Involuntary Entrepreneurship – Evidence from Thai Urban Data*

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Abstract

We structurally estimate a model of occupational choice between wage work and entrepreneurship which allows for 'involuntary entrepreneurship' (running a business out of necessity). Involuntary entrepreneurs would earn higher income as workers but cannot access a wage job because of labor market frictions. Using Thai urban household data, we estimate the share of involuntary entrepreneurs as 19% of all businesses in our sample, with robustness runs yielding a range from as low as 7% to as high as 25%, depending on the data stratification and empirical specification. Involuntary entrepreneurs earn significantly lower income (85% less on average) than the rest of the entrepreneurs and are more likely among low-wealth and low-schooling households. Decomposing the estimated effects of the labor and credit market frictions, our results imply 18.7% excess (involuntary) entrepreneurs because of labor market frictions and 0.6% fewer entrepreneurs because of credit frictions, both relative to the unconstrained optimum. Counterfactual policy evaluations show that involuntary entrepreneurship can only be reduced by directly targeting labor market frictions, with attention paid to the equilibrium effect on the market wage.

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1 Introduction

Ever since Smith, Knight and Schumpeter, entrepreneurship, or running one's own business, has been viewed as an engine of innovation and progress. Many tax and regulatory policies explicitly target small firms and startups. At the same time, self-employment is more widespread in lower-income countries, accounting for up to 80% of total employment (ILO, 2020). The explanation for this apparent contradiction is that not all entrepreneurs are alike (e.g., Banerjee and Duflo 2007, 2011; Djankov et al., 2006). Some people start businesses willingly, 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 may need social safety nets or job skills and qualifications.

In contrast to other studies, which use ex-ante criteria or reduced-form methods to distinguish between types of entrepreneurs,[1] we adopt a structural approach to estimate and quantitatively evaluate an occupational choice model in which "involuntary" entrepreneurship (running a business out of necessity) co-exists with voluntary entrepreneurship. Agents differ in initial wealth, labor market skills and entrepreneurial ability, and choose between running an own business or wage work based on the expected income they can earn. However, an agent's occupational choice may be constrained, because of labor market frictions, forcing the agent to run a business.[2] We call such business owners, who would prefer wage work but cannot access it, "involuntary entrepreneurs".[3] The different types of entrepreneurs arise from the interaction between income-maximization and the credit and labor market constraints, for given observable characteristics.

Our model nests and extends occupational choice models in which entrepreneurship is chosen if and only if an agent's income from running a business is larger than that from wage work (Evans and Jovanovic, 1989; Banerjee and Newman, 1993; Piketty, 1997 among many others). As is common in this literature and well-documented in developing countries, the occupational choice is subject to a credit market friction – the agents face a borrowing constraint in their business investment. In addition to this credit friction, however, we introduce a labor market friction which may prevent an agent from access to a wage job.[4] The credit and labor market frictions are represented by model parameters which we estimate from micro data. We partially incorporate an equilibrium effect in the wage-work sector by allowing the wage to adjust as the agents' occupational choices affect labor supply but not demand.

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 along with demographic and occupation data. 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.[5] Most of the businesses in our data are very small – 86% report that they did not hire any paid worker in the 12

[1] See the "Related literature" section for details.

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

[3] By "involuntary" we do not mean that there is coercion by a third party, only that some agents are constrained to their less preferred occupation. The agents are making rational decisions subject to the constraints they face.

[4] In Section 6 we also consider a version of the model with a fixed cost of accessing the wage sector or, equivalently, non-pecuniary benefit of running an own business, see Hamilton (2000) or Hurst and Pugsley (2011).

[5] In Section 6 we also consider an alternative definition, based on the major source of income.

months prior to the survey. About 60% of the business owners are traders (e.g., food vendors) and 33% own a service business (tailor, laundry, restaurant, repair ship, taxi, etc.). Among the non-business households, 93% earn the majority of their annual income from wages.

Key elements of our model (external demand for wage labor, exogenous interest rate) are motivated by our specific application to Thai urban households. Most business owners in our data run small businesses with no paid employees or work for a wage. Most sampled households (91.4%) have access to formal credit and/or savings via commercial banks or government banks and funds. Our analysis thus abstracts from potentially important macroeconomic considerations such as fully accounting for general equilibrium effects in the labor market[6] or in the credit market[7] and our results are not readily generalizable to the whole economy. We also do not model savings and capital accumulation, treating for simplicity the worker and business outcomes as reduced-form versions of expected values from a dynamic model. Within our structural estimation approach, potential endogeneity in the wealth or schooling observables is addressed by using lagged initial wealth or estimating on stratified sub-samples of the data (in particular, younger agents).[8] Fully acknowledging these limitations, we focus on the micro-level estimation and analysis of how credit and labor constraints shape the composition and incomes of voluntary and involuntary entrepreneurs and wage workers in our setting, given their observed characteristics.

We allow the probability of no access to wage work to depend on the agents' labor market skills, proxied by schooling or other observable characteristics. In addition, the probability depends on an endogenous effort in searching for a wage job – the larger is the income differential between wage work and running a business for an individual, the larger is their search effort. In our data, we find that the households with the highest estimated probability of involuntary entrepreneurship are older and have been in their current occupation for longer, compared to the households with low estimated probability of involuntary entrepreneurship. The estimated fraction of involuntary entrepreneurs is also higher among older households when we use sub-samples based on age and experience. Therefore, the labor market frictions which result in involuntary entrepreneurship in our setting appear related to lack of qualifications or to barriers to finding paid work that stem from having been outside the wage sector for a long time, e.g., absence or loss of skills or ties relevant for the wage market.

We estimate the model using the simulated method of moments (SMM), by matching actual and simulated data on occupational choice and income. Our structural approach reveals whether the labor market friction is significant or negligible in our setting and allows us to disentangle its interaction with the credit friction and to quantify occupational and investment misallocations. We estimate the rate of involuntary entrepreneurship and its distribution over initial wealth and years of schooling. We treat entrepreneurial ability as unobserved heterogeneity, potentially correlated with initial wealth and schooling.

At our baseline estimates, 19% of the households in our sample who run businesses are classified as involuntary entrepreneurs, i.e., subject to a binding labor market constraint. The estimated rate of involuntary

[6]Our setting with external demand for wage labor implies that any market friction or counterfactual which raises entrepreneurship also causes the wage rate to increase. If labor demand was endogenous (the entrepreneurs hired the workers) both the labor demand and supply would be affected by the frictions and the effect on the market wage could go in either direction.

[7]If the interest rate was determined endogenously, a stricter credit constraint would imply a lower equilibrium rate making (unconstrained) entrepreneurship more attractive for lower-ability agents, an additional source of misallocation.

[8]The static occupational choice framework is likely to be more restrictive for older agents whose observable characteristics may be outcomes of past decisions or market frictions.

entrepreneurship varies, from as high as 43% to as low as 4%, with the household's observable characteristics – it is decreasing in the principal earner's schooling and in initial wealth. An estimated 40% of the involuntary entrepreneurs in our data are among the households with both initial wealth and schooling below the median. The voluntary entrepreneurs in our sample earn significantly higher yearly income on average (519 thousand Baht) compared to the involuntary entrepreneurs (75 thousand Baht), and the wage workers (165 thousand Baht).[9] The credit constraint is more likely to bind for the voluntary entrepreneurs (41%) than for involuntary entrepreneurs (17%).

In terms of quantifying the role of the labor and credit market frictions for occupational choice and investment, our model evaluated at the SMM estimates suggests that the vast majority of involuntary entrepreneurs in our sample (18.7% of the estimated 19.1%) stem from the labor market friction; the remainder is due to the interaction of both frictions. Relative to the unconstrained optimum, the estimated effect of the credit constraint alone is relatively small – a 0.6% p.p. reduction in the entrepreneurship rate. Our estimates further imply excess entrepreneurship relative to the unconstrained optimum among the households with low schooling, because of the labor market friction. In contrast, entrepreneurship is depressed for the households with high schooling and low initial wealth, because of the credit friction (see Fig. 3). There is significant under-investment among the business households with low initial wealth. For a fixed initial wealth, the investment of voluntary entrepreneurs is more constrained than that of involuntary entrepreneurs.

Eliminating the labor market friction while holding all other model parameters at their SMM estimates is found to lower the fraction of entrepreneurs in our sample from 65% to 55.4% and to reduce the market wage by 9%, as more agents enter the wage sector. The estimated impact on the agents' incomes is heterogeneous – for ex-post workers relaxing the labor market constraint results in lower income on average (because of the lower wage and low-skill previous involuntary entrepreneurs entering wage work), while the incomes of the ex-post entrepreneurs go up on average.

