotonic, as explained earlier.

Figure 6. Microfinance, income gains



5.3 Increase in the demand for wage labor

We also use the model to evaluate the effects on income and occupational choice of an increase in wage labor demand. This counterfactual can be motivated as a job creation program or urban development policy increasing the demand for wage workers. In the context of the model we simulate this counterfactual by raising the labor demand scale parameter A (see Section 2.4) by 10% while holding all other parameters at their SMM estimates.

The results are reported in Table 12, column (3). Naturally, the increase in labor demand results in a higher wage, lower rate of entrepreneurship, and higher worker incomes (by 5.7% on average). However, we also observe important composition effects, as was the case with the other counterfactuals. The rate of involuntary entrepreneurship goes up to 19.7% as fraction of all entrepreneurs. Intuitively, the higher wage attracts more agents toward the worker occupation and sufficiently many are unsuccessful to secure it, despite the increased job availability. The result is persistent occupational misallocation which suggests that such policies need to be complemented by policies reducing the labor market frictions. On the other hand, the increase in labor demand results in higher ex-post income for all agents. Entrepreneurial income rises on average due to the higher productivity of the ex-post entrepreneurs.

6 Robustness

6.1 Alternative definitions

We study the sensitivity of our results to the definitions of business ownership and labor market characteristics x. Column (2) in Table 13 reports the SMM parameter estimates when we define business ownership by whether a household derives the majority of their gross income from business. With this narrower definition of entrepreneurship, its rate in the sample is 50% (65% in the baseline). The alternative definition of business ownership yields slightly higher estimated rate of involuntary entrepreneurship, 22% – compare columns (2) and (1) in Table 13. The corresponding wider definition for non-business households results in a much larger equilibrium wage rate needed to fit the income data.

Column (3) in Table 13 uses years of schooling of the head of the household as a proxy for labor market characteristics x, instead of the principal earner's years of schooling used in the baseline. The rate of involuntary entrepreneurship is estimated at 17.3% among business households. In column (4) of Table 13, we alternatively define labor market characteristics, x as a composite index of schooling and age, instead of just years of schooling. Specifically, we perform a principal component analysis using the principal earner's years of schooling and the difference between the maximum age and the principal earner's age (divided by 4, to match the range of years of schooling) and define x to be the first principal component, in which the loading on schooling is estimated to be 92%. With this broader definition of labor market characteristics we find a small reduction in the estimated rate of involuntary entrepreneurs to 16.2% of all business households.

6.2 Sub-samples by gender or age

We also estimate the model on data sub-samples stratified by the gender and age of households' principal earners to see whether and how much the estimated rate of involuntary entrepreneurship differs in these characteristics. Table 13, columns (5)–(8) report the results. In columns (5) and (6), in which the sample is stratified by the gender of the principal earner, we see that the estimated rate of involuntary businesses is significantly lower in the male principal earner sample (11.4% of all businesses), as opposed to 18% in the female principal earner sample. The credit friction is estimated as more severe in the female sample (the estimated λ is smaller). The labor market constraint is also tighter (the estimate for η is smaller) for the households with female principal earners. These findings, together with the fact that the actual rate of business ownership in the data is higher for the female principal earner sample (70% vs. 61% for the male sample), suggest that the misallocations due to involuntary entrepreneurship and credit frictions are more pronounced among households with female principal earners. This finding has potential policy significance.

In columns (7) and (8) of Table 13, we stratify the data by age of the principal earner – below or above the median age. We estimate a higher rate of involuntary entrepreneurship and severity of the constraints (the parameters λ and η) among the households with older principal earners.

Table 13 – Robustness and alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	*(9)*	*(10)*
technology parameter, α	0.21	0.29	0.36	0.20	0.25	0.18	0.27	0.39	*0.19*	*0.20*
technology parameter, γ	0.83	0.60	0.00	0.98	1.15	0.83	1.12	0.62	*0.79*	*0.73*
credit market friction, λ	0.35	0.18	0.22	0.55	0.30	0.23	0.41	0.27	*0.15*	*0.32*
labor market friction, η	25.3	17.1	16.9	23.4	7.7	26.4	1.6	58.9	*n.a.*	*n.a.*
labor demand, A	2537	4880	6744	1870	1347	1561	1370	2202	*2646*	*2839*
talent – constant, δ_0	3.33	3.59	3.74	3.61	2.86	3.67	2.62	4.08	*3.38*	*3.15*
talent – wealth, δ_1	0.15	0.02	-0.02	0.16	0.16	0.12	0.16	-0.06	*0.15*	*0.17*
talent – schooling, δ_2	0.13	0.17	0.25	0.00	0.27	0.12	0.26	0.10	*0.15*	*0.20*
talent – std. deviation, σ	0.99	1.10	0.76	0.99	1.03	0.93	0.97	0.71	*1.10*	*1.02*
fixed cost, c									*47.4*	
labor market friction, υ										*0.48*
entrepreneurs, % of all	65.0	49.7	64.9	64.3	60.3	69.2	50.1	74.9	*65.0*	*65.2*
involuntary, % of entr.	19.1	22.1	17.3	16.2	11.4	18.0	6.6	24.5	*20.8*	*20.2*
equilibrium wage, w^*	23.5	50.5	153	12.9	11.2	21.5	10.0	45.9	*25.7*	*29.7*
SMM criterion, $\times 10^{-3}$	*5.6*	*3.7*	*1.8*	*1.1*	*7.7*	*12.2*	*72.4*	*9.9*	6.1	6.6

