Who Works for Whom? Worker Sorting in a Model of Entrepreneurship with Heterogeneous Labor Markets*

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Abstract

Compared to more established firms, young firms tend to hire younger workers and provide them with lower earnings. To understand these facts, a dynamic model of entrepreneurship is constructed, where individuals can become entrepreneurs, or work in corporate or entrepreneurial sector. Sectoral differences in production technology, financial constraints, and labor market frictions lead to sector-specific wages and worker sorting into the entrepreneurial sector by productivity and assets. Individuals with lower assets tend to accept jobs in the entrepreneurial sector, an implication that finds support in the data. The analysis indicates that labor market frictions, uncertainty in entrepreneurial ability, and borrowing constraints faced by entrepreneurs are important in the model's ability to generate worker sorting and to match the key features of the entrepreneurial sector.

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1 Introduction

Job creation by entrepreneurs is an important component of employment dynamics in the United States. In a typical year, new firm startups account for about 3% of total employment but almost 20% of gross job creation.[1] The jobs entrepreneurs create, however, may not always be the most desirable ones. Entrepreneurial firms, which are generally thought of as privately-owned, young and small firms, provide lower earnings on average to their workers compared with older or larger firms.[2] They also tend to hire disproportionately from the pool of workers who are young and have lower education.[3] Jobs in entrepreneurial firms therefore serve an important function in the labor market by providing employment opportunities for those who would otherwise be nonemployed or wait longer for a higher-paying job offer from an established firm. Despite the increasing attention to differences in worker characteristics and earnings, the mechanisms by which workers sort across entrepreneurial versus more established firms, and how this sorting is influenced by various labor market and financial frictions, remain relatively less understood.

The long-run decline in business startups and the diminished business dynamism also call for a better understanding of the connection between the supply of entrepreneurial firms and the market for the type of labor these firms attract.[4] The share of young employers in the population of firms has been falling, and workers are increasingly employed in older firms.[5] The new businesses that have formed recently tend to create fewer jobs and pay lower wages, and the decline of business startups explains part of the decline in worker reallocation rates.[6] Therefore, the decline has implications for those who tend to work for entrepreneurs, as they face an increasingly lower supply of new entrepreneurial jobs. Conversely, changing dynamics of labor markets may have consequences for entrepreneurs' ability to hire and retain workers, and hence, their cost of doing business. This connection between the supply of entrepreneurs and the supply of labor to them leads to several questions. What kind of individuals choose to work

[1] At the same time, about 40% of the jobs created by startups disappear due to failure within 5 years of entry. See Haltiwanger, Jarmin, and Miranda (2013).

[2] See, e.g., Brown and Medoff (1989) for the connection between firm size and earnings. Brown and Medoff (2003), Kölling, Schabel and Wagner (2002), and Dinlersoz, Hyatt, and Nguyen (2013) document, among others, the connection between the age of an establishment or a firm, on the one hand, and the average earnings of workers, on the other.

[3] See, e.g., Ouimet and Zarutskie (2014) and Goetz, Hyatt, McEntarfer, and Sandusky (2015).

[4] For long-run trends in the number of new firm startups and young firms, see, e.g., Decker, Haltiwanger, Jarmin, and Miranda (2014a). Recent work on the decline of entrepreneurship include Siemer (2014), Pugsley and Sahin (2015) and Karahan, Pugsley, and Sahin (2015). These studies focus mainly on the decline in firm startups or age zero firms (a flow measure), which are a subset of the broader set of entrepreneurial firms (a stock measure) in the economy at any point in time, and abstract from labor and financial markets.

[5] See, e.g., Decker, Haltiwanger, Jarmin, and Miranda (2014a) and Hathaway and Litan (2014).

[6] See, e.g., See Sedlacek and Sterk (2014) and Hyatt and Spletzer (2013).

for entrepreneurs, and why? How do financial and labor market frictions affect the decision to become an entrepreneur and to work for one? Which type of friction is critical in generating the observed allocation of workers to entrepreneurial businesses? These questions demand a framework where individuals face not only the decision to become entrepreneurs, but also the decision to work for entrepreneurial versus other firms.

This paper develops a model to study jointly the questions of who becomes an entrepreneur and what kind of workers sort into entrepreneurial firms in the presence of search frictions in the labor market and financial constraints for entrepreneurs. The calibrated model's equilibrium exhibits worker sorting: individuals with low labor productivity and lower assets on average tend to take jobs in the entrepreneurial sector. The empirical findings using a novel matched data on workers' assets and their employers support the implications of the model on worker sorting. The analysis also explores in detail the model's mechanisms that generate worker sorting and entrepreneurship in order to isolate the roles of financial constraints, labor market frictions, and entrepreneurial uncertainty.

In the model, individuals differ in wealth, entrepreneurial ability, and worker productivity. Each individual can become an entrepreneur, or work in one of the two sectors: entrepreneurial and corporate–a label for the set of firms that don't face the constraints entrepreneurial firms do. The constraints entrepreneurs face are of two types. The entrepreneurial production is subject to diminishing returns that arise from the limits to entrepreneurs' span-of-control. In contrast, firms in the corporate sector can scale up production without such restrictions. In addition, entrepreneurs can borrow only up to a limit to operate their businesses–a constraint that does not apply to corporate sector firms.

The choice to become an entrepreneur and to work for one are endogenously determined, along with the price of labor entrepreneurs face. The match between workers and firms is subject to frictions in the labor market. Not all nonemployed individuals who look for a job can find one, and workers can be separated from their employers involuntarily, in addition to voluntary separations. These labor market frictions, however, are allowed to vary across the two sectors. Job offers arrive at different rates, and involuntary separations occur with different probabilities. The differences across the two sectors in production technology and labor market frictions together lead to divergence in sectoral wages per unit of worker efficiency. The wage differential, combined with the heterogeneity in worker productivity and wealth, results in worker sorting across the two sectors based on both productivity and wealth.

The model outlined above is related to recent models of entrepreneurship.[7] What distinguishes it from these models, however, is presence of sector-specific labor market frictions and

[7] See, among others, Quadrini (2000), Cagetti and De Nardi (2006), Kitao (2008), Buera and Shin (2011), Buera, Fattal-Jaef, and Shin (2015), and Bassetto, Cagetti, and De Nardi (2015).

prices of labor. The labor market frictions prevent costless movement of workers across sectors and in and out of nonemployment. Because of these frictions, a two-wage equilibrium emerges where some workers take low-wage jobs in the entrepreneurial sector even though higher-wage corporate jobs are available. As a result, the frictions turn out to be important in generating sectoral earnings differentials and worker sorting. Furthermore, the analysis of the model's equilibrium suggests that differences in labor market frictions across the two sectors are needed for the model's equilibrium to replicate observed facts. The labor market frictions, together with the differences in production technology and financial frictions across the two sectors, enable the model to generate employment shares, worker earnings, and worker flows to and from nonemployment that are consistent with their observed counterparts. At the same time, the model's equilibrium accounts for the observed fraction of entrepreneurs in the population, as well as the distributions of wealth for entrepreneurs and workers.

The model provides an answer to the central question of who works for whom. A key property of the model's equilibrium is that workers in the entrepreneurial sector tend to be less productive and have lower assets, compared to those in the corporate sector.[8] The asset differential is in part a consequence of the fact that individuals who work in the higher-wage corporate sector can accumulate on average more wealth over time than their counterparts in the entrepreneurial sector. However, a selection effect is also present: individuals who take jobs in the entrepreneurial sector tend to be less wealthy even *at the time* they take these jobs. In other words, the wealth and productivity differences across the two sectors also apply to individuals who have just taken jobs in these sectors. Nonemployed individuals with a job offer from the entrepreneurial sector have to decide whether to reject this offer and wait for an offer from the higher-wage corporate sector. Individuals with lower levels of savings and productivity prefer to take jobs in the entrepreneurial sector rather than waiting. This sorting emerges in the absence of any inherent preference for working in entrepreneurial firms, or any form of compensation other than the wages these firms provide.

Worker sorting, both by productivity and by assets, turns out to be a robust feature of the model. To understand the mechanisms behind worker sorting and equilibrium allocations, additional analysis is carried out to isolate the roles of the model's key elements. In particular, the analysis explores the specific roles of the distinct sectoral wages for labor, the differential labor market frictions, the extent of the borrowing constraint for entrepreneurs, and the uncertainty about the entrepreneurial ability at the time of the entrepreneurship decision. Worker sorting

[8] The role of asset heterogeneity in generating differential labor market outcomes has also been explored recently by Eeckhout and Sepahsalari (2014), and Herkenhoff, Phillips, and Cohen-Cole (2015). A similar mechanism is also at work in theoretical study of Browning, Crossley, and Smith (2007). While these studies include directed search in labor markets, they do not model an entrepreneurship versus work decision.

prevails to varying degrees under alternative assumptions about the nature of these key elements.

The model's prediction that workers with lower assets tend to more readily take jobs in entrepreneurial firms is taken to data. The test of this prediction requires data not only on individuals' assets, but also on their employment choices and the characteristics of their employers. While data on worker assets is available from a variety of sources, measuring workers' assets by employer type (e.g. employer size or age) and especially at the time when they start a job is more challenging. The analysis uses a novel combination of data on workers' net worth from the Survey of Income and Program Participation (SIPP) and data at the worker-job level from the Longitudinal Employer-Household Dynamics (LEHD) program that captures employer characteristics and workers' job transitions. The empirical counterpart of the model's entrepreneurial firms are taken to be young firms.[9] The findings suggest that individuals who work in younger firms tend to have fewer assets than their counterparts in old firms. Furthermore, individuals who take jobs in young firms also tend to be less wealthy around the time they take these jobs, compared to those who take jobs in old firms.[10] These findings support the predictions of the model on worker sorting based on assets.

The rest of the paper is organized as follows. The next section documents some key facts about entrepreneurial firms. Section 3 introduces the model, followed by its baseline calibration in Section 4. The properties of the baseline model are discussed in Section 5. Section 6 explores the role of some of the model's key elements in determining equilibrium allocations and worker sorting. Section 7 offers empirical evidence on the predictions of the model on worker sorting by assets. Sensitivity analysis with respect to some of the key assumptions of the model is carried out in Section 8. Section 9 concludes.

2 Some Observations on Entrepreneurial Firms

This section documents some facts about entrepreneurial firms to motivate the model and its analysis. A fundamental question is what constitutes an entrepreneurial firm. Entrepreneurial firms are often thought of as privately-held, young, and small firms.[11] Although there are some

[9] The findings are robust when small firms are used instead, as discussed in the empirical analysis.

[10] Herkenhoff, Phillips, and Cohen-Cole (2015) provide empirical evidence that, among workers who undergo an involuntary job separation, those with more credit card debt spend less time in unemployment and accept lower wages, which is consistent with the evidence here that young and small (i.e., lower-paying) firms disproportionately hire workers with lower assets.

[11] The authors' calculations based on the 2007 Survey of Business Owners confirms this view of entrepreneurial firms. Of young businesses (less than 5 years old), 69.1% are owned by households, while such household-owned businesses account only 45.7% of the employment in these young firms. Of small firms (less than 50 employees), 88.4% are owned by households, and such businesses account for 40.0% of the employment in small firms.

young and small firms that may not be entrepreneurial in nature (e.g. new businesses created by established firms), and some entrepreneurial firms that are young but large, firm age and size are frequently used to approximate the population of entrepreneurial businesses.[12] However, alternative definitions can also be provided.

Table 1 presents various definitions of entrepreneurial firms and some key statistics associated with these firms for the year 2000. In all definitions, non-employer businesses are excluded, as the focus of this paper is on entrepreneurs who create jobs. In addition, each firm is assumed to have a single owner.[13] Assuming that the pool of potential entrepreneurs is the population of males aged 15-64 years in 2000, the fraction of entrepreneurs in the economy can then be approximated by the ratio of the number of entrepreneurial firms to that population.[14]

One way to define entrepreneurial firms is to apply various age and size criteria to the universe of employer-businesses in the U.S. Census Bureau's Longitudinal Business Database (LBD). Based on these criteria, Table 1 reveals that the fraction of entrepreneurs ranges from a rather conservative estimate of 1.7% to a less stringent one of 5.8%. Alternatively, one can define entrepreneurial firms as those that are not publicly owned and that have indicated some ownership demographics in the U.S. Census Bureau's Survey of Business Owners (SBO). This approach yields an estimate of 6.0%. To provide another set of estimates, one can use the responses to the question regarding employer-business ownership in the Survey of Income and Program Participation (SIPP). The estimates in this case vary from 2.3% to 2.9%. Table 1 also indicates that employment share of entrepreneurial firms varies between 3.6% to 44.0% across alternative definitions. The definitions also imply a non-entrepreneurial firm average earnings premium in the range 16.6% to 49.8%.[15]

Consider now some key differences between entrepreneurial and other firms relevant for the analysis in this paper. Suppose that an entrepreneurial firm is defined as a firm that is at most 5 years old or a firm that has at most 20 employees – the findings are similar when other definitions of an entrepreneurial firm in Table 1 are used instead.[16] As Table 2 indicates, entrepreneurial firms offer lower earnings to their workers on average. In 2000, the median of the firm-level average worker earnings for young firms are about 85% of that for older firms, whereas by 2012 this figure drops to about 75%. For small firms, the corresponding figures are 73% and 76%. The

[12] See, e.g., Haltiwanger, Jarmin, and Miranda (2013).