In a counterfactual policy evaluation, we broadly mimic an actual Thai microcredit program (the Million Baht Village Fund program) by allowing all agents in our sample access to a microfinance loan for business investment. Relaxing the credit constraint via microcredit enables larger investment, making running a business more profitable but the estimated impact on the rate of involuntary entrepreneurship in our data is minor – a decrease from our baseline estimate of 19.1% to 18.6% (see Table 13). The microfinance counterfactual is estimated to raise agents' incomes (average increase of 2.2%), with the largest estimated income gains among the low-wealth ex-ante voluntary entrepreneurs.[10]

We assess the role of other observable characteristics not included in our model by estimating the model on different sub-samples of our data stratified by the age or gender of the principal earner. The estimated fraction of involuntary entrepreneurship and the severity of the credit and labor market frictions are lower among the households with younger principal earners or those with less experience in their current occupation. This is consistent with our finding that involuntary entrepreneurs in our setting are more likely to be older and to have been in their current occupation for longer. We also find that the estimated rate of involuntary entrepreneurship is higher in the sub-sample with female principal earner (18% of all businesses) vs. 11.4%

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

[10]We also consider doubling the parameter determining the maximum business investment as fraction of initial wealth from the estimated 35% to 70% which can be interpreted as improvement in loan enforcement or property rights (see Section 4.5).

in the male principal earner sub-sample. The credit and labor market frictions are also estimated as more severe in the female principal earner sample. We also perform sensitivity analysis with alternative definitions for business ownership, labor market characteristics, and different specifications of the labor market constraint (see Section 6).

Our analysis is based 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, the interpretation of some of our results would change. We address this further in Section 6.

Related literature

The observation that entrepreneurs are heterogeneous is well-documented, however, it is often difficult to distinguish 'voluntary' from 'involuntary' businesses in the data.[11] Most of the empirical literature adopts ex-ante criteria based on data availability to define 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 people who started a business after voluntarily quitting a job vs. after losing their job (Block and Wagner, 2010; Fonseca, 2019), informal vs. formal businesses (La Porta and Schleifer, 2014), incorporated vs. unincorporated businesses (Levine and Rubinstein, 2017), or between businesses that existed before vs. after a microcredit intervention (Banerjee et al., 2019).[12] Instead, we characterize voluntary vs. involuntary entrepreneurs in a structural way, as outcome of the interaction between income-maximization and credit and labor market frictions, 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; Buera 2009; Karaivanov 2012; Nguimkeu 2014, among others).[13] Unlike here, a key assumption in these papers is that agents can always freely choose, out of all possible options, the occupation which yields maximum expected income, with credit market imperfections shaping the agents' choices.[14]

Our paper also complements recent research documenting the importance of labor market frictions in developing countries. Poschke (2019) calibrates a search model with heterogeneous firms and finds 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 less productive own-account work. We differ

[11] 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.

[12] 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.

[13] 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.

[14] 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.

in having a less detailed job search model while focusing on quantifying and disentangling the effects of 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).[15]

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'. They also differ in two productive characteristics: $x \in [1, x_{\max}]$ interpreted as labor market skills (qualifications, schooling); and $\theta \in [\theta_{\min}, \theta_{\max}]$ interpreted as entrepreneurial ability.

There are two occupations (technologies). The first occupation, E is an 'entrepreneurship' (business) occupation, which uses capital investment $k > 0$ and yields (expected) output/revenue θk^{α} where $\alpha \in (0, 1)$.[16] 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.[17] 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 $k_u(\theta)$,

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

[15] 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.

[16] Output can be assumed explicitly stochastic as in Evans and Jovanovic (1989) but, because we assume risk neutrality, only its expected value matters. Therefore, without loss of generality, we interpret all revenue or income variables in the model as expected values over stochastic technological or other shocks.

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

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 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

For now we treat the labor market wage w as given. We discuss its 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), each agent always selects 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 depending on the agent's labor market skills, x and an action, e interpreted as job search effort. Formally, an 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 $p(e, x)$ denotes 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 since 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, 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.[18]

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

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. Fig. B1 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 skills x through the direct effect of η and x on the probability $p(e, x)$. On the other hand, agents with lower x would earn lower wage income y^W, which makes wage work less attractive all else equal. 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

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

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

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*$(\mathbf{1}_E = 1|\Delta(\psi, w) < 0) = p^*(\psi, w)$ 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:

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

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

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 one plus 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:

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

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

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 'outside' labor demand 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.[19] 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 defined 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, similar to in Paulson et al., (2006). We back-date household assets to mitigate possible simultaneity between occupational status and current wealth, as the latter could be an outcome of past choices or market frictions. In addition, we also estimate the model on sub-samples of agents who are younger or have less experience, whose observables are less likely to be affected by this potential endogeneity problem. We allow initial wealth z to be correlated with entrepreneurial ability θ and therefore we capture and estimate, in a reduced form, the possibility that higher-ability agents may save more in anticipation of becoming business owners.

We proxy the model variable x interpreted as qualifications or other characteristics determining a person's wage income by the years of schooling of the principal earner in each household.[20] To identify the principal earner we use data on individual occupations and work type within 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 Section 6.

In addition, we 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 incomes as expected values averaging over possible stochastic shocks within the one-year time horizon in the data.

The data sample used in the SMM 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.[21] 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 family-run: 86% of the businesses in our sample did not hire

[19]240 households, 15 per urban community, were randomly selected in each of six target provinces – Buriram, Chachoengsao, Lop Buri, Sisaket, Phrae and Satun. These urban dwellers are more business or commerce oriented; many have modest incomes and are vulnerable to market shocks since they lack access to government assistance which is much more focused on rural areas (Townsend et al., 2013). Full details are available at `cier.uchicago.edu`.

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

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

any paid workers in the prior 12 months and only 5 businesses (0.3% of all) hired more than 10 workers. This motivates our model assumption that the entrepreneurs do not employ the workers (labor demand is exogenous). Among the non-business households, 93% earn the majority of their annual income from wages. Running a business or wage work are the two major sources of income for the sampled 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.

Table 2: Data – 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 presents summary statistics of the main data variables. The business households have statistically significantly larger average wealth and annual gross income than the wage worker households. The income of business households has much larger standard deviation compared to that of wage workers, consistent with substantial heterogeneity among the entrepreneurs. The principal earners in the business households have statistically significantly less schooling, are older, and are less likely to be male, on average. These are characteristics consistent with higher difficulty in obtaining employment in the wage sector.

Table 4 reports the estimates from a probit regression of business ownership (a binary variable equal to one 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 household 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 our modeling of the credit constraint. More schooling is associated with a *lower* observed rate of entrepreneurship, consistent with our assumptions about the labor market friction (the function $p(e, x)$). The households with female or older principal earners and of larger size are more likely to own a business. We view these results as validating our 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 runs using data sub-samples (see Section 6 and Table 14).

Table 3: Data – Summary statistics

	business	wage work	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 1% of the wealth distribution, households with zero income or wealth, and where a principal earner could not be identified. Mean and standard deviation (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% level.

Table 4: Data – Determinants of household business ownership

Dependent variable: owning a business	
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 Results

4.1 Estimation method

Our data is a cross-sectional sample of N households, $i = 1, ..., N$ consisting of 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 structural 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 to 0.5 in our baseline specification and in Section 6 we also do robustness checks using $\beta = 1/3$ and $\beta = 2/3$ which show that our main results are not very sensitive to β.[22]

We estimate the model by minimizing the percentage deviation between eleven model simulated moments and their data analogs. The moments are defined and listed in Table A1 in the Appendix. Their data analogs are obtained from the households' observed occupations E_i and gross incomes, R_i^E (for business households) and y_i^W (for workers) in the data. See Section 4.3 for a detailed discussion on the choice of moments and their role in identifying the structural parameters.

Given parameters ϕ, denote the moment values in the model by $h_j(x, z, \phi)$ for $j = 1, ..., J$ and the respective data analogs by h_j^d. To compute the model simulated moments we draw at random 100 values from the distribution of the entrepreneurial ability random term ε, for each household $i = 1, ...N$ and average over these ε draws.[23] 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 the simulated method of moments (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.[24]

[22]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 $AL^\beta K^\zeta$ (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 $\beta = .57$.

[23]The set of N by 100 epsilon draws is kept fixed across the different simulations for comparability and reproducibility.

[24]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.

4.2 Baseline estimates and 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 – its estimate implies that an increase in years of schooling from 4 (the modal value) 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).[25] For comparison, the median business assets in the data are 19,700 Baht (6.5% of median initial wealth). The labor market friction parameter η is estimated at 25.3. At the modal years of schooling $x = 4$, this implies a 40% average probability that an agent is subject to the labor constraint (see also Figure B1 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, although δ_2 is not statistically significantly different from zero). We note that the credit market friction λ and the labor market friction η are not precisely estimated and have large bootstrap standard errors.[26] We address this further in Section 4.3.

Table 5: SMM Estimates

Parameter		Estimate
business technology parameter	α	0.21 (0.06)
non-business technology parameter	γ	0.83 (0.24)
credit market friction parameter	λ	0.35 (1.10)
labor market friction parameter	η	25.3 (17.6)
labor demand scale	A	2,537 (616)
entrepreneurial skill θ, constant	δ_0	3.33 (0.47)
skill θ, elasticity to initial wealth z	δ_1	0.15 (0.06)
skill θ, elasticity to schooling x	δ_2	0.13 (0.15)
skill θ, standard deviation	σ	0.98 (0.14)

Notes: Bootstrap standard errors in the brackets. We calibrate $r = 1.06$ and $\beta = .5$.