Notes: (1) baseline; (2) alternative definition of business households based on major source of income; (3) alternative definition of labor characteristics, x – head of household's years of schooling; (4) alternative definition of labor characteristics, x – first principal component of age and schooling (5) subsample, male principal earner; (6) subsample, female principal earner; (7) subsample, principal earner with age below median; (8) subsample, principal earner with age above median; (9) entry cost specification; (10) no search effort specification.

6.3 Alternative labor market constraint specifications

We consider two alternative specifications for the labor market constraint with results reported in columns (9) and (10) in Table 13.

Entry cost. In the baseline model an agent faces an endogenous probability $p^*(\psi, w)$ of not finding a wage job. Suppose instead that households must pay a fixed cost c to access wage work. In the estimation we allow c to be either positive or negative. That is, we let the data determine whether entry into wage work is costlier or more beneficial than running a business, beyond the potential income comparison. Formally, given c, an agent with initial wealth z and labor market skills x would choose to run a business if

$$y^E(\theta, z) \geq y^W(x, w) - c.$$

The results from estimating this 'entry cost' alternative specification of the labor market friction are reported in column (9) of Table 13. Reassuringly, the estimates of the nine common parameters are close to those in our baseline model. The parameter c is estimated to be positive, $c = 47.4$. This can be interpreted as a *cost* of accessing the wage occupation equivalent to 47,400 Baht, which is relatively large, about 30% of the average income of non-business households in the data.

In the entry cost specification the rate of involuntary entrepreneurship is defined as the difference between the entrepreneurship rate at the estimated $c = 47.4$ and the entrepreneurship rate that would have resulted at $c = 0$ (no friction), holding all other parameters fixed at their SMM estimates in Table 13, column (9). The estimated rate of involuntary entrepreneurship in the entry cost specification is 21%, which is a bit larger than the 19.1% estimated rate in the baseline model. A possible reason is that the entry cost specification assumes that the labor market friction is uniform across all households. Note also that the entry cost specification achieves worse fit with the data than the baseline.

The estimated positive cost of entry into the wage occupation is also isomorphic to a (non-pecuniary) benefit of running a business, that is, an agent runs a business if her income from running it, y^E plus an additional benefit, c exceeds her wage income, y^W. However, we view our preferred interpretation of $c > 0$ as wage-market *entry cost* or friction as more plausible in the Thai setting, given the evidence reported in the introduction about the large self-reported number of businesses run out of necessity.

No search effort. We also estimated a simplified specification of the labor market constraint, in which the probability of no access to the wage occupation depends only on the agent skills x and there is no job search effort choice. Specifically, suppose the probability of no access to the W occupation is

$$\tilde{p}(\psi, w) = 1 - \left(\frac{1+x}{1+x_{\max}}\right)^{\upsilon}$$

where $x_{\max}$ is the largest observed value of x in the data (16 years of schooling). The interpretation is that agents with larger values of x are less likely to be constrained. The parameter υ captures the severity of the constraint, with $\upsilon = 0$ corresponding to unconstrained choice. The results from estimating this specification are in Table 12, column (10). The estimates and the rate of involuntary entrepreneurship are similar to the baseline values (column 1), however, the specification without search effort attains lower fit with the data.

Alternative β. We also ran the SMM estimation for alternative values of β – the capital share parameter in the wage market sector which was calibrated at .5 in the baseline (see Section 2.4). Setting $\beta = 1/3$, the estimated rate of involuntary entrepreneurship is 18.8% and the equilibrium wage is 23.2. For $\beta = 2/3$ we estimate a rate of involuntary entrepreneurship of 17.8% and wage $w^* = 22.5$. These results and also the values of the targeted moments are very close to those for our baseline specification with $\beta = .5$ (involuntary entrepreneurship 19.1% and $w^* = 23.5$). We conclude that our main results are not very sensitive to varying β within a realistic range.