[13] The datasets used to construct Table 1 have different definitions of business ownership. For example, household surveys count business owners who may operate multiple businesses, while business-level surveys often do not identify which businesses have owners who also own other businesses.

[14] In 2000, the population of males aged 15-64 years amounted to approximately 93 million based on U.S. Census Bureau's American Fact Finder.

[15] The average worker earnings premium is defined as excess average worker earnings in non-entrepreneurial firms expressed as a percentage of the average worker earnings in entrepreneurial firms.

[16] For instance, using a 10-year threshold for an entrepreneurial firm leads to similar qualitative results.

documented gap in average earnings is consistent with the broader empirical literature on firm age and size premia in worker earnings.[17]

Table 2 also contains information on the prevalence and size of entrepreneurial firms. Young firms accounted for nearly half of all firms in 1987, but only one-third in 2012. Compared to their frequency in the firm population, young firms account for a relatively small share of total employment: nearly one-fifth in 1987, and only about one-tenth in 2012. A similar pattern holds for small firms. The number and employment share of entrepreneurial firms are in line with the typical high skewness in firm size and age distributions–much of the economic activity is concentrated in a relatively small fraction of firms in the right tail of these distributions. The average scale of young firms measured by employment is only about one-quarter of that for other firms, and much smaller for small firms. In addition, entrepreneurial firms also tend to have higher hiring and separation rates, and rely more on those individuals without jobs for filling vacancies, as documented by Haltiwanger, Hyatt, and McEntarfer (2015) and Goetz et al. (2015). These observations suggests that entrepreneurial firms disproportionately draw their workforce from the nonemployed, and lose their workers disproportionately to nonemployment, compared to other firms.[18]

Taken together, the documented differences in employment shares, average earnings, and worker flow patterns hint at potentially different labor market frictions for workers in entrepreneurial versus other firms. Moreover, the discrepancy in the employment share and average scale of these two types of firms can result, in part, from the more stringent financial and managerial constraints entrepreneurs face. The model in the next section studies how the differences in labor market frictions, financial constraints and technology give rise to worker productivity, earnings, and wealth differentials across the two types of firms. While alternative definitions of entrepreneurial firms are explored in Tables 1 and 2 for establishing the robustness of the motivating facts, the rest of the analysis adopts an empirical definition of an entrepreneurial firm as a young firm of age 0-5 years. Adhering to this definition ensures consistency in the presentation of the subsequent findings. Robustness of the results to this definition is assessed in the empirical

[17] Brown and Medoff (2003) find that average worker earnings are lower in younger firms in a sample of U.S. firms. This finding has repeatedly emerged in studies using a variety of datasets. For instance, Kölling, Schabel and Wagner (2002) largely confirm Brown and Medoff's (2003) findings using data that links establishments to workers in Germany. Heyman (2007) also finds a similar pattern in Swedish data. More recently, Dinlersoz, Hyatt, and Nguyen (2013) provide evidence that new manufacturing establishments in the U.S. provide lower average earnings to their workers than older ones. Ouimet and Zarutskie (2014) also observe a similar gap in average earnings in the matched employer-employee data for the U.S.

[18] While the differences in worker flow rates for entrepreneurial and non-entrepreneurial firms are interesting on their own right, they are not the focus of the analysis conducted here. The model presented in subsequent sections allows sectoral differences in worker flows, but does not feature determinate job-to-job flows between firms within a sector.

analysis.

3 The Model

Based on the differences between entrepreneurial and other firms highlighted in the previous section, the model considers an economy with two sectors: entrepreneurial and corporate. The sectors differ in production technologies, labor market frictions, and financial constraints. The model extends the framework of incomplete markets with occupational choice in the spirit of Quadrini (2000) and Cagetti and De Nardi (2006) to include heterogeneous labor markets, as in the "islands" economy of Lucas and Prescott (1974).[19] It also features indivisible labor choice characterized by frictions between production and leisure "islands", as in Krusell, Mukoyama, Rogerson, and Sahin (2011).

3.1 The Setup

There is a unit mass of infinitely-lived individuals. Time, t, is discrete and the discount factor is $\beta \in (0,1)$. Each period an individual is endowed with one unit of time, which can be used for production as a worker or an entrepreneur. Individuals have identical preferences represented by the period utility

$$u(c_t, h_t) = \ln c_t - \alpha h_t,$$

where $c_t \geq 0$ is the consumption, $\alpha > 0$ is the disutility from labor, and $h_t \in \{0,1\}$ is an indicator of participation in the labor market as a worker or entrepreneur.

Each individual possesses an amount, $a_t \geq 0$, of assets.[20] Individuals also differ in their ability (or productivity), both as a worker and an entrepreneur. Worker productivity is summarized by $z_t > 0$–the efficiency units of labor an individual can supply in a period. The productivity, z_t, evolves over time independently across individuals according to the process

$$\ln z_t = \rho_z \ln z_{t-1} + \epsilon_t^z, \qquad (1)$$
$$\epsilon_t^z \sim N(0, \sigma_z^2).$$

Similar to the worker ability, the entrepreneurial ability, θ_t, is also subject to random fluctuations independently across individuals

$$\ln \theta_t = (1-\rho_\theta)\mu + \rho_\theta \ln \theta_{t-1} + \epsilon_t^\theta, \qquad (2)$$
$$\epsilon_t^\theta \sim N(0, \sigma_\theta^2).$$

[19] See also Alvarez and Veracierto (2000).

[20] The index for an individual is suppressed for notational simplicity.

Production takes place in corporate and entrepreneurial sectors, denoted by $j \in \{e, f\}$, respectively. The sectors possess different production technologies. There is a representative firm in the corporate sector. It generates output, Y_t, by combining capital, K_t, and efficiency units of labor, L_t, through a constant-returns-to-scale production technology

$$Y_t = AK_t^{\nu}L_t^{1-\nu},$$

where $\nu \in (0, 1)$, and $A > 0$ is the corporate sector's total factor productivity.

Each firm in the entrepreneurial sector is operated by an entrepreneur with ability θ_t, who uses capital, k_t, and efficiency units of labor, l_t, to produce output, y_t, via a decreasing-returns-to-scale technology

$$y_t = \theta_t(k_t^{\nu}l_t^{1-\nu})^{\xi}, \tag{3}$$

where $\xi \in (0, 1)$ is a span-of-control parameter, which reflects the diminishing returns to the entrepreneur's managerial ability. Entrepreneurs also face a constant, exogenous probability of having their business bought out by the corporate sector. This feature captures, in a reduced form, the transition of firms from the entrepreneurial sector to the corporate sector.

There are two types of frictions. The first type pertains to the labor markets. Employment opportunities for nonemployed individuals arrive every period with a constant probability. Job offers can come from the corporate sector or the entrepreneurial sector. Let γ_j denote the employment offer probability from sector $j \in \{e, f\}$. The probability that an individual does not receive a job offer is then $1 - \gamma_e - \gamma_f$. Employed individuals maintain a deterministic match to their sector for the duration of their tenure. Every period workers can separate from their employers either voluntarily or involuntarily. Involuntary separations occur with probability ϕ_j. Those individuals who are separated from firms or quit entrepreneurship transition into nonemployment and stay there for at least one period before receiving offers (if any), and face the decision to work or become an entrepreneur again. The frictions in the labor market are completely specified by the parameters $\{\gamma_j, \phi_j\}$ for $j \in \{e, f\}$.

The second type of frictions is financial in nature. There are borrowing constraints for entrepreneurs, and individuals are not allowed to carry negative assets, $a_t \geq 0$. Each period, the amount of capital, k_t, an entrepreneur with assets, a_t, can access is bounded: $k_t \leq ba_t$, where $b \geq 1$ is an exogenously given borrowing limit. When $b = 1$, entrepreneurs can only use their accumulated assets to finance production in any given period. The parameter b is the only parameter that governs the financial frictions for entrepreneurs. Capital rental rate is $r > 0$, and the depreciation rate is $\delta \in (0, 1)$.

The timing of events within a period is as follows. Individuals first realize their current-period labor productivity, z. Each nonemployed individual then receives a job offer from one of the sectors. All individuals then make their decisions about whether to work, become an entrepreneur, or not work. Following this decision, entrepreneurs realize their current-period ability, θ, and choose their inputs for production. Each individual subsequently chooses how much to consume and save. At the end of the period, some of the employed individuals get separated from their employers exogenously. At the same time, some entrepreneurs' businesses are bought out by the corporate sector with some (exogenous) probability, p. The entrepreneurs whose businesses transition into the corporate sector become nonemployed in the next period.

3.2 Individuals' Problems

Consider a stationary environment where policies and payoffs do not depend on calendar time. Let $s = (a, z, \theta)$ summarize an individual's assets, and worker and entrepreneurial ability in a period. In addition to s, each individual is differentiated by current-period location or island, which can be nonemployment (n), working in the corporate sector (f), working in the entrepreneurial sector (e), or being an entrepreneur (m).

The value of nonemployment is defined as

$$V^n(s) = \max_{c,a'\geq 0}(\ln c + \beta \mathbb{E}_{z'|z}[\sum_{j\in\{e,f\}} \gamma_j \max\{\tilde{V}^j(s'), \tilde{V}^n(s'), \tilde{V}^m(s')\} \\ + (1-\gamma_e-\gamma_f)\max\{\tilde{V}^n(s'), \tilde{V}^m(s')\}]) \tag{4}$$

subject to the budget constraint

$$c + a' = (1+r)a,$$

Equation (4) reflects the fact that a nonemployed individual obtains the utility from consumption in the current period, and in the next period the expected value depends on whether a job offer is received, and the sector this offer comes from. Note that the value functions $\tilde{V}^i(s')$, $i \in \{n, f, e, m\}$ give the expected value of being in location i in the next period, i.e. $\tilde{V}^i(s') = E_{\theta'|\theta}[V^i(a', z', \theta)]$.

Let w_j be the wage per unit of worker efficiency in sector $j \in \{e, f\}$. The value of an individual who works in sector j is given by

$$V^j(s) = \max_{c,a'\geq 0}(\ln c - \alpha + \beta \mathbb{E}_{z'|z}[(1-\phi_j)\max\{\tilde{V}^j(s'), \tilde{V}^n(s'), \tilde{V}^m(s')\} \\ + \phi_j \max\{\tilde{V}^n(s'), \tilde{V}^m(s')\}]) \tag{5}$$

subject to

$$c + a' = w_j z + (1+r)a,$$

Equation (5) indicates that an employed individual receives a current utility from consumption minus the disutility of work. In the next period, the individual's expected value depends on whether he gets separated. In the event of no separation, the individual can continue employment or quit to nonemployment or entrepreneurship. In the event of separation, he transitions to nonemployment where he can choose to remain, or become an entrepreneur.