In Table 6 we report model results computed at the SMM estimates. The estimated proportion of involuntary entrepreneurs among all business owners is 19.1%. This number is consistent with the range reported in the GEM surveys discussed in the introduction. The remaining 80.9% of business owners are classified by the model as voluntary entrepreneurs.

The market wage w^* computed at the SMM estimates is 23.5. Reassuringly, this wage value is consistent with the estimates from an auxiliary non-linear least squares (NLLS) regression of observed wage earnings

[25] The parameter λ can also reflect the liquidity or collateralizability of household wealth, as defined here (land, household durables and agricultural assets). A λ estimate less than 1 can be thus interpreted as households not able to completely use their wealth to finance their businesses.

[26] In about 5-7% of the bootstrap runs (drawing with repetition from our sample), the estimation routine reaches extreme values at the bounds of the parameter space which inflates the standard errors. We analyze the sensitivity of our results to these estimates in Section 4.3.

Table 6: SMM Baseline results

Statistic	Value
entrepreneurs, % of all agents	65.0
involuntary entrepreneurs, % of all entrepreneurs	19.1
voluntary entrepreneurs, % of all entrepreneurs	80.9
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
wage, w^*	23.5
credit constrained, % of all entrepreneurs	36.5
credit constrained, % of voluntary entrepreneurs	41.2
credit constrained, % of involuntary entrepreneurs	16.8

Note: we average first over the draws ε for each i, and then over the respective occupation. The income values are the averages of $y^E(\theta, z)$ or $y^W(x, w)$ over the respective agent types.

in our data on years of schooling, x using the functional form $y^W = bx^\gamma$ which yields a b estimate of 23.54 (remember, in our model $y^W = w^* x^\gamma$). The same NLLS regression yields a γ estimate of 0.82 which is also very close to the SMM estimate 0.83 in Table 5.

We compute average income by occupation by first integrating $y^E(\theta, z)$ over the unobserved ability shock ε for the entrepreneurs and then averaging the incomes y^E and y^W across all households of each type (using the values for x_i and z_i, $i = 1, ...N$ from the data). Table 6 shows that the 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 the entrepreneurs in our sample are estimated as credit constrained – their investment λz is less than their unconstrained optimum $k_u(\theta)$. The fraction of credit-constrained agents is relatively large among the voluntary entrepreneurs (41%) and 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 in our data. This implies that, compared to the voluntary entrepreneurs, involuntary entrepreneurs are estimated to be about 78% less entrepreneurially skilled (lower θ) on average; the wage workers are about 80% less skilled.

Table 7 breaks down the estimated distribution of involuntary and voluntary entrepreneurs in our sample by initial wealth, z and years of schooling, x (both taken from the data). The majority of involuntary entrepreneurs (62%) 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 pushing 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 in our data 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 estimated 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.

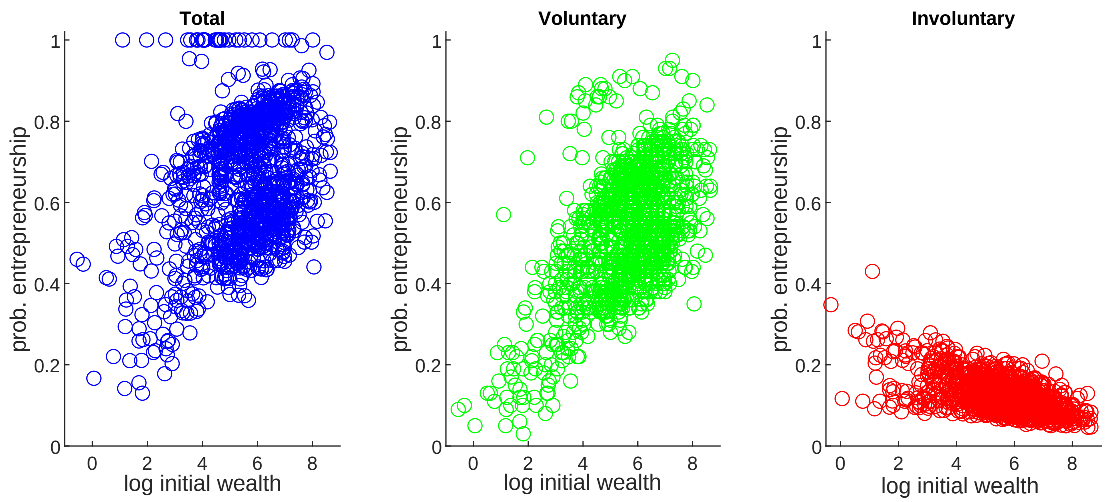
Table 7: Distribution of entrepreneurs by wealth and schooling

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	

The model evaluated at the SMM estimates and the observed household characteristics in our data allow us to describe and compare the businesses which are the most likely to be involuntary (the top quintile of the estimated probability of involuntary entrepreneurship, P_I) or the least likely to be involuntary (bottom quintile). The business households with the highest estimated probability of involuntary entrepreneurship (top quintile) are more likely to be traders, compared to those in the lowest quintile (42% vs. 26%), and less likely to be shop owners (14% vs 27%). The businesses in the top quintile also have significantly lower median business assets (8700 Baht), vs. 39,000 Baht for the lowest quintile, and fewer paid workers on average (0.13 vs. 0.68). Both these differences are statistically significant at the 1% level. In addition, the principal earners in the households in the top quintile of the estimated probability of involuntary entrepreneurship are on average older, more likely to be female, have lower schooling, and have been in their current occupation longer, compared to those in the bottom quintile. These differences are statistically significant at the 1% level for all variables except gender.

While we do not have direct survey or other evidence on the nature of labor market frictions in our data, the above findings suggest that involuntary entrepreneurship in our setting appears related to the lack of qualifications or lack of access to paid work from having been outside the wage sector for a long term. Possible example could be the absence or loss of skills or ties relevant for finding wage work among older 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). Fig. 1 further clarifies how our model, by allowing for labor market frictions, differs from the standard income-maximization occupational choice models. The left panel 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 lower dispersion (the middle panel). We conclude that the positive relationship between initial wealth and entrepreneurship symptomatic of credit constraints is weakened by the estimated negative relationship between initial wealth and involuntary entrepreneurship (the right panel of Fig. 1). This emphasizes the importance of accounting for both credit and labor market frictions in the data.

4.3 Identification and model fit

The first seven moments which we use in the model estimation ($j = 1, ...7$ in Table A1) correspond to the expected rate (percent) of entrepreneurship in different data subsets $\{x_s \in X, z_s \in Z\}$ based on the observables x and z – overall and by x and z tercile. We chose these moments to fit the occupational choice pattern in our data given the agents' observable characteristics.[27] Targeting the entrepreneurship rate among the richer households (top z tercile) with schooling x in the top tercile (moment 7 in Table A1) 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 in Table A1) is informative about the labor constraint parameter η since 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 (the bottom tercile vs. the rest) is informative of the credit

[27]Since the distribution of observables is fixed in the data, other 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, etc.

constraint parameter λ.

The remaining four moments used in the estimation ($j = 8, .., 11$ in Table A1) correspond to the average gross business revenue and wage earnings in our sample and the gross business revenue for initial wealth below the median ($j = 10$) or schooling below the median ($j = 11$).[28] Because of the fixed distribution of the observables, this also implies matching other moments (e.g., gross revenue of the entrepreneurs with wealth above the median). Matching gross earnings in each occupation is important for identifying the business technology and wage earnings parameters α and γ.

The impact of the labor and credit market frictions can be disentangled by comparing the probability of entrepreneurship between low-wealth and low-schooling households (affected by both frictions) vs. low-wealth and high-schooling households (mostly affected by the credit friction) vs. high-wealth and low-schooling households (mostly affected by the labor friction).

In Table 8 we assess the fit between the data and the model evaluated at the SMM estimates for each moment. The occupational choice moments based on the entrepreneurship rate in different stratifications (lines 1-7) are all within 5% deviation of their data analogs. The income moments (8-11) are matched very closely, to within 0.3% of their data analogs.

In the last four columns of Table 8 we also investigate the role of the market friction parameters, λ and η for the model's fit with the data. In addition, these parameters were estimated with relatively large standard errors (see Table 5) and hence we evaluate the sensitivity of our results with respect to their values. We hold all other parameters fixed at their SMM estimates and vary either the credit friction parameter λ or the labor friction parameter η to one half or two times its SMM estimate, observing how the moment values change. When varying λ (columns 5 and 6 in Table 8), the following moments are the most sensitive: % 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 for pinning down λ. Varying η (columns 7 and 8 in Table 8) affects the fit of almost all targets, with some of the occupational moments being especially sensitive: % entrepreneurs with z in the bottom 1/3, % entrepreneurs with x in the bottom 1/3, and % entrepreneurs with z and x in the bottom 1/3. These results are consistent with the earlier theoretical discussion about how the parameters λ and η affect the agents' occupational choices and incomes.