7 Conclusions

In this paper, we model and empirically evaluate the idea that some observed occupational choices can be ‘involuntary’ or constrained, especially in a developing country context. We structurally estimate a model that endogenizes the possibility that some agents do not have access to wage employment, nesting as a special case the standard models of income-maximizing occupational choice. We call involuntary entrepreneurs the business owners who would maximize their income in the wage sector but are not able to access it because of labor market frictions. We estimate that about 19% of all business owners in the 2005 Thai urban data are involuntary entrepreneurs, with other robustness runs yielding a range from as low as 7% to as high as 25%, depending on the data stratification or variables definitions.

We use the estimated model to quantify the magnitude and distribution of occupational and investment misallocations across households with different observable characteristics. We find significant misallocations on both the occupational choice margin and the investment margin. Inefficiencies exist in both directions (too many or too few entrepreneurs, too much or too little capital used) depending on the interaction between the labor and credit market frictions for different observables. Broadly speaking, credit constraints suppress entrepreneurship and investment while labor market frictions cause an excess of involuntary entrepreneurs and affect the equilibrium wage rate.

We measure the effects of relaxing the credit and labor constraints and the impact of a microfinance policy and a policy increasing wage labor demand on the rate of entrepreneurship (voluntary and involuntary) and on household income, on average and stratified by wealth and years of schooling. Our results suggest that there are sizeable potential income gains, especially for poorer households, from reducing either the labor or credit frictions and from providing access to microcredit. However, the number of involuntary entrepreneurs can only be significantly reduced by addressing the labor market friction.

In this paper we view involuntary entrepreneurship as a symptom of occupational misallocations that can be addressed by reducing labor market frictions. Our counterfactual analysis reveals that a combination of active labor market policies that reduce search and matching frictions (Abebe et al. 2020; Bassi and Nansamba 2018; Banerjee and Chiplunkar 2018; Beam 2016) and urban industrial policies to promote wage growth would be the most effective in addressing occupational misallocations while increasing the welfare of involuntary entrepreneurs.

A limitation of our approach, also present in most of the cited literature, is that while we quantify the effects of credit and labor market frictions on households' occupational choice, including involuntary entrepreneurship, our model does not capture multi-period decision making by households. An extension to a dynamic model with savings or capital accumulation, could yield a non-linear relationship between wealth and entrepreneurship over time and occupational choice transitions, as in Buera (2009). While we incorporate equilibrium effects from wage adjustment in the counterfactual policy evaluations, the interest rate is fixed, as in a small open economy, and we treated wage labor demand as exogenous. A more extensive analysis of general equilibrium effects, e.g., as in Kaboski and Townsend (2011) or Buera, Kaboski and Shin (2020), can help clarify further the joint determination of occupational choice, investment and wealth accumulation subject to credit and labor market frictions.

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Appendix – Additional tables and figures

Table A. Targeted moments

moment	model	data analog
1. Average rate of entrepreneurship	$\frac{1}{N}\sum_{i=1}^{N} P_E(x_i, z_i, w^*)$	$\frac{1}{N}\sum_{i=1}^{N} E_i$
2. Rate of entrepreneurship, $x \leq x_{t1}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_{t1}\}} P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_{t1}\}}}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_{t1}\}} E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_{t1}\}}}$
3. Rate of entrepreneurship, $z \leq z_{t1}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}\}} P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}\}}}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}\}} E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}\}}}$
4. Rate of entrepreneurship, $x > x_{t3}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{x_i > x_{t3}\}} P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{x_i > x_{t3}\}}}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{x_i > x_{t3}\}} E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{x_i > x_{t3}\}}}$
5. Rate of entrepreneurship, $z > z_{t3}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}\}} P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}\}}}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}\}} E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}\}}}$
6. Rate of entrepreneurship, $z \leq z_{t1}, x \leq x_{t1}$	$\frac{\sum_{i=1}^{N} 1_{\{z_i \leq z_{t1}, x_i \leq x_{t1}\}} P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}, x_i \leq x_{t1}\}}}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}, x_i \leq x_{t1}\}} E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_{t1}, x_i \leq x_{t1}\}}}$
7. Rate of entrepreneurship, $z > z_{t3}$, $x > x_{t3}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}, x_i > x_{t3}\}} P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} 1_{\{z_i > z_{t3}, x_i > x_{t3}\}}}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}, x_i > x_{t3}\}} E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i > z_{t3}, x_i > x_{t3}\}}}$
8. Average output, entrepreneurs	$\frac{\sum_{i=1}^{N} E(R^E \mid \mathbf{1}_E=1,z_i,x_i,\phi))}{\sum_{i=1}^{N} P_E(x_i,z_i,w^*)}$	$\frac{\sum_{i=1}^{N} R_i^E E_i}{\sum_{i=1}^{N} E_i}$
9. Average labor earnings, workers	$\frac{\sum_{i=1}^{N} E(y^W \mid \mathbf{1}_E=0,z_i,x_i,\phi))(1-P_E(x_i,z_i,w^*))}{\sum_{i=1}^{N} (1-P_E(x_i,z_i,w^*))}$	$\frac{\sum_{i=1}^{N} y_i^W (1-E_i)}{\sum_{i=1}^{N}(1-E_i)}$
10. Average output, entrepreneurs, $z \leq z_m$	$\frac{\sum\limits_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_m\}} E(R^E \mid \mathbf{1}_E=1,z_i,x_i,\phi)) P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_m\}} P_E(x_i,z_i,w^*)}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_m\}} R_i^E E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{z_i \leq z_m\}} E_i}$
11. Average output, entrepreneurs, $x \leq x_m$	$\frac{\sum\limits_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_m\}} E(R^E \mid \mathbf{1}_E=1,z_i,x_i,\phi)) P_E(x_i,z_i,w^*)}{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_m\}} P_E(x_i,z_i,w^*)}$	$\frac{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_m\}} R_i^E E_i}{\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq x_m\}} E_i}$