Finally, the value of an entrepreneur is

$$V^m(s) = \max_{c,a'\geq 0}(\ln c - \alpha + \beta \mathbb{E}_{z'|z}[(1-p)\max\{\tilde{V}^n(s'), \tilde{V}^m(s')\} + p\tilde{V}^n(a'+\tau(s), z', \theta')]) \tag{6}$$

subject to

$$c + a' = \pi(s) + (1+r)a,$$

where the entrepreneurial profit, $\pi(s)$, is given by

$$\pi(s) = \max_{l\geq 0, 0\leq k\leq ba} \theta(k^\nu l^{1-\nu})^\xi - w_e l - (r+\delta)k. \tag{7}$$

The entrepreneurial value in (6) consists of the current period utility, and the next period's expected value, which depends on whether the entrepreneur's business is bought out by the corporate sector. The individual can continue to be an entrepreneur or choose to be nonemployed in the event the corporate sector does not purchase the entrepreneur's firm (with probability $1-p$). If the firm is purchased (with probability p), the entrepreneur receives a transfer of $\tau(s)$ and becomes nonemployed in the following period.[21] The transfer, $\tau(s_t)$, is equal to the present discounted value of future stream of profits of the entrepreneur starting from the period of transfer, t

$$\tau(s_t) = \sum_{j=1}^{\infty} \left(\frac{1}{1+r}\right)^j \mathbb{E}_{\theta_{t+j}|\theta_{t+j-1}}[\pi^f(s_{t+j})]. \tag{8}$$

In other words, the corporate sector pays a transfer to an entrepreneur with state s that equals the expected value from perpetual operation the entrepreneurial technology at its optimal scale by the corporate sector starting from period t. In the value of the business on the right hand side of (8), the discount rate is $1/(1+r)$, rather than the subjective discount rate, β, of individuals. The former rate is the relevant one here since the corporate sector uses capital to purchase an entrepreneurial business, and the capital rental rate is r. The optimal scale operated by the corporate sector is determined by the following profit maximization problem

$$\pi^f(s_{t+j}) = \max_{k,l\geq 0} \theta_{t+j}(k^\nu l^{1-\nu})^\xi - w_f l - (r+\delta+\delta_\tau)k.$$

[21]The fact that p is exogenous and does not depend on entrepreneurial ability is a crude way of formulating the transition of an entrepreneurial firm to the corporate sector. One could think of a more elaborate formulation where p is a function of the state s. However, the goal here is not to provide a model of transition over the life-cycle of an entrepreneur. In practice, the way this transition is modelled makes little difference in the framework here as long as such transitions are rare events – at least, the low frequency of IPOs and M&A activity in the U.S. economy supports this view, as discussed in the model's calibration.

Note that there is no upper bound on capital in this maximization problem, since the corporate sector faces no financial frictions, unlike the entrepreneurial sector. This simplified optimization problem ensures that the transfer can be calculated without considering future asset states or employment transitions of the entrepreneur. In equilibrium, the total amount of transfers from the corporate sector to the entrepreneurs is financed by a portion, δ_τ, of the capital used by the corporate sector, K. The effect of this transfer is to increase the marginal cost of capital in the corporate sector by δ_τ.

3.3 Equilibrium

Let $i \in \{n, f, e, m\}$ denote the labor status of an individual in any given period. In addition, let $d \in \{n, f, e, m\}$ be the "island" or "location" of the individual at the end of the previous period. Denote the remaining state space of agents making their labor choice decisions by $\tilde{s} = (a, z, \theta_{-1})$, where θ_{-1} denotes the previous period's entrepreneurial ability. A stationary competitive equilibrium for the model is a collection of value functions, $V^i(s)$, wage in each sector, w_j for $j \in \{e, f\}$, an interest rate, r, a transfer rate, δ_τ, labor supply rules, $h^d(\widetilde{s})$, decision rules to become an entrepreneur, $m^d(\widetilde{s})$, saving and consumption rules, $a'^i(s)$ and $c^i(s)$, an entrepreneur's capital and labor choice rules, $k(s)$ and $l(s)$, and measures of individuals by labor status, $\Psi^i(s)$, such that

1. The saving and consumption rules, $a'^i(s)$ and $c^i(s)$, labor supply rules, $h^d(\widetilde{s})$, and the decision rules to become an entrepreneur, $m^d(\widetilde{s})$, solve the individuals' problems defined in (4), (5), and (6),

2. The interest rate, r, and the corporate sector wage, w_f, satisfy

$$r = \nu A K^{\nu-1} L^{1-\nu} - \delta - \delta_\tau, \tag{9}$$

$$w_f = (1-\nu) A K^{\nu} L^{-\nu}, \tag{10}$$

3. The transfer rate, δ_τ, ensures that total amount of transfers to entrepreneurs are accounted for by a portion of the corporate sector capital

$$\int p\tau(s) d\Psi^e(s) = \delta_\tau K, \tag{11}$$

4. The capital and labor choices, $k(s)$ and $l(s)$, solve the entrepreneur's problem in (7),

5. The measures, $\Psi^i(s)$, are consistent with the transitions of the individuals across islands,

6. Labor, capital, and goods markets clear

$$\int l(s)d\Psi^m(s) = \int zd\Psi^e(s) \quad \text{(entrepreneurial sector labor)} \quad (12)$$

$$L = \int zd\Psi^f(s) \quad \text{(corporate sector labor)} \quad (13)$$

$$K + \int k(s)d\Psi^m(s) = \sum_i \int ad\Psi^i(s) \quad \text{(capital)} \quad (14)$$

$$Y + \int y(s)d\Psi^m(s) = \sum_i \int c(s)d\Psi^i(s) + \delta_\tau K + \delta\left(K + \int k(s)d\Psi^m(s)\right) \quad \text{(goods)} \quad (15)$$

where $y(s)$ denotes the output of an entrepreneur with state s.

While the corporate sector wage, w_f, depends on the representative corporate firm's labor choice (10), the entrepreneurial sector wage, w_e, is the value that equates the labor demand by all entrepreneurs to the labor supply of all workers in the entrepreneurial sector – equation (12). The amount of capital used by the two sectors must equal the total assets of all individuals in the economy, as ensured by (14). Finally, the total output of the economy must account for the total consumption by individuals, the replacement of the depreciated capital, and the transfers to entrepreneurs from the corporate sector, as shown in (15). Appendix A outlines the algorithm that is used to solve for the stationary equilibrium numerically.

4 Calibration

The parameter values used in the calibration of the baseline model are shown in Table 3. Each period corresponds to one quarter. The discount rate, β, is set to 0.98, to match an annual interest rate of 4%. The process for labor productivity, z, in (1) is assigned the quarterly counterparts of annual parameters estimated by Heathcoate, Storesletten, and Violante (2010). The annual parameters are $\{\rho_z, \sigma_z\} = \{0.97, 0.13\}$.[22]

The annual values of the parameters $\{\rho_\theta, \sigma_\theta\}$ of the process for managerial ability θ in (2) and the returns-to-scale parameter, ξ, are estimated separately for entrepreneurial firms (young firms aged 0-5 years) versus non-entrepreneurial firms (older firms aged 6+ years) in the manufacturing sector. The unavailability of data on inputs other than labor precludes the estimation of these parameters for firms in other sectors of the economy. The estimation follows the econometric methodology used in Abraham and White (2015), which allows joint estimation of the parameters $\{\rho_\theta, \sigma_\theta, \xi\}$ based on Castiglionasi and Ornaghi (2013) – see Appendix B.[23] The framework of

[22] The support of the labor productivity process is discretized using 21 grid points based on the Rouwenhorst method – see Kopecky and Suen (2010).

[23] See also the earlier version, Abraham and White (2006).

Abraham and White (2015) has a number of desirable features. Notably, it allows for heterogeneity in the parameters $\{\rho_\theta, \sigma_\theta, \xi\}$ across industries. Abraham and White (2015) demonstrate that restricting these parameters to be the same across industries can lead to upward bias in the estimate of the persistence parameter, ρ_θ.[24] The estimated parameters for the entrepreneurial ability process for θ at an annual rate turn out to be $\{\rho_\theta, \sigma_\theta\} = \{0.3, 0.18\}$, which are the averages across narrowly defined industries at the level of 4-digit SIC codes. The span-of-control parameter for young firms, ξ, has an average estimated value of 0.88 across industries. This value is smaller than the corresponding one for old firms (around 0.97), suggesting a lower span-of-control for entrepreneurial (young) firms.

Following Kitao (2008) and Buera and Shin (2011), the borrowing constraint parameter, b, is set to 1.5, implying that an entrepreneur can borrow up to 50% of his assets at the beginning of the period. Based on the business-cycle literature, the capital's share of output, ν, is set to 0.36, and the quarterly depreciation rate, δ, is taken to be 0.015, which corresponds to an annual depreciation rate of 0.06. The productivity of the corporate sector, A, is normalized to $\exp(-1)$.

In the model, entrepreneurs face a constant probability, p, of transitioning into the corporate sector. One can think of this transition as an IPO, an acquisition of the entrepreneurial business by a corporate firm, or an exceptionally high firm growth that essentially removes the financial and managerial constraints the entrepreneur faces. Consider the case of an IPO. Based on Dun and Bradstreet's Compustat database, the number of publicly-traded firms in any given year during the period 2002-2012 varies in the range of 5 to 6 thousand. This set of firms represent about 0.1% of the entire set of employer businesses in the U.S. during the same period, which range around 5-6 million. Similarly, the number of announced mergers and acquisitions in the U.S. ranged approximately from 8 to 14 thousand during the period 2000-2015, indicating that at most a fraction of about 0.1%-0.2% of firms engage in this type of announced merger and acquisition activity.[25] Given these estimates, a value of $p = 0.001$ was chosen to approximate the flow of entrepreneurial firms into the corporate sector. The analysis is robust to different choices of p. In fact, a value of $p = 0$ on the low end, or $p = 0.002$ on the high end, produce very similar results.

The remaining parameters, denoted by the set $M = \{\alpha, \gamma_e, \phi_e, \gamma_f, \phi_f, \mu\}$, are chosen to match six different targets that constitute a system of non-linear equations. While these equations are simultaneous in nature and involve all relevant parameters of the model, each equation plays

[24] Other recent approaches to estimating the productivity persistence parameter include Lee and Mukoyama (2015) and Foster, Haltiwanger and Syverson (2008). The former does not allow for heterogeneity in the persistence parameter, and the latter provides estimates for a sample of 11 narrowly defined manufacturing product categories. These approaches generally result in higher estimates for the persistence parameter.

[25] These figures are provided by Institute of Mergers and Acquisitions, available at https://imaa-institute.org/m-and-a-us-united-states/.

an instrumental role in setting a specific parameter. The values of the targets are chosen to be the average value of their empirical counterparts in the early 2000s. For the disutility of labor, α, the key target is the employment-to-population ratio (0.80) among males aged 15-64 years. Two other targets, the share of employment in non-entrepreneurial firms (84%) and the average worker earnings premium for these firms (17%), are important in pinning down a value for the job offer rates, γ_j. The job separation rates, ϕ_j, are set so that the aggregate job separation rate (employment-to-nonemployment flows) is 1.9% as a fraction of total employment, and the aggregate job finding rate (nonemployment-to-employment flows) is 45%, based on Shimer (2012). Finally, the fraction of entrepreneurs, 4%, is targeted in assigning a value to the entrepreneurial ability parameter, μ. This fraction is within the range of various estimates provided in Table 1. See Appendix A for details of the calibration procedure.

The calibration procedure yields job offer rates $\gamma_e = 0.04$ and $\gamma_f = 0.48$, which imply significant frictions that impede worker flows into the entrepreneurial sector relative to the corporate sector. The exogenous separation rates are $\phi_e = 0$ and $\phi_f = 0.012$. The value $\phi_e = 0$ implies that workers are essentially never exogenously separated from employment in the entrepreneurial sector. In contrast, workers in the corporate sector face a relatively large exogenous separation rate. The calibrated value $\phi_e = 0$ is consistent with the fact that in the model employment in the entrepreneurial sector does not correspond to any particular firm-worker match, but rather employment at any one of the firms within that sector. In other words, in the entrepreneurial sector the firm that employs any given individual is indeterminate. As a result, a separation rate of $\phi_e = 0$ means that an individual employed in the entrepreneurial sector continues to be employed in any firm in that sector until there is a voluntary separation. The separation rates should therefore be thought of as separation shocks to employment in a sector that may correspond to continuous employment spells at one or more firms in that sector. Similarly, within-sector job-to-job transitions are not determined in this framework, since workers that are employed in a sector for more than one period may be transitioning across firms in that sector without any friction.

5 Properties of the Baseline Model

This section provides an evaluation of the ability of the model to match the targets described in the previous section, as well as other moments that are not specifically targeted. The key features of the calibrated model's equilibrium are shown in Table 4. Overall, the model comes close to matching the targeted values. It produces an employment-to-population ratio of 82%. Around 5% of the individuals choose to become entrepreneurs. As shown in Figure 1a, individuals with a higher level of entrepreneurial ability tend to become entrepreneurs – the distribution of managerial ability for entrepreneurs stochastically dominates that for non-entrepreneurs, in a first order stochastic sense. Entrepreneurs also tend to have higher levels of assets (Figure 1b). The capital input for entrepreneurial firms exhibits a skewed distribution (Figure 1c). Similarly, the distribution of the labor input (in efficiency units) for the entrepreneurial firms in Figure 1d is also highly-skewed.[26] The features of the model discussed so far also emerge in recent models of entrepreneurship, indicating that the model is able to capture the salient aspects of these models.[27]

The model's main distinguishing aspect, heterogeneous labor markets, provides further insight to the functioning of the labor markets and the nature of worker sorting. In fact, the model captures the underlying worker allocations and prices across the two labor markets that drive the observed worker sorting. The model's equilibrium is broadly consistent with the behavior of the key metrics for the U.S. labor market. In the baseline model, 15% of the employees work for entrepreneurial firms, close to the data counterpart of 16%. The model also delivers a corporate earnings premium consistent with its observed value. The average worker earnings in the corporate sector is about 19% higher than that in the entrepreneurial sector – the targeted value is 17%.