We also evaluate the sensitivity of our results by computing 10-90 percentile confidence bands around the targeted moments, see Table A3 in the Appendix. Specifically we use the bootstrap sample draws (with repetition) from our data which were used to compute the standard errors in Table 5 and report a confidence band around each moment, constructed based on the range of its simulated values across the bootstrap samples. Most of the bands in Table A3 are relatively narrow, with the exception of the lower bounds for the % entrepreneurs with x in the top 1/3 and the % entrepreneurs with z and x in the top 1/3. The estimated rate of involuntary entrepreneurship (the last row of Table A3) is however more sensitive to the bootstrap sample draws and ranges from 8.8% to 26.2%, with our baseline estimate near the mid-point of this range.

In Tables 9 and 10 we further assess the model fit by stratifying over the observables in our data, initial

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

Table 8: Model fit and sensitivity

	model fit at SMM estimates			alternative parameter values			
moment	data	model	% deviation	$\lambda = 2\lambda^{\text{SMM}}$	$\lambda = .5\lambda^{\text{SMM}}$	$\eta = 2\eta^{\text{SMM}}$	$\eta = .5\eta^{\text{SMM}}$
% entrepreneurs	66.1	65.0	-1.7	65.2	64.6	68.3	62.4
% entrepreneurs with x in bottom 1/3	79.5	79.2	-0.4	79.3	79.0	83.4	75.9
% entrepreneurs with z in bottom 1/3	58.9	59.2	0.4	60.0	57.8	63.4	55.9
% entrepreneurs with x in top 1/3	52.1	50.6	-2.8	50.9	50.2	52.8	49.0
% entrepreneurs with z in top 1/3	71.9	69.2	-3.9	69.1	69.3	71.6	67.3
% entrepreneurs with z and x in bottom 1/3	72.5	74.2	2.4	74.7	73.4	79.3	70.2
% entrepreneurs with z and x in top 1/3	54.3	57.0	4.9	56.9	57.1	58.8	55.6
mean output – entrepreneurs, R^E	513.6	512.3	-0.3	547	469	491	530
mean earnings – workers, y^W	164.7	164.6	-0.0	165	164	175	158
mean output, entr. with $z <$ median	350.3	350.2	-0.0	389	309	335	363
mean output, entr. with $x <$ median	385.7	386.4	0.2	410	355	371	399

Note: The 'model' column contains the moment values computed at the SMM estimates from Table 5. In the last four columns a single parameter, λ or η, is varied to either half or double its SMM estimate, holding all other parameters fixed at their SMM estimates. Business output R^E and wage earnings y^W are measured in '000 Baht.

wealth z and schooling x. Table 9 shows that the model matches well the observed fraction of entrepreneurs in each tercile cell (the largest deviations, of about 10%, are observed for medium schooling and medium or high wealth). The fit by z tercile alone (the last row) or by x tercile (the last column) is within 2%. We conclude that our targets achieve good fit with the observed rates of entrepreneurship in the data conditional on observables at the tercile level of aggregation.

Table 9: 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.

In Table 10 we compare the average estimated vs. actual business output (revenue), R^E stratifying over the observables. The estimated model fits the data well overall and for x or z separately. The model results are less close to the data (up to 12% deviation) in matching business output R^E for the households with wealth and schooling both below or both above the median. The estimated model over-predicts the dispersion of business revenue over wealth for schooling below the median (compare the x_L row in the model vs. data tables) and under-predicts the revenue dispersion over wealth for schooling above the median.

Finally, on Fig. 2 we plot lowess regression lines and confidence intervals for the the rate of entrepreneurship in the estimated model vs. the data. The model matches well the overall level and slope in the data, both with respect to initial wealth and schooling. It under-predicts entrepreneurship for very low levels of wealth

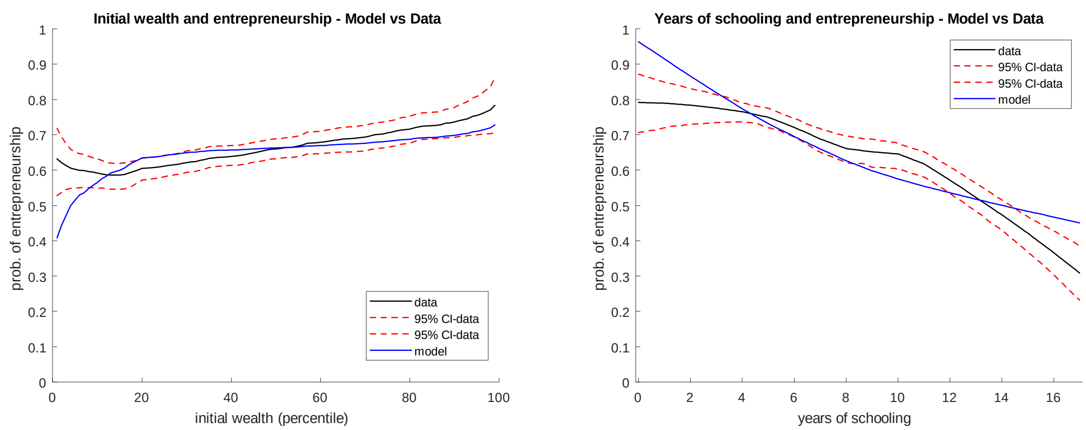
Table 10: Business output R^E by initial wealth z and years of schooling x

	Model ('000 Baht)				Data ('000 Baht)		
	z_L	z_H	all z		z_L	z_H	all z
x_L	295	495	386*	x_L	335	441	386
x_H	462	797	667	x_H	378	858	681
all x	350*	640	512*	all x	350	651	514

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

(the bottom 10%) and over-predict entrepreneurship for low and high levels of schooling.[29]

Figure 2. Rate of entrepreneurship, lowess fit



4.4 Market frictions and misallocations

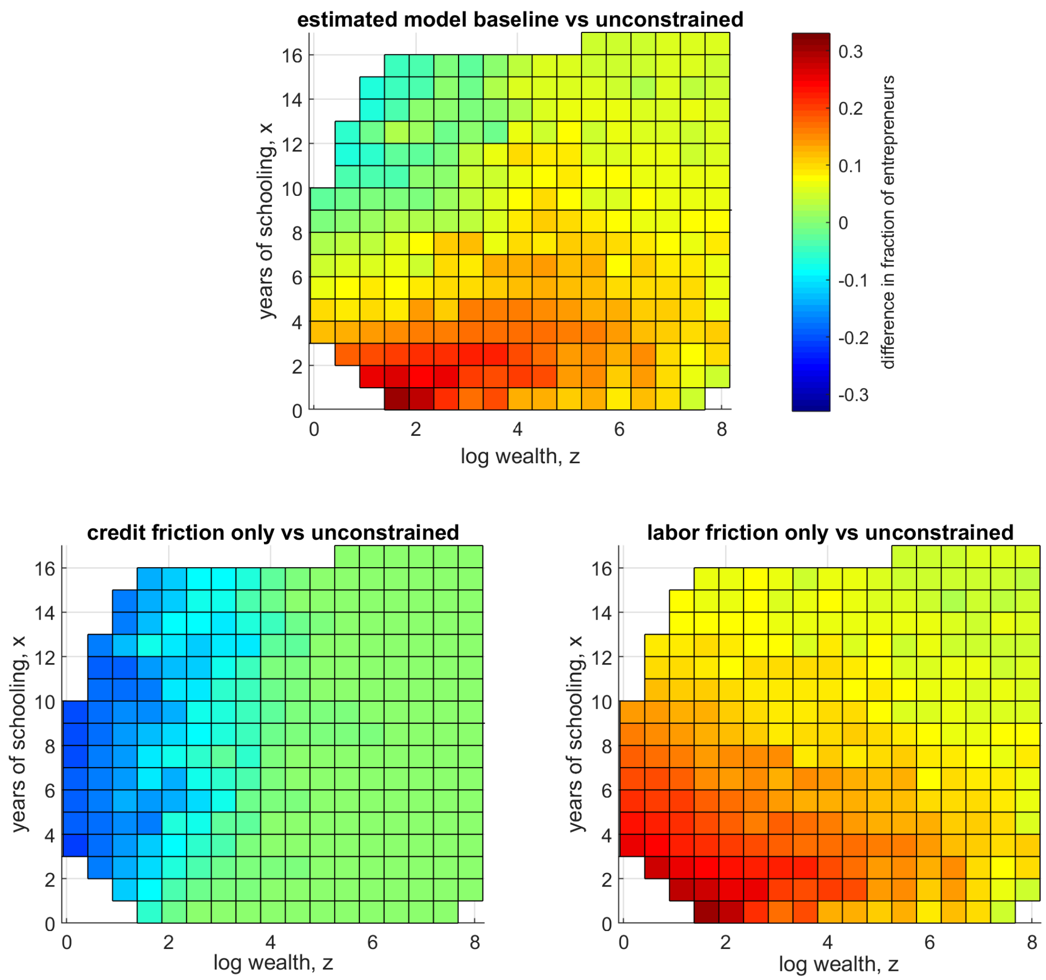
We next use the model evaluated at our SMM estimates to assess the effects of the labor and credit market frictions in our setting, relative to the unconstrained benchmark with $\eta = 0$ (no labor friction) and $\lambda \to +\infty$ (no credit friction; 10^8 used in the computation), while keeping all other parameters fixed at their estimates. There are two main allocation decisions in the model. First, households differing in their initial wealth z, entrepreneurial ability θ and labor market characteristics x allocate across the two occupations. Second, capital k is chosen by the households who run businesses. The labor and credit market frictions may cause misallocations in both these dimensions. On the extensive margin (occupational choice), a household may end up in a suboptimal occupation relative to the unconstrained optimum. This can be expressed either as involuntary entrepreneurship, arising 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 credit constraint and make inefficiently low investment k relative to the unconstrained level $k_u(\theta)$. In addition, all capital used by

[29] 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. 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.

involuntary entrepreneurs is misallocated.