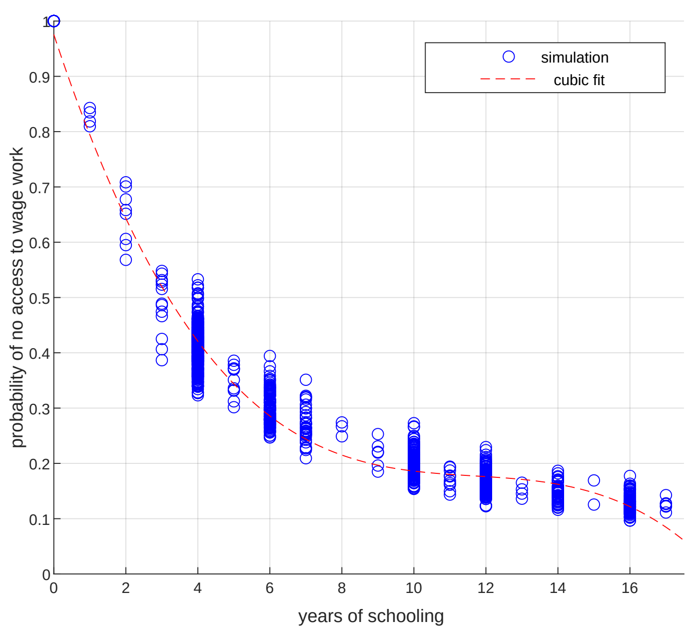
Notes: x = years of schooling; z = initial wealth; subscript m = median; $t1$ = 33rd percentile; $t3$ = 67th percentile. Nine parameters are estimated: $\alpha, \lambda, \gamma, \eta, \mu, \delta_0, \delta_1, \delta_2$ and σ.

Table B. Model fit at the SMM estimates and alternative parameters

targeted moment	SMM	$\lambda = 2\lambda^{smm}$	$\lambda = .5\lambda^{smm}$	$\eta = 2\eta^{smm}$	$\eta = .5\eta^{smm}$
% entrepreneurs	65.0	65.2	64.6	68.3	62.4
% entrepreneurs with x in bottom 1/3	79.2	79.3	79.0	83.4	75.9
% entrepreneurs with z in bottom 1/3	59.2	60.0	57.8	63.4	55.9
% entrepreneurs with x in top 1/3	50.6	50.9	50.2	52.8	49.0
% entrepreneurs with z in top 1/3	69.2	69.1	69.3	71.6	67.3
% entrepreneurs with z and x in bottom 1/3	74.2	74.7	73.4	79.3	70.2
% entrepreneurs with z and x in top 1/3	57.0	56.9	57.1	58.8	55.6
average output – entrepreneurs, R^E	512	547	469	491	530
average earnings – workers, y^W	165	165	164	175	158
average output, entr. with $z <$ median	350	389	309	335	363
average output, entr. with $x <$ median	386	410	355	371	399

Note: column 2 (SMM) reports the targeted moment values computed at the baseline SMM estimates. In columns 3 to 6 a single parameter, λ or η, is varied while all other model parameters are held fixed at their SMM estimates.

Figure A1. Probability of no access to wage work



Note: The Figure plots the simulated probability of no access to wage work, $p^*(\psi, w)$ computed at the baseline SMM estimates from Table 5. Each circle corresponds to a (x_i, z_i) data point.