Note that the sectoral average worker earnings depends on the distribution of worker productivity (z) in each sector, as well as the wages per efficiency units of labor (w_e, w_f). The values for w_e and w_f are obtained in the calibrated model's equilibrium, but there is no observable target to discipline their values. The wage per efficiency unit of labor in the corporate sector turns out to be 2% higher than that in the entrepreneurial sector. Moreover, a worker in the corporate sector is 17% more productive, on average, than a worker in the corporate sector. This sorting of individuals based on productivity drives in part the corporate earnings premium, as explored in more detail later. The fraction of corporate capital transferred from the corporate sector to the entrepreneurs is estimated to be $\delta_\tau = 0.0006$. This small fraction ensures that about 0.1% ($p = 0.001$) of entrepreneurs are bought out by the corporate sector every period.

Figure 2a shows that individuals with higher managerial ability tend to become entrepreneurs. As managerial ability increases, individuals tend to shift from corporate sector employment to entrepreneurship, with little change in the allocation of individuals into entrepreneurial sector work across managerial ability levels. Figure 2b illustrates how individuals at a given worker productivity level are allocated across the two sectors and entrepreneurship. As worker productivity increases, the fraction of individuals who work in the corporate sector increases, whereas the

[26] This shape is in line with the typical shape of the firm-level distributions of labor input in empirical studies. However, note that the labor input in the model (worker efficiency units) is different from the employment measure (the number of workers) typically used in empirical studies of firm size.

[27] See, e.g., Quadrini (2000), Cagetti and De Nardi (2006), Kitao (2008), Buera and Shin (2011), Buera, Fattal-Jaef, and Shin (2015), and Bassetto, Cagetti, and De Nardi (2015).

fraction of individuals who are entrepreneurs declines. Apart from the spikes at the lowest and highest levels of labor productivity, the fraction of workers in the entrepreneurial sector tends to decrease as labor productivity increases.

A striking feature of the baseline calibration is that the average assets of the workers in the corporate sectors is about 2.2 times that in the entrepreneurial sector, as seen in Table 4. Figure 2c shows the distribution of worker assets by sector. The distribution in the entrepreneurial sector is much more skewed, with a large mass over the range of low asset levels. This finding suggests that workers with low asset levels are more likely to choose entrepreneurial sector employment, rather than waiting for a corporate sector job. However, these results are also in part due to the effect that corporate sector workers accumulate more assets during their employment spells than entrepreneurial sector workers.

To disentangle the two effects, consider the distribution of workers in their first quarter of a job. These workers are precisely the ones whose decisions reflect selection based asset holdings right around the time they chose where to work. As seen in Table 4, in the model the average assets for such workers in the corporate sector is about 1.3 times that of those in the entrepreneurial sector. This indicates a 30% gap in average assets for workers in their first quarter. This gap amounts to 25% of the total gap of 120% in average assets when all employed individuals in the two sectors are considered, not just the recently employed ones. In the data, the corresponding gaps in average assets for workers in their first quarter of job and for all employed workers are 10% and 20%, respectively.[28] Therefore, the gap in the first quarter of job is about 50% of the gap for all levels of worker tenure. The data thus indicates a somewhat larger role for selection based on assets at the time of taking a job in explaining the difference in average assets for workers in the two sectors. The distribution of assets for workers in their first quarter of job is plotted in Figure 2d and shows a similar pattern to Figure 2c–individuals with lower assets are more likely to take jobs in the entrepreneurial sector than in the corporate sector. Note also that the assets distribution for recent hires lacks the pronounced spike that is observed in the overall distribution, which demonstrates that there are differences in asset accumulation behavior across the two labor markets.

Is this pattern of worker sorting by assets consistent with the data? Unfortunately, there are no survey data that allow for a detailed analysis of wealth holdings by firm type, in particular, by firm age, on which the definition of entrepreneurial firms is based. Section 7 uses a novel combination of administrative records and survey data to confirm the presence of asset differentials by firm age, even after controlling for other, potentially confounding observables, such as worker demographics and industry composition. As the results in Section 7 suggest, the worker asset differential across the two sectors in the model is broadly consistent with the sorting by assets

[28] See Section 7 on the details of the calculation of asset values for individuals based on data.

observed in the data, even though the asset ratios are not explicitly targeted in the calibration of the model.

The model also embeds mechanisms that generate earnings and wealth inequality. While high-wage corporate sector employment and entrepreneurship options help individuals accumulate wealth at a higher rate, episodes of low-wage entrepreneurial sector employment and nonemployment can slow down such accumulation. The availability of jobs in the entrepreneurial sector nevertheless allows individuals who would otherwise be nonemployed to generate wealth, compared to an environment where there is no entrepreneurial sector. Additionally, the option to become an entrepreneur itself enables some individuals to reach the right tail of the wealth distribution. Note that the wealth or earnings inequality moments are not targeted as part of the baseline calibration. However, one can get a sense of how well the model performs in these dimensions by comparing the shares of wealth and earnings in different quintiles of the respective distributions to those obtained from the Panel Study of Income Dynamics (PSID) (see An, Chang, and Kim (2009)). Table 5 indicates that the model does fairly well in capturing the observed distribution of earnings and wealth for the first four quintiles, though less so for the top quintile's share of total wealth in the economy – 61% in the model versus 76% in the data. A model that reflects tax and transfer programs might better capture the amount of wealth held by each wealth quintile. A life-cycle motive can also improve model fit by providing an incentive for the highest wealth quintile to hold more wealth in anticipation of retirement. Both of these mechanisms have been separately able to better match the wealth distribution (see for example, Alonso and Rogerson (2010) and Kopecky and Koreshkova (2014)). The model's performance regarding inequality is similar to more standard models of a heterogenous agent economy (e.g., An, Chang, and Kim (2009)), rather than the models of entrepreneurship such as Cagetti and De Nardi (2006) or Buera and Shin (2011), where calibration explicitly targets the moments of the wealth distribution.

If entrepreneurial firms pay lower wages per efficiency unit, why does anyone work for them at all? The answer lies in the patterns exhibited by the average assets ratios in the two sectors. Because nonemployed individuals with low assets are not wealthy enough to secure a smooth stream of consumption while unemployed, they cannot afford to reject a job offer from the entrepreneurial sector and wait for a job offer from the corporate sector. In other words, the opportunity cost of waiting for a corporate offer is high for these individuals. Therefore, they more readily take entrepreneurial job offers. This sorting of workers also has implications on earnings and wealth inequality. On the one hand, the presence of the entrepreneurial sector allows nonemployed, low-wealth individuals to build assets. On the other hand, the wage and earnings differentials between the two sectors leads to a faster accumulation of wealth for workers in the corporate sector, who are already more wealthy on average when they take corporate sector jobs. While the former effect works to reduce wealth inequality, the latter can propagate it. Because worker sorting based on assets and productivity is a key feature of the model, the next section explores in further detail the model's mechanisms that generate worker sorting.

6 An Analysis of the Model's Key Features

This section explores how key features of the model drive the nature of worker sorting and equilibrium allocations across the two sectors. Worker sorting is a result of the model's assumptions on financial and labor market frictions, and production technology, which together generate different labor prices for the entrepreneurial and corporate sectors. Since workers differ by assets and productivity, they have different incentives to choose work in one sector versus the other, given different labor prices and frictions. At the same time, the technology operated by the entrepreneurial sector and the timing of entrepreneurial ability shocks determine the scale of an entrepreneurial firm along with the presence of borrowing constraints. To disentangle and isolate various factors that determine the degree of sorting in the model, key features of the model are altered one by one, and the effects on sorting are studied.

6.1 Labor Prices

The model is distinguished by the presence of two different prices for labor, unlike most models of entrepreneurship which feature a uniform price. A key question is then to what extent the presence of different sectoral wages drive worker sorting and equilibrium allocations. To answer this question, two approaches are considered. In the first approach, the value of the entrepreneurial wage is forced to be equal to the value of the baseline model's corporate sector wage. The remaining prices and all other model parameters, including search frictions, are held at their baseline values. This approach explores the effects of raising the entrepreneurial sector wage to the corporate level without allowing the rest of the model parameters to respond to this change.

The second approach is to let the corporate sector set a uniform wage for the entire economy, and to do the calibration exercise again to recover a new set of values for the parameters, M, that match the data targets under this uniform price – instead of leaving the parameters fixed at their baseline values as in the first exercise. One obvious drawback of this approach is that the wage set by the corporate sector does not necessarily clear the labor market for the entrepreneurial sector. Note that both the first and second approaches are necessarily partial-equilibrium exercises.

Table 6 compares the results of the first approach with the baseline. When the entrepreneurial sector wage is raised to match the corporate sector wage, allocations change. The higher wage in the entrepreneurial sector substantially increases incentives for individuals to work in this sector. As a result, the entrepreneurial sector employment share increases from 15% in the baseline to 33%. This sharp increase illustrates that relatively low wage in the entrepreneurial sector in the baseline model plays a significant role in reducing the incentives for workers to take jobs in this sector. Note also that when the entrepreneurial sector wage is as high as that in the corporate sector, the entrepreneurship rate declines from 5% to 3%, as entrepreneurs now have higher labor costs. More importantly, worker sorting prevails, even though the degree of sorting is not as pronounced as in the baseline. The question is then what else drives worker sorting, if not the wage differential alone.

Recall that the corporate separation rate is higher than the entrepreneurial separation rate ($\phi_f > \phi_e$). Now, suppose ϕ_e is forced to equal ϕ_f, in addition to the equal wages ($w_e = w_f$). As shown in the third column of Table 6, the ratios of worker productivity and average assets are now all unity. That is, worker sorting vanishes, suggesting that differential separation rates are important in inducing worker sorting in the absence of a wage differential. When workers face a shorter expected tenure in the corporate sector and the wages are equal across the two sectors, the relatively more productive and wealthy workers sort into the corporate sector.

Next, the calibration procedure is allowed to search over all parameters as in the baseline calibration, with the restriction of equal labor prices across the two sectors. The wage rate is set by the corporate sector and is taken as given by the entrepreneurial sector. Table 7 summarizes the results of the this approach. While most of the model's parameters change to some extent with respect to the baseline, the most notable change occurs in the job offer rates, γ_j. The probability of a corporate sector job offer increases modestly from 0.48 to 0.49, but entrepreneurial sector job offer probability declines dramatically from 0.04 to 0.02. This increase is needed to counter the higher flow of workers into the entrepreneurial sector which offers a wage as high as that in the corporate sector, and to ensure that the targeted entrepreneurial sector employment share is achieved. In other words, imposing a uniform price for labor requires even larger job finding frictions in the entrepreneurial sector to match this sector's employment share. The slightly lower separation rate in the corporate sector also helps in matching this target by making the corporate sector more attractive for workers than in the baseline. Finally, note that the average entrepreneurial ability increases from its baseline value. Entrepreneurs now have to be more productive on average to be able to afford the higher wages they face.

The above partial equilibrium exercises illustrate that worker sorting prevails even in the absence of any wage differential across sectors. Next, in order to understand further the different features of the economic environment that generate sorting, some key features of the model are altered, while allowing the labor prices to adjust to their equilibrium values. These general equilibrium exercises are useful in identifying the degree of worker sorting that can be attributed to each feature.

6.2 Labor Market Frictions

In the baseline model, most job offers come from the corporate sector ($\gamma_f > \gamma_e$) and separation rate is larger in the corporate sector ($\phi_f > \phi_e$). To evaluate the extent to these labor market frictions account for worker sorting, labor market frictions are now equalized across sectors. In particular, a stationary equilibrium is found with equal job finding probabilities by sector ($\gamma_e = \gamma_f = 0.26$), as well as equal separation rates ($\phi_f = \phi_e = 0$). These choices keep the overall job finding rate at the baseline model level, $\gamma_e + \gamma_f = 0.52$. The remaining parameter values are fixed at their baseline values, and the prices for labor are allowed to adjust to clear the labor markets.

The results from this experiment are in the column labelled "Frictions" in Table 8. The key finding is that removal of the differences in labor market frictions has an important effect on the degree of sorting. Employment share of the entrepreneurial sector increases from 15% to 28%, while the average productivity and the average asset ratios decrease to 1.13 and 1.2, respectively. In other words, worker sorting becomes weaker, but does not disappear. Additionally, the corporate sector wage premium prevails, and the wage differential between the two sectors increases.