We first show the estimated incidence of misallocations across households with different observables in our sample – initial wealth z and schooling, x. We then disentangle the contributions of the labor market and the credit market frictions. Involuntary entrepreneurship arises in our model if both of the following conditions hold: (i) an agent does not have access to wage work and (ii) the agent's income is larger in the wage occupation. The labor market friction is important for (i), while the credit constraint affects (ii).

Figure 3. Effect of market frictions on occupational choice



Note: warmer colors (red, orange, yellow) correspond to values larger than the unconstrained setting; colder colors (cyan, blue) correspond to values smaller than the unconstrained setting.

Fig. 3, the top panel ("estimated model vs unconstrained") plots the differences between the estimated probability of entrepreneurship in our model with both labor and credit frictions (using the estimates in Table 5) and the unconstrained setting ($\eta = 0$, $\lambda \to +\infty$) across the sampled households. Warm colors (red, orange, yellow) show more predicted entrepreneurs relative to the unconstrained benchmark, while cool colors (blue, cyan) show less entrepreneurs relative to the unconstrained benchmark. In absence of misallocations all differences between the model and the unconstrained optimum would be zero (depicted in green). We see, however, that the labor and credit frictions cause over-supply of entrepreneurs among some households in the data and under-supply among others. Specifically, for low schooling, the model-predicted rate of entrepreneurship is higher (by up to 30 percentage points) than that in the unconstrained benchmark. The reason is involuntary entrepreneurship, since the labor market constraint is more likely to bind for low schooling. The differences are the largest at low wealth (the bottom left corner), where the involuntary entrepreneurship effect is amplified by a tighter credit constraint. In contrast, for the households with high schooling and low wealth in our sample (the top left corner), the model predicts *less* entrepreneurship (by up to 10 percentage points) than there would be in the unconstrained setting – the reason is the credit constraint. For agents with 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 wage w^*. We analyze this equilibrium effect further in Section 4.5.

The bottom panels of Fig. 3 disentangle the effects of the labor and credit frictions by decomposing the total difference in the rate of entrepreneurship between the estimated model and the unconstrained benchmark. In the bottom left panel ("credit friction only vs. unconstrained") we set $\eta = 0$ (no labor market friction) and keep the credit friction parameter λ and all other parameters at their SMM estimates. This eliminates involuntary entrepreneurship. The result is a (weakly) lower rate of entrepreneurship compared to the unconstrained optimum for all z and x, 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 the low-wealth households in our sample and obviously has no effect on the 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 positively correlated with x.

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

Adding up over all households in our sample further reveals that the main cause of excess entrepreneurship (estimated 19.1% involuntary entrepreneurs) is the labor market friction, which accounts for 18.7% of this total – see columns (1) and (3) in Table 11. On the other hand, the fraction of missing voluntary entrepreneurs because of the credit constraint is estimated as small – 0.6% of all households (56% in column 4 (unconstrained) minus 55.4% in column 2 of Table 11).

We also analyze the effect of the labor and credit market frictions on business investment. Fig. 4 illustrates investment in the estimated model relative to the unconstrained level, for given observed initial wealth and schooling in our data. We plot the ratio (integrated over θ) of actual investment k to the unconstrained level $k_u(\theta)$ for voluntary and involuntary entrepreneurs. For both types, underinvestment is most severe for low-wealth households as expected. For the same wealth level, underinvestment by the voluntary entrepreneurs is, however, larger than that of the involuntary entrepreneurs. The reason is that the voluntary entrepreneurs have higher estimated ability θ on average and hence larger investment needs $k_u(\theta)$.

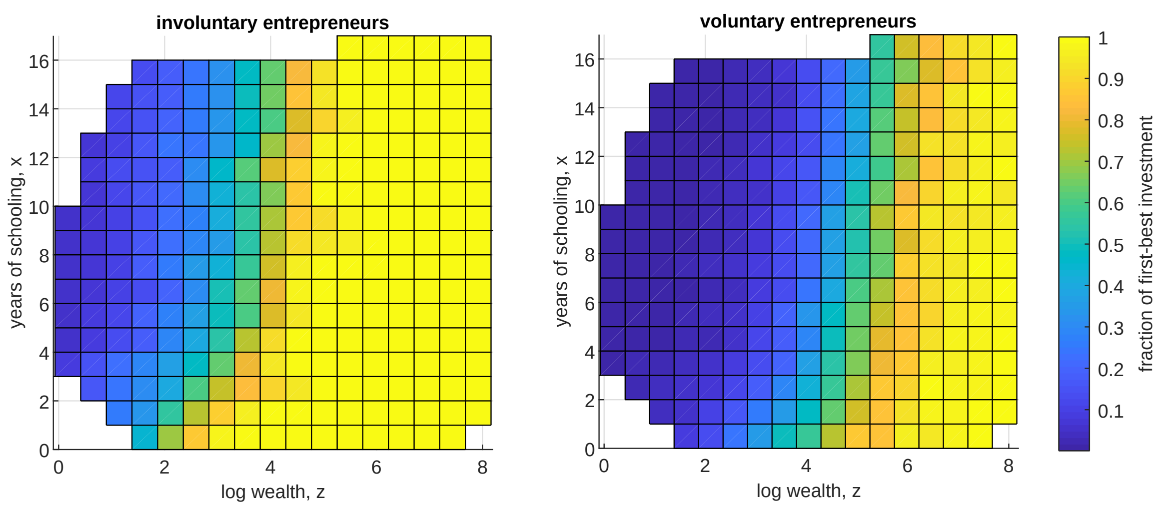
Table 11: Effects of the market frictions on entrepreneurship

	(1) baseline	(2) credit friction only	(3) labor friction only	(4) unconstrained
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

Notes: "baseline" is the estimated model with both credit and labor market frictions using the SMM estimates in Table 5; "credit friction only" sets $\eta = 0$ keeping all other parameters as in Table 5; "labor friction only" sets $\lambda = 10^8$ keeping all other parameters as in Table 5; "unconstrained" sets $\eta = 0$ and $\lambda = 10^8$ keeping all other parameters as in Table 5.

Adding over all households in our data shows that in the estimated model with both frictions the entrepreneurs invest 61.2% of the unconstrained level in total (see Appendix Table A2). Out of total 2.7% is used by involuntary entrepreneurs – a misallocation. The credit friction alone (Table A2, column 2) reduces investment to 59.6% of the unconstrained benchmark while the labor friction alone (column 3) results in over-investment by 1.7%, because of the capital use by involuntary entrepreneurs.

Figure 4. Effect of market frictions on investment



Note: warmer colors correspond to values larger than in the unconstrained setting; colder colors correspond to values smaller than in the unconstrained setting.

4.5 Income effects of relaxing the labor and credit market frictions

We next analyze the impact of the labor and credit market frictions on household income. Since we assume risk-neutrality, changes in household income from relaxing the frictions in our model can also be interpreted as welfare effects. In addition, we isolate the effects from the endogenous change in the market wage w^*, compared to holding the wage fixed at its baseline level.

We first consider relaxing the labor friction by setting $\eta = 0$ in (7) while keeping all other parameters at their SMM estimates (see Table 12, 'no labor friction'). This affects agents' incomes, e.g., since previously involuntary entrepreneurs enter the wage occupation and there is also an equilibrium effect from the change in the wage (compare the 'fixed wage' and 'equil. wage' columns in Table 12). Ex-ante voluntary entrepreneurs are not directly affected by eliminating the labor friction, however, their ex-post occupational choice can be affected by the change in the wage.

Table 12: Relaxing the labor and credit market frictions

	baseline	relaxed labor friction		relaxed credit friction	
		fixed wage	equil. wage	fixed wage	equil. wage
	(1)	(2)	(3)	(4)	(5)
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%
wage, w^*	23.47	*23.47*	21.39	*23.47*	23.54

Notes: column 'baseline' displays the model results at the SMM estimates from Table 5; columns 'relaxed labor friction' set $\eta = 0$ holding all other parameters at the SMM estimates; columns 'relaxed credit friction' set $\lambda = 2\lambda^{\text{SMM}}$ holding all other parameters at the SMM estimates; columns 'fixed wage' fix the wage w^* at the value from Table T6; columns 'equil. wage' recompute the market wage w^*.

Eliminating the labor market friction is estimated to significantly reduce the rate of entrepreneurship in our sample from 65% to 55.4% (Table 12, part A). If the wage w were fixed at its baseline estimated value, the fall in the entrepreneurship rate would have been even larger, to 52.6%, however, this effect is partially offset by the decrease in w^* from 23.5 to 21.4 thousand Baht.