6.3 Uncertainty

The previous section has demonstrated that when labor market frictions are the same, the sectoral difference in wage rate still arise, owing to the differences in technology and borrowing constraints. In particular, the technology of entrepreneurial firms is defined by the entrepreneurial ability process and the parameters of the production function. In the baseline model, the timing of the resolution of the entrepreneurial uncertainty is such that the entrepreneurial ability draw is realized *after* the decision to become an entrepreneur is made. How much does this uncertainty matter for worker sorting and equilibrium allocations?

The column labelled "Uncertainty" in Table 8 shows allocations and prices for a stationary equilibrium where entrepreneurial ability shocks are revealed *before* the occupational choice is made. Relative to the baseline economy, there is now an increase in the entrepreneurial sector employment share (from 15% to 19%) and an increase in the share of entrepreneurs (from 5% to 6%). Additionally, observe that all firms in the entrepreneurial sector now operate below their optimal scale: all entrepreneurs are borrowing constrained. This is accompanied by a decrease in the average worker productivity ratio and the ratio of average worker assets. Relative to the economy without the differences in labor market frictions, worker sorting based on productivity is now reduced even further with the removal of uncertainty. Elimination of labor market frictions reduces the ratio of average worker productivity from 1.17 to 1.13. In contrast, the removal of uncertainty about entrepreneurial ability decreases this ratio to 1.08. Turning to the ratio of average assets, the reduction in sorting is almost equally pronounced. The asset ratio in the economy with no uncertainty is 1.3, compared to 1.2 when labor market frictions are removed. Both values represent sizeable declines from the baseline value of 2.3.[29]

6.4 Borrowing

In the baseline model, the vast majority (90%) of entrepreneurs are borrowing constrained when operating their business. The exercise in the previous section demonstrated that the removal of the uncertainty about entrepreneurial ability reduces the incidence of small entrepreneurial firms, while rendering all entrepreneurs borrowing-constrained. This finding suggests that borrowing constraints are critical in determining the scale of businesses operated by entrepreneurs, and consequently the wage rates and worker sorting.

To explore how borrowing constraints change incentives for worker sorting, the borrowing constraint parameter (b) is raised to 2 from its baseline value of 1.5. This represents a doubling of the assets that entrepreneurs are able to borrow. The properties of the stationary equilibrium are shown in the last column of Table 8 (labelled "Borrowing"). Relaxing the borrowing constraint has a large effect on the distribution of employment across the two sectors. The share of employment in the entrepreneurial sector increases from 15% in the baseline to 22%. This increase occurs despite the fact that the vast majority of job offers come from the corporate sector. The ratios of average worker productivity and assets also decline even more compared to the analysis in the previous two sections. In particular, the ratio of average worker productivity is now less than unity, compared with 1.17 in the baseline. Worker sorting based on productivity essentially disappears when borrowing constraints are relaxed. Comparing average worker assets across the two sectors also indicates a reduction in worker sorting based on assets. The ratio is near unity, compared to its baseline value of 2.3.

The three exercise above aimed to illustrate the mechanisms that drive worker sorting in the baseline economy. The analysis suggests that labor market frictions, uncertainty in entrepreneurial ability, and borrowing constraints are important drivers of worker sorting. However, there is room for exploring further how these key elements impact worker sorting. Further robustness analysis under alternative assumptions about the key factors driving worker sorting is done in a separate sensitivity analysis section (Section 8).

[29] In the sensitivity analysis section below, the model's parameters are also re-calibrated to match the calibration targets without the entrepreneurial ability uncertainty. It turns out this type of uncertainty is critical in capturing the observed earnings premium for the corporate sector.

7 Evidence on Worker Sorting by Assets

A key prediction of the baseline model is that the average asset holdings of workers in the entrepreneurial sector is lower than that of workers in the corporate sector. This difference emerges as a combination of two effects. First, workers holding fewer assets tend to accept job offers from the entrepreneurial sector. Second, workers in the corporate sector tend to accumulate assets at a higher rate because of higher wages in that sector. Is there empirical evidence on these two types of worker sorting based on assets? The analysis to follow indicates evidence in favor of the model's predictions.

7.1 Data

Testing the model's implications on worker sorting by assets is challenging because it demands data on both workers' assets and the types of firms they work for. However, household survey data that include information on worker assets typically do not contain information on the age of a worker's employer to identify the entrepreneurial (young) firms with which workers are affiliated. This shortcoming, this paper brings together two sets of data. The wealth data for workers in the Survey of Income and Program Participation (SIPP), which contains information on various assets held by individuals, are merged with the Longitudinal Employer-Household Dynamics (LEHD) data that captures employment spells, earnings, and some employer characteristics for those workers.

To measure worker assets, the responses in the Asset and Liabilities Topical Module collected in the 1996, 2001, 2004 and 2008 SIPP panels are used to create a net worth variable, excluding housing equity. Housing equity is initially excluded to prevent the undue influence on assets of large amount of wealth accumulation that results from the appreciation in house values during the sample period. Nevertheless, the results are robust to inclusion of the housing equity, as discussed below. The net worth variable is calculated at the household level, and used as the primary empirical counterpart to assets in the model. The net worth is the sum of the market value of assets (except housing) owned by every member of the household minus the liabilities of household members.[30] For the analysis, the net worth variable is winsorized at the top 1% to reduce the effects of some likely outliers. The SIPP data also provide a set of variables that describe individuals' characteristics, including gender, race, marital status, education, and age. These variables offer a rich set of controls in testing the model's implications on assets.

[30] The assets included in this definition are interest-earning assets held at financial institutions, stocks and mutual fund shares, rental property value and rental income, IRA, 401K and thrift savings plans, and values of vehicles owned. The excluded assets are equities in pension plans, the cash value of life insurance policies, home value, and the value of home furnishings and jewelry.

The individuals in the SIPP panels are linked to the LEHD data based on unique time-invariant individual identifiers called Protected Identification Keys (PIKs). The LEHD data are the universe of quarterly wage data for available states, and the SIPP quarter is the calendar quarter in which an individual's response to the survey is recorded. Because different states enter LEHD data at different times, the sample is restricted to data starting one year after the inclusion of a state's data series in the LEHD. This approach reduces spurious identification of new hires. The LEHD data also provide age and size measures for the firms individuals work for. In addition, industry affiliation for these firms are also available. For workers holding more than one job during the relevant quarter, firm age and size pertain to the firm where worker earnings were the greatest among all jobs held in that quarter.[31] In the analysis to follow, all variables denominated in dollars are converted to 2014 constant dollars, and survey weights in SIPP are used to obtain estimates that are representative of the population.

7.2 Results

Table 9 shows the mean and quasi-median of net worth for workers in the sample. To be consistent with the calibrated model, the sample is restricted to male workers aged 15-64 in entrepreneurial (young firms with 0-5 years of age) versus other firms (older firms with 5+ years of age).[32] All statistics indicate a stark difference in the average asset holdings of workers in entrepreneurial firms relative to others. In particular, workers in older firms have a mean net worth that is about 17% percent higher than that of workers in young firms. Based on the quasi-median, this difference is even larger – about 85%.[33] Note, however, that higher wages in old firms relative to entrepreneurial firms would imply an asset differential even when workers accept job offers randomly regardless of their asset holdings, as long as employment has some persistence. On this point, Table 9 shows that the earnings of workers in older firms are in general much higher, regardless of whether the earnings is measured by the mean or quasi-median.

Further evidence on sorting of workers based on assets at the time when they take jobs can be provided by examining the assets of recently hired workers only. For this purpose, the sample is restricted to those workers who are within their first year of employment following

[31] For details on how separate jobs and employment spells are identified in the LEHD data, see Hahn, Hyatt, and Janicki (2017).

[32] Quasi-median is calculated as an alternative to percentiles to satisfy U.S. Census Bureau's requirements for disclosure. It is the average of the observations in the data between the 45th and the 55th percentiles. The standard error for the quasi-median is obtained using a bootstrap procedure that calculates the quasi-median on 100 different 50% samples taken from the data.

[33] In addition, the gap between the net worth of workers generally persists at the first and third quartiles, indicating that worker sorting prevails at different parts of the asset distribution. The results for these quartiles are available upon request.

an unemployment spell. This subsample allows for an approximation to the asset holdings of workers in the model who have recently transitioned into employment from unemployment. The results are shown in Table 9. There is a statistically significant asset differential across workers in the two types of firms when measured by either the mean or quasi-median net worth. Therefore, the asset gap is not merely a result of the fact that working for older, more established firms allows individuals to accumulate more assets over time. Workers accepting jobs in these firms are on average wealthier to start with, in line with the model's prediction on sorting based on assets.

One obvious question is how much of the observed worker sorting by assets is driven by other confounding factors, such as worker characteristics. For instance, an individual's assets are likely correlated with marital status, education, and experience. To further isolate the connection between the type of the firm an individual works for and the worker's assets, Table 10 presents several estimates based on linear models of the form

$$\widetilde{a}_{it} = \sum_k \alpha_k d_{ikt} + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it}, \tag{16}$$

where $\widetilde{a}_{it}$ is the inverse hyperbolic sine transformation of the net worth a_{it} for individual i in year t

$$\widetilde{a}_{it} = \ln(a_{it} + \sqrt{a_{it}^2 + 1}). \tag{17}$$

The transformation in (17) is used for at least two reasons.[34] First, the net worth variable a_{it} has a highly-skewed, non-normal distribution. Second, there are some zero and negative values for a_{it}, which lead to omitted observations when the standard log transformation is used. On the right hand side of specification (16), d_{ikt} is a dummy variable for the age category k the firm the individual works for is classified in, $\mathbf{x}_{it}$ is a vector of controls, and ε_{it} is an error term. The controls $\mathbf{x}_{it}$ include the individual's gender, race, marital status, education level, age, and age-squared, as well as industry and year fixed effects. The model in (16) is estimated using OLS for mean effects. In addition, median regression is used to assess the effects at the median of the net worth distribution. The primary coefficients of interest are α'_ks, which measure the connection between net worth and firm age categories.

Table 10 indicates that age categories are significantly associated with net worth, even after controlling for a large set of observables. The estimates for firm age and size categories suggest that, compared to the omitted category of older firms (11+ years of age), workers in entrepreneurial firms tend to have much lower net worth. This result holds for both the mean (OLS) and median regressions, and for all young firm categories considered in the regressions. More

[34] Other transformations of the net worth variable were also used for robustness checks. In addition, the results were also robust when different measures of assets were used. These additional results are available upon request.

importantly, the net worth is also lower for recent hires by young firms. The baseline model is consistent with this finding. Note also that the results are generally stronger for all workers compared to recent hires. This finding supports the prediction of the baseline model that assets differential is higher, relative to recent hires, for workers who have been employed for at least a quarter. The estimates reveal that a worker in a 0-1 year old firm has approximately 49% less net worth than a worker in an 11+ year old firm, holding all else fixed.[35] The analogous difference is about 33% for a 4-5 year old firm. For recent hires, the corresponding differences are 23% and 13%, respectively.

Overall, the estimates in Table 10 support the model's key finding of worker sorting based on assets. Not only the workers in entrepreneurial (younger) firms tend to have lower net worth, but also the recent hires in these firms have on average fewer asset holdings compared to their counterparts in older firms. Additional analysis indicates that the findings in Tables 9 and 10 are robust to different definitions of net worth. For instance, including home value in net worth leads to similar conclusions. In addition, quantile regressions for the 25th and 50th percentiles also broadly yield qualitatively similar patterns, indicating that the differences in net worth tend to prevail in different parts of the net worth distribution, not just at the mean and median. Furthermore, the results are not very different, qualitatively speaking, if small firms, instead of young firms, are used as the empirical-counterpart of entrepreneurial firms – see Tables C.1 and C.2 in Appendix.

8 Sensitivity Analysis

The baseline model makes several stark assumptions to facilitate the analysis of various factors at work in generating worker sorting. In this section, the model is re-calibrated to match the targets of the baseline economy using alternative assumptions about two key elements of the model: entrepreneurial uncertainty and borrowing constraints. These exercises contrast with the analysis of the model's key features in Section 6, which isolates these features in a partial equilibrium context with other parameters of the model kept fixed at their baseline values.

8.1 Uncertainty about Entrepreneurial Ability

In the baseline model, the timing of the resolution of the entrepreneurial uncertainty is such that the entrepreneurial ability draw is realized *after* the decision to become an entrepreneur is

[35] Note that (16) implies that the percent change in $\widetilde{a}_{it}$ going from $d_{kit} = 0$ to $d_{kit} = 1$ can be estimated as $100\left(\exp(\widehat{\alpha}_k) - 1\right)$. For values of a_{it} that are not small, $\ln \widetilde{a}_{it} \simeq \ln(2a_{it}) = \ln 2 + \ln a_{it}$, and the percent change in $(a_{it} + \sqrt{a_{it}^2 + 1})$ approximates the percent change in a_{it}.

made. How much does this uncertainty matter for worker sorting and equilibrium allocations? Table 11 compares key features of the baseline economy with an alternative economy where individuals *know* their initial entrepreneurial ability draw at the time of the entrepreneurship decision.

While the economy without uncertainty replicates the overall employment rate, the sectoral employment shares, and the entrepreneurship rate, there is a notable difference in the sectoral wages compared to the baseline model. In particular, in the economy with no uncertainty w_e exceeds w_f, in a reversal of the baseline ranking. This discrepancy reflects the changes in the types of individuals who become entrepreneurs. The absence of uncertainty leads to larger entrepreneurial businesses, on average, relative to the baseline economy. This effect is seen in Figure 3. The entrepreneurial ability distribution in the economy with no uncertainty has more mass at larger entrepreneurial projects (higher θ) compared to the baseline economy. As a result, while 90% of the entrepreneurs are borrowing constrained in the baseline economy, virtually all are constrained in the economy with no uncertainty. Because entrepreneurs now have larger and more profitable businesses, the entrepreneurial sector can support a higher wage than the corporate sector.

How does the model with no uncertainty generate a corporate sector earnings premium of 15%, despite the fact that the corporate sector wage is now lower? The parameters M recovered for the economy with no uncertainty are shown in Table 11. While there is some change in all parameter values relative to the baseline model, most notably the probability of a corporate job offer increases from 0.48 to 0.50, and the entrepreneurial sector job offer probability halves from 0.04 to 0.02. This increase makes jobs in the entrepreneurial sector more scarce, and restricts the flow of workers into that sector, despite the higher wage in that sector. Consequently, the model is able to approximate the relatively small employment share of the entrepreneurial sector and the corporate sector wage premium, but not as well as the baseline model. Notice also that worker sorting prevails under no uncertainty, even though sorting is less pronounced.

8.2 Borrowing Constraint

The baseline model sets the borrowing limit at 50% of an entrepreneur's assets ($b = 1.5$). While this value of b is common in earlier models of entrepreneurship (see, e.g., Kitao (2008) and Buera and Shin (2011)), it is certainly not the only way to specify the extent of limits to borrowing. To assess the role of the borrowing constraint further, the borrowing constraint parameter b is increased to 2.0. The parameters, M, are again recovered to match the targets in the baseline with the new borrowing constraint in place.

Table 12 compares the equilibrium allocations, prices, and parameters for the baseline economy to that for the economy with $b = 2.0$. The corporate sector job offer rate, γ_f, in the case of $b = 2.0$ is higher than that in the baseline economy. The ratio of wages is similar to that found in the case with no uncertainty for entrepreneurial ability. Note that w_e exceeds w_f, as entrepreneurs now operate larger and more profitable businesses on average. In order to match the sectoral employment shares and the corporate sector earnings premium, the entrepreneurial job offer rate decreases to generate higher job finding frictions. While a higher borrowing limit encourages entrepreneurs to expand, a lower average entrepreneurial ability compared to the baseline case is now needed to limit the employment in the entrepreneurial sector. Again, as in the case of no entrepreneurial uncertainty, a corporate earnings premium of 15% emerges, despite the higher wage rate in the entrepreneurial sector. Worker sorting by productivity and assets prevail under $b = 2.0$, albeit to a lesser degree.

9 Conclusion

Entrepreneurial firms, often thought of as new or young businesses, disproportionately hire younger individuals and provide lower earnings compared to more established firms. To understand what kind of workers match with entrepreneurial firms versus others, this paper proposed a dynamic model of entrepreneurship, which features two sectors, entrepreneurial and corporate, that differ in labor market frictions and prices of labor. These elements distinguish the framework from that of many existing models of entrepreneurship, which typically features a single price of labor and a unified labor market. The two sectors also possess different production technologies and face different financial constraints. These differences together lead to a divergence in sectoral wages per unit of worker efficiency and induces a sorting of workers across the two sectors based on both productivity and wealth.

The calibrated model's equilibrium offers an answer to the main question of who works for whom. Among individuals who look for work, less wealthy ones tend to take up job offers from the low-paying entrepreneurial sector, instead of waiting for a corporate job offer. This tendency results in a sorting of individuals across the two sectors by assets and productivity. The model is also able to account for the observed differences across the two sectors in employment shares, average worker earnings, and worker flows. The model's key prediction on worker sorting based on assets finds support in the data. The workers employed in young or small firms and those workers who were recently hired by these firms possess, on average, fewer assets than their counterparts in more established firms.

Analysis of the model reveals that the differences in the price of labor and labor market frictions both play an important role in the model's ability to replicate key features of the entrepreneurial sector and to generate worker sorting. In addition, worker sorting emerges as a robust feature of the model when alternative specifications of the model's key elements are considered. The model also provides a rich framework to study the effects of various search frictions and financial constraints on the entrepreneurial sector and its workers. One avenue for future work is to assess the effect of changes in these frictions and constraints on the long-run decline of entrepreneurship in the United States, and the implications of this decline on income inequality, and the earnings and wealth of workers who tend to take jobs in entrepreneurial firms.

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Table 1. The fraction of entrepreneurs in the U.S. economy in 2000

Basis	**Fraction of entrep.**	**Non-entrep. Pay Premium**	**Employment Share**	**Source**
Young and small firms (0-5 yr & emp $\leq$ 7)	1.7%	20.8%	3.6%	LBD
Young and small firms (0-5 yr & emp $\leq$ 15)	2.0%	18.5%	5.9%	LBD
Young firms (0-5 yr)	2.2%	17.2%	15.7%	LBD
Young (0-5 yr) + small old (6+ yr & emp $\leq$ 7) firms	4.9%	39.7%	20.8%	LBD
Young (0-5 yr) + small old (6+ yr & emp $\leq$ 15) firms	5.5%	44.7%	25.4%	LBD
Small firms (emp $\leq$ 10)	4.9%	33.5%	11.8%	LBD
Small firms (emp $\leq$ 20)	5.5%	36.7%	18.6%	LBD
Small firms (emp $\leq$ 25)	5.7%	37.4%	21.0%	LBD
Young firms (0-10 yr)	3.2%	16.6%	24.8%	LBD
Young (0-10 yr) + small old (11+ yr & emp $\leq$ 20) firms	5.8%	49.8%	33.1%	LBD
Firms classified with certainty as non-public	6.0%	45.2%	44.0%	SBO
Business owners with employees (Males 25-64)	2.9%	NA	NA	SIPP
Business owners with employees (Males 25-54)	2.8%	NA	NA	SIPP
Business owners with employees (All)	2.4%	NA	NA	SIPP
Business owners with employees (All 25-54)	2.3%	NA	NA	SIPP

Notes: The data sources are Longitudinal Business Database (LBD), Survey of Business Owners (SBO), and Survey of Income and Program Participation (SIPP). Estimates pertain to the year 2000. The denominator used to calculate fraction of entrepreneurs is the population of males aged 15-64 years, unless indicated otherwise. The calculations assume that each entrepreneurial firm is owned by a single entrepreneur.

Table 2. Some facts about entrepreneurial firms

Variable	Young Firms (0-5 years of age) 1987	2000	2012	Small Firms ($\leq$ 20 employees) 1987	2000	2012
Share of firms	0.48	0.41	0.33	0.90	0.89	0.90
Share of employment	0.21	0.16	0.11	0.21	0.19	0.18
Relative median of the firm-level average earnings	0.79	0.85	0.75	0.72	0.73	0.76

Notes: The data sources are Longitudinal Business Database (LBD) and Longitudinal Employer-Household Database (LEHD). A young firm is defined as one that is 0-5 years old. A small firm is defined as one that has at most 20 employees.

Table 3. The parameter values in the baseline model

Selected using a priori information or estimated using data

Parameter	**Value**	**Source**
Discount rate, β	0.98	Business cycle literature (Annual int. rate = 0.04)
Capital share in production, ν	0.36	Business cycle literature
Capital depreciation rate, δ	0.015	Business cycle literature (Annual rate = 0.06)
Productivity of the corporate sector, A	0.36	Normalization ($A = e^{-1}$)
Labor productivity, $\{\rho_z, \sigma_z\}$	$\{0.97, 0.13\}$	Heathcoate et al. (2010)
Entrepreneurial ability (Persistence), $\{\rho_\theta, \sigma_\theta\}$	$\{0.30, 0.18\}$	Estimated based on Abraham and White (2015)
Returns-to-scale in entrepreneurship, ξ	0.88	Estimated based on Abraham and White (2015)
Entrepreneur transition rate into corporate sector, p	0.001	IPO and Merger and Acquisition rates

Recovered using the calibration procedure

Parameter	**Value**	**Target**
Disutility from labor, α	0.82	Fraction employed–15-64 yrs old males (80%)
Job offer rate, $\{\gamma_e, \gamma_f\}$	$\{0.04, 0.48\}$	Job finding rate and employment shares
Job separation rates, $\{\phi_e, \phi_f\}$	$\{0.000, 0.012\}$	Separation rate from employment
Entrepreneurial ability (Mean), μ	0.24	Fraction of entrepreneurs (4.0%)

Notes: See Appendix B for the estimation of returns-to-scale for entrepreneurs and the parameters for the entrepreneurial ability process. Job separation and finding rates are taken from Shimer (2012). The fraction of entrepreneurs is based on the estimates in Table 1.

Table 4. The properties of the baseline model

Variable	**Model**	**Data**
Targeted Moments		
Employment-to-population ratio	82%	80%
Share of employment (Entrepreneurial sector)	15%	16%
Fraction of entrepreneurs	5%	4%
Corporate average earnings premium	19%	17%
Employment-to-nonemployment (E-to-N) flow	2%	2%
Nonemployment-to-employment (N-to-E) flow	45%	45%
Untargeted Moments		
Ratio of average worker productivity (Corporate/Entrepreneurial)	1.17	NA
Ratio of average worker assets (Corporate/Entrepreneurial)	2.20	1.20
Ratio of average worker assets in first quarter of job (Corporate/Entrepreneurial)	1.30	1.10
Wage ratio (w_f/w_e)	1.02	NA
Transfer rate, δ_τ	0.0006	NA

Notes: Employment-to-population ratio is based on the male population 15-64 years old. Share of employment in the entrepreneurial sector and corporate earnings premium are based on the Longitudinal Business Database (LBD). Fraction of entrepreneurs is based on the estimates in Table 2. The estimates for average worker assets are based on Survey of Income and Program Participation (SIPP)–see Section 7. E-to-N and N-to-E flows are taken from Shimer (2012).

Table 5. Inequality in the baseline model

	Share of Wealth		Share of Earnings	
Quintile	**Model**	**Data**	**Model**	**Data**
1st	0.9%	−0.5%	3.2%	7.5%
2nd	5.1%	0.5%	12.8%	11.3%
3rd	11.2%	5.0%	12.9%	18.7%
4th	21.4%	18.7%	16.6%	24.2%
5th	61.3%	76.2%	54.6%	38.2%

Notes: Wealth is measured by assets. The only negative value in the table is due to the high prevalence of negative assets at the bottom of the wealth distribution.

Table 6. The role of wages in worker sorting and equilibrium allocations

Variable	**Baseline**	**Equal Wages** ($w_e = w_f$)	**Equal Wages and Separation Rates** ($w_e = w_f, \phi_e = \phi_f$)
Employment-to-population ratio	82%	85%	83%
Share of employment (Entrepreneurial sector)	15%	33%	8%
Fraction of entrepreneurs	5%	3%	4%
Ratio of worker productivity (Corporate/Entrepreneurial)	1.17	1.15	1.00
Ratio of average worker assets (Corporate/Entrepreneurial)	2.30	1.90	1.00

Notes: The column "Equal Wages" pertains to the case where the entrepreneurial sector wage is set to be equal to the corporate sector wage in the baseline. The column "Equal Wages and Separation rates" pertains to the case where the entrepreneurial sector wage and separation rate are set to be equal to their corporate sector counterparts in the baseline model. All other parameters are fixed at their baseline values.

Table 7. Parameters under wage setting by the corporate sector

Parameter	Baseline	Wage Setting by Corporate Sector
Disutility from labor, α	0.82	0.84
Entrepreneurial sector job offer rate, γ_e	0.04	0.02
Corporate sector job offer rate, γ_f	0.48	0.49
Entrepreneurial sector job separation rate, ϕ_e	0.000	0.000
Corporate sector job separation rate, ϕ_f	0.012	0.011
Entrepreneurial ability (Mean), μ	0.242	0.244

Notes: The model where wage is set by the corporate sector re-estimates all model parameters to match the data targets.