In Table 12 part B we report the mean and percentiles of household income (as defined in Table 6 and the surrounding discussion) and the resulting income changes from relaxing the labor friction. The estimated average effect on income is small (0.1% increase in mean income), as the income gains for the agents who can access wage work after relaxing the labor market constraint are offset by the lower wage.[30]

Relaxing the labor market friction (setting $\eta = 0$) also triggers compositional changes across the sample. The estimated average entrepreneurial income goes up by 15.1% relative to the baseline – a significant increase caused by the exit of involuntary entrepreneurs. The average income of voluntary entrepreneurs, however, is 3.8% lower than in the baseline since some lower-ability agents become entrepreneurs when $\eta = 0$ because

[30]The mean income increase would have been larger (+2%), if the wage w were fixed, see column (2).

of the lower wage (compare columns 1, 2 and 3). The mean income of workers falls significantly, by 13.8%. This is is mainly caused by the decrease in the market wage and partly a compositional effect, as some ex-ante unproductive involuntary entrepreneurs become workers (compare with the 'fixed wage' column).[31]

We next analyze relaxing the credit friction, by doubling the estimated value of λ from 0.35 to 0.7, keeping all other parameters at their SMM estimates (see Table 12, columns 4 and 5). This could be interpreted as improvement in credit enforcement or property rights. Given the ample evidence for credit constraints in developing countries we consider doubling λ more informative than completely eliminating the credit friction. In theory easier access to credit may reduce involuntary entrepreneurship if ex-ante constrained agents can borrow more, earn higher income and prefer to run a business. This effect, however, can be offset by the labor market friction. Indeed, our simulations in Table 12 show that relaxing the credit constraint by doubling λ has only minor effect on the estimated rate of involuntary entrepreneurship in our sample (a decrease from 19.1% to 18.9%) and entrepreneurship overall (an increase from 65.0% to 65.2%). This reinforces our conclusion that labor market frictions are the main cause of involuntary entrepreneurship in our setting.

Relaxing the credit constraint (Table 12, columns 4 and 5) affects agent incomes in our setting by mitigating under-investment. Since the estimated impact on the market wage is minimal, there is no strong offsetting equilibrium effect, unlike in columns 2 and 3. The estimated increase in mean income from relaxing the credit friction is 3.5%. Households at the 10th income percentile experience the largest income gains (+7.7%), as they can invest amounts closer to their unconstrained optima. 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 in our data would obtain only minor income gains, the former since they are constrained by ability, the latter because of the small compositional shift towards entrepreneurship.

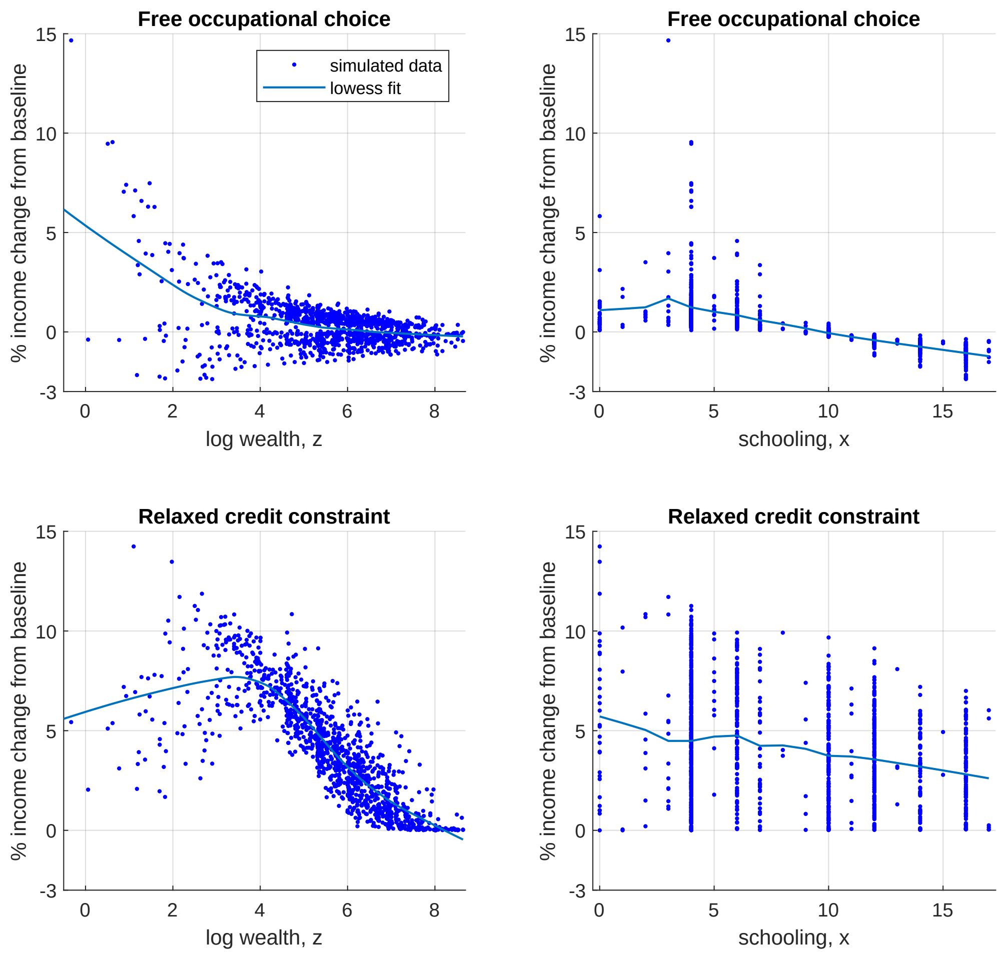
On Fig. 5 we use simulated data from the model at the SMM estimates to further assess the impact of relaxing the labor and credit market frictions on agents' income by conditioning on years of schooling x_i and initial wealth z_i in our data. That is, we quantify the effects for different households – e.g., low-wealth vs. high-wealth, low-schooling vs. high schooling. Since the income distribution percentiles in Table 12 shift ex-ante vs. ex-post when we relax the constraints, the assessment of the income effects on Fig. 5 helps clarify the magnitude and incidence of income gains or losses for given household characteristics.

Relaxing the labor friction (Fig. 5, top panels) is estimated to yield income gains of up to 10% for some low-wealth households in our sample who become able to access their income-maximizing occupation W. For others, however, the decrease in the market wage w^* causes an income decrease of up to 3%.[32] On average, the income gains from eliminating the labor market friction diminish in initial wealth z, see the 'lowess fit' line. The income gains also mostly decrease in the years of schooling x, except for the agents with very low schooling. The reason is that households are less likely to be involuntary entrepreneurs for high x. In contrast, the income gains from relaxing the credit constraint (Fig. 5, bottom panels) are non-monotonic in the agents' initial wealth z – the intermediate-wealth agents gain the most as they are most likely to be credit-constrained entrepreneurs. The income gains from relaxing the credit constraint decline in schooling x on average, since

[31] Changes also occur within the income distribution, e.g., some ex-ante involuntary entrepreneurs who can access wage work when the labor constraint is relaxed, move to higher income percentiles. Removing the labor friction has strongest effect on the 10th income percentile (1.4% increase) at which many households are likely to be involuntary entrepreneurs in the baseline.

[32] If the wage were held fixed, all agents would experience income gains by construction.

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



the households with larger x are also more likely to have higher ability θ and are less likely to be credit constrained.

As an additional illustration of the impact of the labor and credit frictions in our setting, we also simulated (at the SMM estimates) an increase in the wage labor demand.[33] Specifically, we raise the parameter A (see Section 2.4) by 10% holding all other model parameters at their SMM estimates. The results are reported in Appendix Table A4. Naturally, the increase in labor demand results in a higher wage, lower rate of entrepreneurship, and higher incomes. Interestingly, the estimated rate of involuntary entrepreneurship goes up to 19.7%, as the higher wage attracts more agents toward wage work, however, because of the still present labor market friction, sufficiently many agents are unsuccessful in securing jobs, despite the increased demand. This suggests that programs aiming to stimulate labor demand may need to be complemented by policies directly addressing existing labor market frictions.

[33]For example, such increase could be result of a job creation or urban development program.