Table 8. Decomposing sources of worker sorting in baseline model

Variable	**Baseline**	**Frictions**	**Uncertainty**	**Borrowing**
Share of employment (Entrepreneurial sector)	15%	28%	19%	22%
Fraction of entrepreneurs	5%	9%	6%	9%
Share of entrepreneurs with binding borrowing constraint	0.90	0.78	1.00	0.75
Ratio of average worker productivity (Corporate/Entrep.)	1.17	1.13	1.08	0.99
Corporate average earnings premium	19%	7%	6%	−8%
Ratio of average worker assets (Corporate/Entrep.)	2.30	1.20	1.30	1.10
Wage ratio (w_f/w_e)	1.02	1.07	0.98	0.93

Notes: The column "Frictions" refers to the model where job finding rates and separation rates are equal across sectors.

The column "Uncertainty" refers to the model where the uncertainty about the initial draw of entrepreneurial ability is removed at the time entrepreneurship decision is made. The column "Borrowing" refers to the model where the borrowing limit is increased to 2.0 for entrepreneurs.

Table 9. Household net worth by firm age

	Mean		**Quasi-median**	
Firm Age (years):	**0-5**	**6+**	**0-5**	**6+**
Net worth (All workers)	$108,308	$125,506	$13,105	$24,121
s.e.	(2,491)	(853)	(455)	(260)
N	12,000	101,000	12,000	101,000
Net worth (Recent hire)	$90,921	$97,837	$9,396	$11,624
s.e.	(1,175)	(1,328)	(502)	(287)
N	6,000	27,000	6,000	27,000
Earnings (All workers)	$13,400	$16,601	$9,743	$12,284
s.e.	(181)	(600)	(93)	(35)
N	11,000	98,000	11,000	98,000
Earnings (Recent hire)	$10,505	$13,904	$7,452	$8,242
	(191)	(1,172)	(111)	(57)
N	5,000	23,000	5,000	23,000

Notes: Standard errors in parentheses. The number of observations N is rounded to the nearest 1000 to prevent disclosure of confidential information. The sample is males aged 15-64 years. For quasi-median the standard error is calculated using bootstrap.

Table 10. Regression analysis of household net worth

	All Workers		**Recent Hires**	
Firm Age Category	**OLS Regression**	**Median Regression**	**OLS OLS Regression**	**Median Regression**
0-1 years	-0.675^{***}	-0.319^{***}	-0.267^{**}	-0.142^{**}
	(0.101)	(0.047)	(0.134)	(0.063)
2-3 years	-0.510^{***}	-0.236^{***}	-0.132^{*}	-0.036^{*}
	(0.096)	(0.040)	(0.063)	(0.020)
4-5 years	-0.403^{***}	-0.218^{***}	-0.139^{**}	-0.132^{**}
	(0.097)	(0.041)	(0.077)	(0.072)
6-10 years	-0.556^{***}	-0.215^{***}	-0.459^{***}	-0.197^{***}
	(0.061)	(0.022)	(0.118)	(0.055)
N	$235,000$	$235,000$	$66,000$	$66,000$

Notes: Standard errors in parentheses. All regressions include the individual's gender, race, marital status, education level, age, and age-squared, as well as industry and year fixed effects. The number of observations N is rounded to the nearest 1000 to prevent disclosure of confidential information. The regressions include all workers. The omitted category for firm age is 11+ years. *,**, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 11. The properties of the model with no entrepreneurial uncertainty

Variable	**Baseline**	**No Uncertainty**
Share of employment (Entrepreneurial sector)	15%	18%
Fraction of entrepreneurs	5%	5%
Share of entrepreneurs with binding borrowing constraint	0.90	1.00
Ratio of average worker productivity (Corporate/Entrepreneurial)	1.17	1.19
Corporate average earnings premium	19%	15%
Ratio of average worker assets (Corporate/Entrepreneurial)	2.30	2.10
Wage ratio (w_f/w_e)	1.02	0.98
Disutility from labor, α	0.82	0.82
Entrepreneurial sector job offer rate, γ_e	0.04	0.02
Corporate sector job offer rate, γ_f	0.48	0.50
Entrepreneurial sector job separation rate, ϕ_e	0.000	0.000
Corporate sector job separation rate, ϕ_f	0.012	0.012
Entrepreneurial ability (Mean), μ	0.242	0.242

Notes: The column "No Uncertainty" refers to the model where the uncertainty about the initial draw of entrepreneurial ability is removed at the time entrepreneurship decision is made. All model parameters are re-estimated to match the data targets.

Table 12. The properties of the model with relaxed borrowing constraint

Variable	**Baseline** ($b = 1.5$)	**Higher Borrowing Limit** ($b = 2.0$)
Share of employment (Entrepreneurial sector)	15%	18%
Fraction of entrepreneurs	5%	5%
Share of entrepreneurs with binding borrowing constraint	0.90	0.92
Ratio of average worker productivity (Corporate/Entrepreneurial)	1.17	1.16
Corporate average earnings premium	19%	15%
Ratio of average worker assets (Corporate/Entrepreneurial)	2.30	1.90
Wage ratio (w_f/w_e)	1.02	0.99
Disutility from labor, α	0.82	0.82
Entrepreneurial sector job offer rate, γ_e	0.04	0.02
Corporate sector job offer rate, γ_f	0.48	0.51
Entrepreneurial sector job separation rate, ϕ_e	0.000	0.000
Corporate sector job separation rate, ϕ_f	0.012	0.011
Entrepreneurial ability (Mean), μ	0.242	0.204

Notes: In the model with higher borrowing limit, all model parameters are re-estimated to match the data targets.

Figure 1. The distributions of entrepreneurial ability, assets, capital input and labor input – baseline model

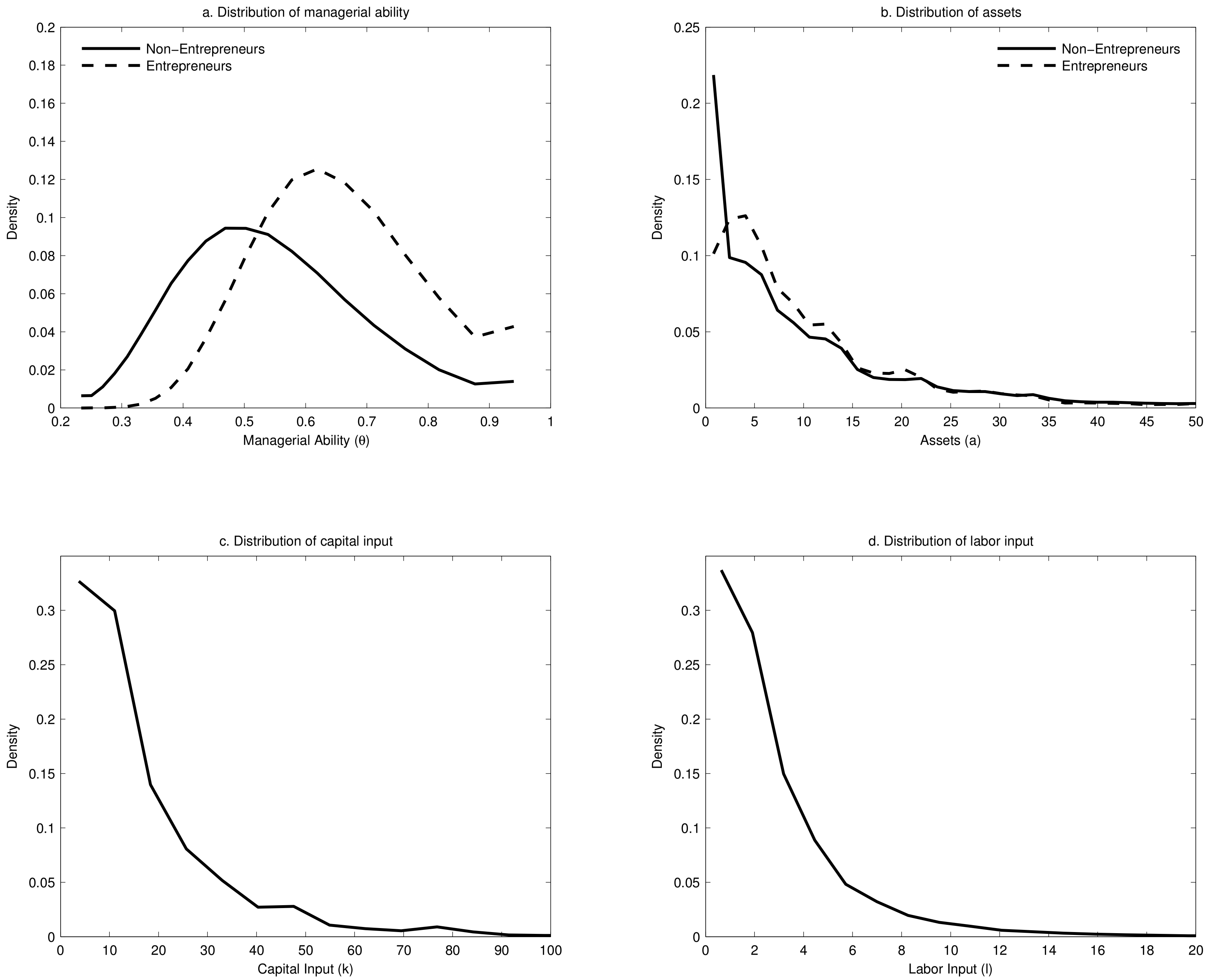


Figure 2. The allocation of individuals – baseline model

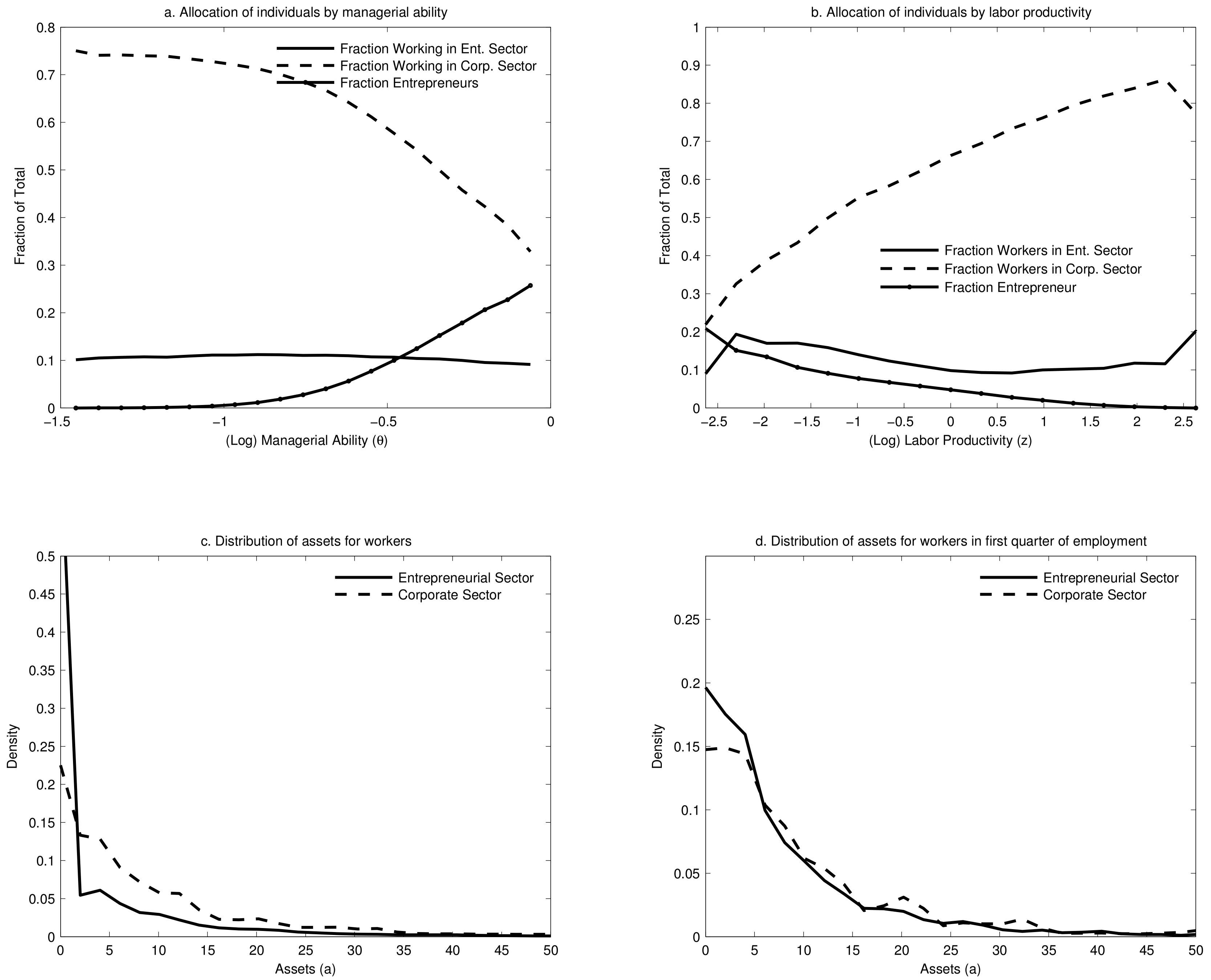
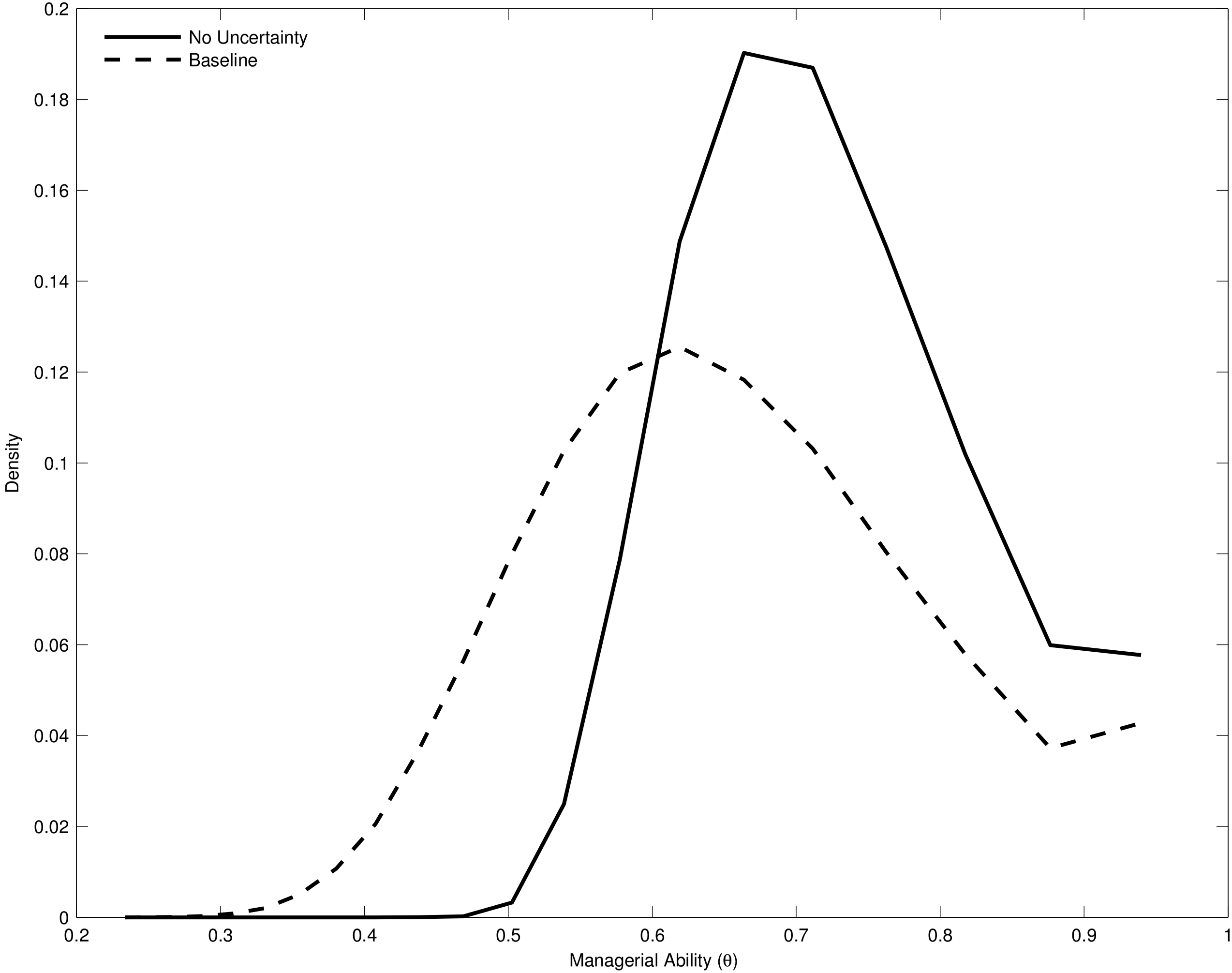


Figure 3: The Distribution of managerial ability among entrepreneurs



Appendix

A Algorithm for Solving The Model's Equilibrium

A stationary equilibrium of the model is computed using an algorithm based on Huggett and Ventura (1999). The algorithm finds an equilibrium by iterating over value functions and decision rules over a discretized state space. Discretization of the continuous worker and entrepreneurial ability processes in (1) and (2) is done using the Rouwenhorst method (Kopecky and Suen, 2010) with a 21-point support for the distribution implied by the process. The support is bounded below and above the mean by 2.5 times the standard deviation. The asset grid is discretized to 201 points with linear interpolation of all functions between grid points. The spacing between points on the asset grid increases with asset levels. Asset grid points are placed according to $a_1 = 0$, $a_j = \psi j^{\chi}$ for $j = 2, ..., 201$, where $\chi = 3.0$, $\psi = \bar{a}/(201^{\chi})$ and $\bar{a}$ is an upper bound. The algorithm is as follows.

1. Guess a value for the capital-labor ratio in the corporate sector, K/L, and δ_τ,

2. Calculate the values $w_f = (1-\nu)AK^{\nu}L^{-\nu}$ and $r = \nu AK^{\nu-1}L^{1-\nu} - \delta - \delta_\tau$,

3. Set the initial value for the entrepreneurial sector wage equal to the corporate sector wage: $w_e = w_f$,

4. Calculate the optimal decision rules $c^i(s)$, $a^{i\prime}(s)$, $h^d(\widetilde{s})$, $m^d(\widetilde{s})$, $k(s), l(s)$, $(i, d \in \{n, f, e, m\})$

5. Calculate K'/L', $\int l(s)d\Psi^m(s)$, $\int p\tau(s)d\Psi^e(s)$, and $\int zd\Psi^e(s)$ implied by the optimal decision rules,

6. If

$$
\begin{aligned}
|K'/L' - K/L| &< \eta_1, \\
|\int l(s)d\Psi^m(s) - \int zd\Psi^e(s)| &< \eta_2, \\
\left|\int p\tau(s)d\Psi^e(s) - \delta_\tau K\right| &< \eta_3
\end{aligned}
$$

   for small $\eta_1, \eta_2, \eta_3 > 0$, then a stationary equilibrium has been found. Otherwise, update K/L, $\{w_e, w_f\}$, and δ_τ, and repeat steps 4-6.

The parameter vector $M = \{\alpha, \lambda, \gamma, \phi_e, \phi_f, \mu\}$ is recovered using a Nelder-Mead Simplex algorithm, where the objective function is set to minimize the distance between the target and simulation moments. Target moments m_j ($j = 1, ..., J$) are described in Section 4. The objective function used is

$$\sum_{j=1}^{J} [(\ln(m_j/d_j))^2],$$

where m_j is the moment j calculated using simulated data in the stationary equilibrium and d_j is the corresponding data moment. The Fortran 90 code for the simplex algorithm is taken from the public domain and was written by Alan Miller.[36]

B Estimation of the Parameters $\rho_\theta, \sigma_\theta$, and ξ

The estimation of the decreasing returns parameter, ξ, for entrepreneurial firms, and the parameters for the entrepreneurial productivity process, $\{\rho_\theta, \sigma_\theta\}$, is based on the framework of Abraham and White (2015).[37] The framework allows the estimation of the parameters $\{\rho_\theta, \sigma_\theta, \xi\}$ simultaneously. Consider a production function for a manufacturing firm i in the form of

$$y_{it} = \theta_{it} \left(k_{it}^{a_k} l_{it}^{a_l} x_{it}^{1-a_k-a_l} \right)^{\xi}, \tag{18}$$

which includes materials and energy, x_{it}, as an input, and a productivity process $\ln \theta_{it} = (1 - \rho_\theta)\mu_i + \delta_t + \rho_\theta \ln \theta_{it-1} + \epsilon_t$, where μ_i is a firm-specific productivity parameter, δ_t is a year effect that captures general changes in productivity that apply to all firms, and $\epsilon_t \sim N(0, \sigma_\theta)$. The parameters ρ_θ and σ_θ are allowed to vary across industries. The inclusion of the materials and energy in the production function controls for the use of intermediate inputs (materials and energy) in estimating the underlying total factor productivity process. The estimation also allows for a markup, η, common to all firms in an industry, which can be thought of as the average markup across firms that is assumed to be constant over time. Abraham and White (2015) estimate the parameters, ξ, ρ_θ and σ_θ in a GMM framework using the log-linear form of the production function and the Solow residual obtained from the gross output and cost shares of the inputs. See Abraham and White (2015) or Castiglionesi and Ornaghi (2013) for a derivation of the exact model estimated.

The data used for the estimation is the U.S. Census Bureau's Annual Survey of Manufactures (ASM), which provides an unbalanced panel of manufacturing establishments for the period 1972-2009. The data include, for each establishment, annual measures of output (value of shipments) and inputs (employment, materials/energy use, capital). This information is aggregated to the firm level. The age of the firm is also available, which is the age of the oldest establishment of the firm. The establishments included in the ASM sampling frame typically have size 20

[36] Available at `http://jblevins.org/mirror/amiller/`.

[37] Also see Castiglionesi and Ornaghi (2013) for a similar estimation methodology.

employees or more, so the parameter estimates are not representative of very small firms. The model yields estimates of ξ, ρ_θ, and σ_θ for young versus old firms at the 4-digit SIC industry level. The estimated values for young firms are then averaged across industries to be used in the calibration of the baseline model. The analysis is limited to the manufacturing sector because of the unavailability of similar data for other sectors of the economy to calculate the revenue-based productivity of an establishment.

A remark is in order for how the estimated parameters of the three-input production function in (18) are used to calibrate the model's two-factor production function in (3). In the production function (18) used for estimation, the decreasing returns parameter, ξ, is the same for each of the three inputs. Because the decreasing returns parameter is common to all inputs, in the model's calibration the estimated decreasing returns parameter $\xi = 0.88$ is applied to the two-factor production function in (3). Similarly, the total factor productivity process is not specific to any input (i.e. Hicks neutral) in (18). Therefore, the estimated productivity process based on the three-factor production function in (18) is assumed to apply to the two-factor production in (3).

C Additional Tables

Table C1. Household net worth by firm age and size

	Mean		Quasi-median	
Firm Size (employees):	**0-49**	**50+**	**0-49**	**50+**
Net worth (All)	$111,167	$127,801	$15,045	$25,777
s.e.	(1,620)	(930)	(392)	(305)
N	28,000	85,000	28,000	85,000
Net worth (Recent hire)	$91,214	$97,812	$10,181	$12,621
s.e.	(1,842)	(1,670)	(453)	(316)
N	10,000	22,000	10,000	22,000
Earnings (All)	$12,813	$17,383	$12,915	$15,028
s.e.	(144)	(711)	(48)	(38)
N	26,000	82,000	26,000	82,000
Earnings (Recent hire)	$10,022	$14,826	$7,300	$8,542
s.e.	(150)	(1,392)	(76)	(64)
N	9,000	19,000	9,000	19,000

Notes: Standard errors in parentheses. The number of observations N is rounded to the nearest 1000 to prevent disclosure of confidential information. The sample is males aged 15-64 years. For quasi-median, the standard errors are calculated using bootstrap.

Table C2. Regression analysis of household net worth

	All Workers		**Recent Hires**	
		Median		**Median**
Firm Size Category	**OLS**	**Regression**	**OLS**	**Regression**
0-19 employees	-0.310^{***}	-0.196^{***}	-0.077^{**}	-0.056^{*}
	(0.055)	(0.023)	(0.039)	(0.033)
20-49 employees	-0.461^{***}	-0.186^{***}	-0.151^{***}	-0.093^{**}
	(0.065)	(0.024)	(0.057)	(0.053)
50-249 employees	-0.365^{***}	-0.212^{***}	-0.333^{***}	-0.175^{***}
	(0.051)	(0.019)	(0.103)	(0.043)
250-499 employees	-0.440^{***}	-0.213^{***}	-0.188^{**}	-0.140^{**}
	(0.073)	(0.027)	(0.087)	(0.060)
N	236,000	236,000	67,000	67,000

Notes: Standard errors in parentheses. All regressions include the individual's gender, race, marital status, education level, age, and age-squared, as well as industry and year fixed effects. The number of observations N is rounded to the nearest 1000 to prevent disclosure of confidential information. The regressions include all workers. The omitted category of firm size is 500+ employees.

*,**, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.