5 Microfinance

We simulate and evaluate a policy counterfactual in which we offer the households in our sample the option to borrow and invest in their business up to additional M Baht. This can be interpreted as a microfinance program,[34] with the requirement that the loan is used to buy or rent business capital at the interest rate r. We analyze the effects of this policy on the rate of entrepreneurship and household incomes in our setting. We set the maximum microfinance loan to $M = 20,000$ Baht (about 10% of the average gross income in our data) which is calibrated to equal the maximum loan size (applicable for 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 13: Microfinance counterfactual

	(1) baseline	(2) microfinance
A. % entrepreneurs	65.0%	65.5%
of which voluntary	80.9%	81.4%
of which involuntary	19.1%	18.6%
B. income		income change
mean, all	339	+2.2%
10th percentile	186	+10.5%
30th percentile	266	+3.4%
median	327	+1.8%
70th percentile	392	+1.2%
90th percentile	506	+0.4%
mean, entrepreneurs	434	+2.1%
mean, voluntary entr.	519	+1.6%
mean, involuntary entr.	75	+0.6%
mean, workers	165	+0.1%
wage, w^*	23.5	23.6

Table 13 shows the estimated impact of the microfinance program on occupational choice and household income in our setting. All reported values in the "microfinance" column include the equilibrium effects from the change in wage, although these effects are relatively minor (this is similar to the results in the 'relaxed credit' columns of Table 12). The entrepreneurship rate only goes up by half percentage point, from 65% to 65.5%. Within this larger number of businesses, the microcredit policy induces more voluntary entrepreneurship (+0.5%), while the fraction of involuntary entrepreneurs falls from 19.1% to 18.6%. These results are

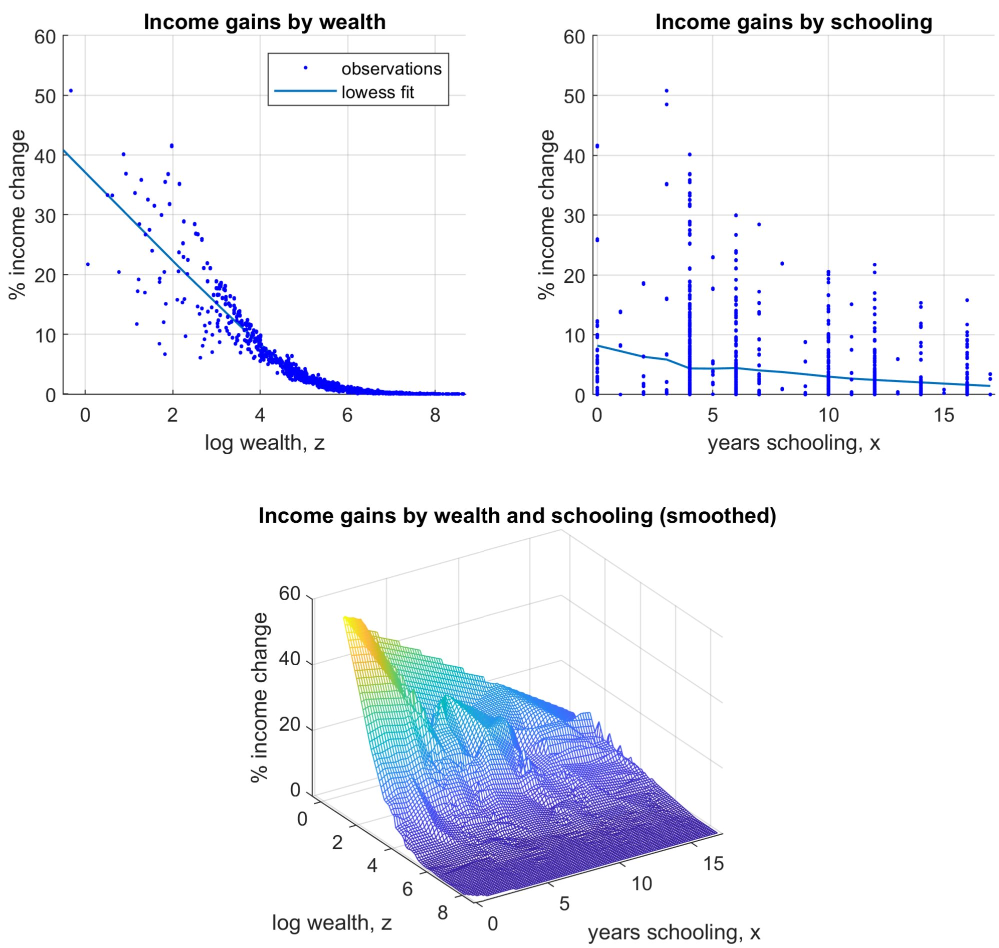
[34] In our data over 80% of the households report being members of the Thai Million Baht village fund.

consistent with the relatively small occupational effects from relaxing the credit constraint seen in Table 12.

The microfinance counterfactual is estimated to raise average income by 2.2% but the income gains are uneven across the income distribution. The poorest households in our data, at the 10-th income percentile, would 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, would benefit only slightly (+0.4%), as they are more likely to be unconstrained ex-ante.

The mean income of entrepreneurs is estimated to increase by 2.1% for two reasons. First, the additional microfinance 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 income goes up slightly (+0.1%) as some ex-ante constrained agents with low skills x exit wage work and since the market wage rate goes up slightly.

Figure 6. Microfinance counterfactual, income gains



The income effects of the microfinance policy are further illustrated on Fig. 6 where we stratify the agents in our data by initial wealth and years of schooling. The dots represent the estimated income change for each household with characteristics (z_i, x_i) from the data. The microfinance policy benefits the 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 smaller on average (less than 10%) and more evenly spread by years of schooling (the top right panel). Considering wealth and schooling jointly, the bottom panel of Fig. 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 gain from access to microfinance.

The main difference between the results of the microfinance counterfactual (Table 13, column 2) and the counterfactual of relaxing the credit constraint by doubling the credit constraint parameter λ (Table 12) is that in the microfinance counterfactual the income gains are monotonically decreasing in household wealth – compare Fig. 5 and 6. The reason is that under the microfinance policy poorer (low z) households 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, if the credit constraint is relaxed by increasing λ (for example, better enforcement or better property rights enabling posting more collateral) the effect is non-monotonic, as explained earlier.

6 Robustness and sensitivity analysis

6.1 Sub-samples by age

To address the concern that household wealth (5 years prior to the survey) or labor skills may be potentially dependent on past occupational or investment choices, we estimate the model on sub-samples of younger and/or less experienced households. We stratify our data by age and/or experience of the principal earner, and present the results in Table 14, columns (2)–(5). Comparing column (2), households with principal earners with age below the median, with column (5), principal earners with age above the median, we find that the estimated fraction of involuntary entrepreneurship and the severity of the credit and labor market frictions (the estimates of λ and η) are lower among households with younger principal earners. We also estimate a lower fraction of involuntary businesses compared to the baseline in the sub-sample with principal earners with no more than 5 years of experience in their current occupation (Table 14, column 3), and in the sub-sample with principal earners with experience $\leq$ 5 years and age lower than the median (column 4). These results are consistent with our findings in Section 4.2 that the involuntary entrepreneurs in our setting are more likely to be older and to have been in their current occupation for longer.

6.2 Sub-samples by gender

In Table 14, columns (6)–(7) we stratify the data by gender of the principal earner. We see that the estimated rate of involuntary businesses is significantly lower in the sub-sample with male principal earner (11.4% of all businesses), compared to 18% in the female principal earner sample. The credit friction is estimated as more severe in the female principal earner sub-sample (the λ estimate is smaller). The labor market constraint is also tighter (the estimate for η is larger) for the households with female principal earners. These results, 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.

Table 14: Robustness and alternative specifications

	baseline		by age			by gender	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
technology parameter, α	0.21	0.27	0.21	0.24	0.39	0.25	0.18
technology parameter, γ	0.83	1.12	1.42	1.42	0.62	1.15	0.83
credit market friction, λ	0.35	0.41	0.76	1.75	0.27	0.30	0.23
labor market friction, η	25.3	1.6	6.0	2.1	58.9	7.7	26.4
labor demand, A	2537	1370	537	500	2202	1347	1561
talent – constant, δ_0	3.33	2.62	3.16	2.77	4.08	2.86	3.67
talent – wealth, δ_1	0.15	0.16	0.11	0.13	-0.06	0.16	0.12
talent – schooling, δ_2	0.13	0.26	0.15	0.26	0.10	0.27	0.12
talent – std. deviation, σ	0.99	0.97	1.01	0.85	0.71	1.03	0.93
entrepreneurs, % of all	65.0	50.1	57.2	49.6	74.9	60.3	69.2
involuntary, % of entrepreneurs	19.1	6.6	11.7	7.8	24.5	11.4	18.0

Notes: (1) baseline, from Table 5; (2) sub-sample, principal earner with age below median; (3) sub-sample, principal earner with ≤ 5 years experience in current occupation; (4) sub-sample, principal earner with age below median and ≤ 5 years of experience in current occupation; (5) sub-sample, principal earner with age above median; (6) sub-sample, male principal earner; (7) sub-sample, female principal earner.

6.3 Alternative definitions

We also study the sensitivity of our results to the definitions of business ownership and labor market characteristics x. Column (2) in Table 15 reports the SMM 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 data is 50% (compared to 65% in the baseline) and the estimated rate of involuntary entrepreneurship, 22% is slightly higher than the baseline.

In column (3) of Table 15 we use 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 fraction of involuntary entrepreneurship is estimated as 17.3%. In column (4) of Table 15, we alternatively define labor market characteristics, x as a composite index of schooling and age, instead of only years of schooling.[35] 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. Our baseline estimate of 19.1% is at the mid-point of the range 16.2%–22.1% found in Table 15, columns (2)-(4).

[35] Specifically, we perform 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%.

Table 15: Robustness and alternative specifications (continued)

	baseline	alt. definitions			alt. specifications		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
technology parameter, α	0.21	0.29	0.36	0.20	0.19	0.20	0.21
technology parameter, γ	0.83	0.60	0.00	0.98	0.79	0.73	0.78
credit market friction, λ	0.35	0.18	0.22	0.55	0.15	0.46	0.36
labor market friction, η	25.3	17.1	16.9	23.4	n.a.	n.a.	n.a.
labor demand, A	2537	4880	6744	1870	2646	2843	n.a.
talent – constant, δ_0	3.33	3.59	3.74	3.61	3.38	3.23	3.35
talent – wealth, δ_1	0.15	0.02	-0.02	0.16	0.15	0.18	0.16
talent – schooling, δ_2	0.13	0.17	0.25	0.00	0.15	0.15	0.15
talent – std. deviation, σ	0.99	1.10	0.76	0.99	1.10	0.95	0.93
entry cost, c					47.4		
labor market friction, υ						0.44	0.38
wage parameter, μ							26.0
entrepreneurs, % of all	65.0	49.7	64.9	64.3	65.0	65.3	65.4
involuntary, % of entrepreneurs	19.1	22.1	17.3	16.2	20.8	18.3	15.1

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) specification with fixed entry cost; (6) specification without search effort; (7) specification without search effort and exogenous wage, $y^W = \mu x^\gamma$.

6.4 Alternative specifications

We consider three alternative specifications for the labor market friction in columns (5)–(7) in Table 15.

Entry cost. In our baseline model an agent faces an endogenous probability $p^*(\psi, w)$ of not being able to access a wage job. Suppose instead that the agent must pay a fixed entry 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 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' specification for the labor market friction are reported in column (5) of Table 15. Reassuringly, the estimates of the nine common parameters are close to those in the baseline model. The parameter c is estimated to be positive, $c = 47.4$. This can be interpreted as a *cost* of accessing wage work equivalent to 47,400 Baht, which is relatively large, about 30% of the average income of non-business households in our 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 entry cost), holding all other parameters fixed at their SMM estimates. The estimated rate of involuntary entrepreneurship is 21%, which is a bit larger than the 19.1% in the baseline model. A possible reason is that the entry cost specification assumes that the labor market friction is uniform across all households.

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 business income y^E plus an additional benefit c exceeds her wage income y^W. However, we consider our preferred interpretation of $c > 0$ as wage-work *entry cost* or friction as more plausible in our 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 sector depends only on the agent skills x and there is no job search effort. Specifically, suppose the probability of no access to the W occupation is

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

where $x_{\max}$ is the largest observed value of x in the data (years of schooling). The interpretation is that agents with larger values of x are less likely to be constrained. The parameter υ controls the tightness of the labor friction, with $\upsilon = 0$ corresponding to unconstrained choice. We show results from estimating two versions of this specification in Table 15 column (6) (with endogenous wage, as in the baseline model) and column (7) (with fixed wage μ which is estimated). The parameter estimates and rate of involuntary entrepreneurship are close to those in the baseline specification.

Alternative β. We also ran the SMM estimation for alternative values of β – the capital share parameter in the wage sector which was calibrated at .5 in the baseline (see Section 2.4). Setting $\beta = 1/3$ yields estimated rate of involuntary entrepreneurship 18.8% while for $\beta = 2/3$ it is 17.8%. These results and also the values of the targeted moments are very close to the results from our baseline specification with $\beta = .5$. We conclude that our main results are not very sensitive to varying β within a reasonable range of values.

7 Conclusions

We model and empirically evaluate the idea that some observed occupational choices can be ‘involuntary’, in the sense of being severely constrained, in a developing country context. We structurally estimate a model which allows the possibility that some agents do not have access to wage employment, nesting as a special case standard models of income-maximizing occupational choice between wage work and entrepreneurship. 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 business owners in our 2005 Thai urban data sample are involuntary entrepreneurs, with additional robustness runs yielding a range from as low as 7% to as high as 25%, depending on the data stratification, model specification, or variables definitions used.

We use the estimated model to quantify the magnitude and distribution of occupational and investment misallocations across households with different observable characteristics in our setting. We find sizable 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 wage rate.

We quantify the effects of relaxing the credit and labor frictions and simulate the impact of a microfinance program on the rate of entrepreneurship (voluntary and involuntary) and on household income, on average and conditional on the agents' wealth and years of schooling. Our results suggest that there are sizable potential income gains, especially for the poorer households in our sample, from reducing the labor or credit frictions and from 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 which can be addressed by alleviating labor market frictions. Our results suggest that a combination of labor policies that reduce these frictions (see, for example 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 the occupational misallocations, while also increasing the incomes of involuntary entrepreneurs.

A limitation of our approach, also present in much of the previous occupational choice literature, is that we abstract from 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 and occupational transitions over time, e.g., Buera (2009). While we partially incorporate an equilibrium effect from wage adjustment through changes in the labor supply, the labor demand and the interest rate were assumed exogenous, as in a small open economy, motivated by our urban household setting and data. A more extensive macroeconomic analysis including general equilibrium effects in the credit and labor markets, e.g., as in Kaboski and Townsend (2011) or Buera, Kaboski and Shin (2020) would 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 A1: 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 revenue R^E, 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 wage earnings y^W, 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 revenue, 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 revenue, 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, x_m = median x; z = initial wealth; z_m = median z; $x \leq x_{t1}$ – bottom tercile of years of schooling; $z \leq z_{t1}$ – bottom tercile of initial wealth; $x > x_{t3}$ – top tercile of schooling; $z > z_{t_3}$ – top tercile of initial wealth; $z \leq z_m$. The estimated parameters are: $\alpha, \lambda, \gamma, \eta, \mu, \delta_0, \delta_1, \delta_2$ and σ.

Table A2: Market frictions and investment

	(1) baseline	(2) credit friction only	(3) labor friction only	(4) unconstrained
investment by all entr.	61.2	59.6	101.7	100
investment by vol. entr.	58.5	59.6	98.7	100
investment by invol. entr.	2.7	0	3.0	0

Notes: We normalize total investment (capital used) in the unconstrained setting to 100. Each table cell reports the fraction of total investment by setting and entrepreneur type. “Baseline” refers to the estimated model with both frictions (Section 4.2).

Table A3: Bootstrap confidence bands

moment	baseline	10^{th} percentile	90^{th} percentile
% entrepreneurs	65.0	61.6	67.1
% entrepreneurs with x in bottom 1/3	79.2	76.6	83.5
% entrepreneurs with z in bottom 1/3	59.2	55.6	63.0
% entrepreneurs with x in top 1/3	50.6	39.6	53.8
% entrepreneurs with z in top 1/3	69.2	64.0	72.2
% entrepreneurs with z and x in bottom 1/3	74.2	70.5	79.9
% entrepreneurs with z and x in top 1/3	57.0	46.4	61.1
mean output – entrepreneurs, R^E	512	466	554
mean earnings – workers, y^W	165	155	173
mean output, entrepreneurs with $z <$ median	350	315	388
mean output, entrepreneurs with $x <$ median	386	356	429
% involuntary entrepreneurs	19.1	8.8	26.2

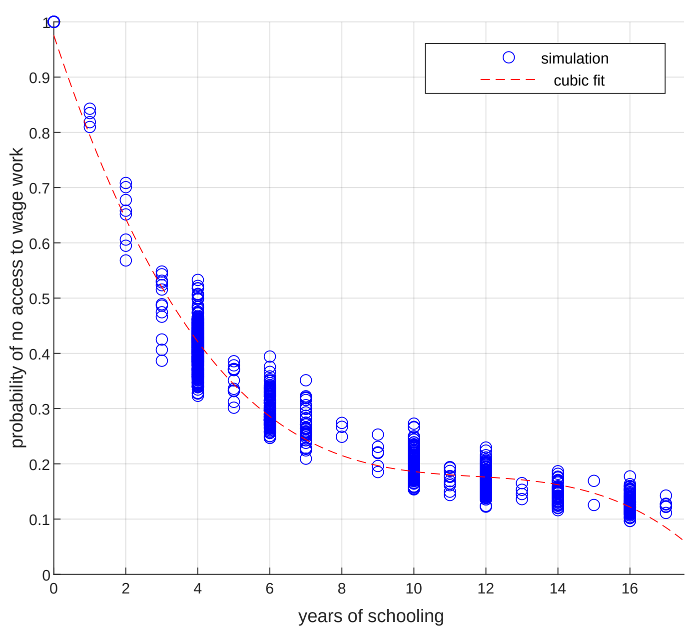
Notes: The ‘baseline’ column reports the moment values computed at the SMM estimates from Table 5. The last two columns report the moment values from the 10-th and 90-th percentiles of the bootstrap simulations.

Table A4: Increase in labor demand

	baseline	10% increase in labor demand
A. % entrepreneurs	65.0%	62.9%
of which voluntary	80.9%	80.3%
of which involuntary	19.1%	19.7%
B. Income		income change
mean, all	339	+1.4%
10th percentile	186	+2.3%
median	327	+1.5%
90th percentile	506	+1.2%
mean, entrepreneurs	434	+2.3%
mean, voluntary entrepreneurs	519	+2.9%
mean, involuntary entrepreneurs	75	+4.4%
mean, workers	165	+6.6%
wage, w^*	23.47	25.15

Notes: The 'baseline' column reports the targeted moment values computed at the SMM estimates from Table 5. In the last column the value of the labor demand scale parameter A is raised by 10% from its SMM estimate, while all other model parameters are held fixed at their SMM estimates.

Figure B1. Labor market friction



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