

Keeping Options Open: What Motivates Entrepreneurs?

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Abstract

To study the motivations of entrepreneurs, I develop a life-cycle model in which risk-averse individuals can become entrepreneurs and possibly return later to paid employment. While they are entrepreneurs, individuals learn about the productivity of their firm and enjoy nonpecuniary benefits. I estimate the model using detailed French administrative data which allow me to follow transitions in and out of entrepreneurship and to match entrepreneurs' employment records with their firm's accounting data. My main findings are as follow. First, estimated nonpecuniary benefits represent 6,700€ per year (some 15% of profits) and sum up to 74,000€ over the average entrepreneurial spell. Second, despite being small, nonpecuniary benefits are critical to entrepreneurship: without them, the number of firm creations would be cut by 16% and exit rates would increase so that overall the number of entrepreneurial firms would be 31% smaller. Third, the option to return to paid employment is worth 82,000€ to new entrepreneurs. This option is equally important for entrepreneurship: it explains 19% of firm creations on its own, and 45% together with nonpecuniary benefits. Finally, entrepreneurs face large permanent productivity shocks, which generate substantial option value and drive the evolution of the firm size distribution.

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1 Introduction

Entrepreneurs play a key role for job creation and productivity improvements ([Haltiwanger et al. \(2013\)](#), [Gennaioli et al. \(2013\)](#)). This makes it important to understand what drives individuals to leave paid employment and strike out on their own. Early cross-sectional studies suggest that financial earnings alone cannot explain this decision because entrepreneurs appear to earn less and bear more risk than employees ([Hamilton \(2000\)](#), [Moskowitz and Vissing-Jorgensen \(2002\)](#)). One possible resolution of this puzzle is that earnings data understate the benefits of entrepreneurship. Indeed, beside declared earnings, entrepreneurs may enjoy other, unobserved benefits, be they nonpecuniary (psychic) benefits or simply unreported earnings. Another possibility is that cross-sectional studies overstate the downsides of entrepreneurship by overlooking the entrepreneurs' option to return to paid employment if and when they fail. This option's value may motivate individuals to experiment with entrepreneurship ([Manso \(2016\)](#)).

Though some studies quantify entrepreneurs' unreported earnings ([Pissarides and Weber \(1989\)](#), [Hurst et al. \(2014\)](#)), little is known about the size of nonpecuniary benefits. Likewise, evidence exists that policies mitigating downside risk foster entrepreneurship ([Hombert et al. \(2017\)](#), [Gottlieb et al. \(2017\)](#)), but no estimate exists of the value of the option to return to paid employment. Neither do we know the extent to which this option and unobserved benefits affect the creation of entrepreneurial firms or the earnings differential between entrepreneurs and paid employees. Answering these questions is difficult: it requires estimating a structural model, and therefore access to detailed longitudinal data on entrepreneurs and young entrepreneurial firms, which are not publicly available.

This paper sets up and estimates a life-cycle model in which risk-averse individuals can become entrepreneurs and possibly return later to paid employment. While they are entrepreneurs, individuals learn about the productivity of their firm and enjoy nonpecuniary benefits, which in the model capture all unobserved benefits. I estimate the model using detailed French administrative data which allow me to follow transitions in and out of entrepreneurship and to match entrepreneurs' employment records with their firm's accounting data. My main findings are as follow. First, estimated nonpecuniary benefits represent 6,700€ per year (some 15% of profits) and sum up to 74,000€ over the average entrepreneurial spell. Second, despite being small, nonpe-

cuniary benefits are critical to entrepreneurship: without them, firm creations would drop by 16% and exit rates would increase so that, overall, the number of entrepreneurial firms would be 31% smaller. Third, the option to return to paid employment is worth 82,000€ to new entrepreneurs. This option is equally important for entrepreneurship: it explains 19% of firm creations on its own, and 45% together with nonpecuniary benefits. Finally, an important byproduct of my estimation is the finding that entrepreneurs face large permanent productivity shocks, which generate option value and drive the evolution of the firm size distribution.

I start by developing a standard life-cycle model of optimal consumption under income uncertainty, in which individuals work until retirement and experience persistent and transitory labor income shocks. The model's main specificity is that individuals can also leave paid employment when they have an entrepreneurial idea. In that case, they invest in a firm with Cobb-Douglas technology and decreasing returns to scale. Ideas arrive randomly and their quality determines the initial productivity of capital. As in [Lucas \(1978\)](#), heterogeneity in the quality of ideas drives the dispersion of firm size. As in [Jovanovic \(1982\)](#), initial productivity is not perfectly known and entrepreneurs only learn about it by observing their firm's profits. Learning is slowed down by transitory productivity shocks, which, together with permanent shocks, make investment risky. Entrepreneurs can borrow to invest in their firm but are not protected by limited liability. Finally, they observe how much they would earn in paid employment and can return to the labor market.

I then take the model to the data using French corporate tax files and individual employment records from 1994 to 2013. These data allow me to estimate the consequences of entrepreneurial spells on earnings by matching each new entrepreneur with a paid employee who had the same occupation, sex, age and similar wages over the three years preceding firm creation. Unlike many previous studies, I focus on job-creating entrepreneurs. Specifically, I restrict my sample to entrepreneurs whose firm hired at least one employee in the year of its creation.¹ These restrictions acknowledge the growing literature arguing that self-employment alone is a poor proxy of entrepreneurship.² For example, [Levine and Rubinstein \(2017\)](#) argue that incorporation is a better

¹Only 17% of other firms ever hire an employee other than their owner.

²[Hurst and Pugsley \(2011\)](#) document that most self-employed workers have no intention to grow or innovate. [Haltiwanger et al. \(2013\)](#) show that after controlling for firm age, small businesses do not create jobs. [Henrekson and Sanandaji \(2014\)](#) find that the rate of self-made billionaires correlates negatively with self-employment rates. [Schoar \(2010\)](#) discusses in details why researchers should differentiate subsistence and transformational entrepreneurs.

proxy and find that, unlike their unincorporated peers, incorporated US entrepreneurs earn slightly more than they would in paid employment. This finding raises the possibility that reported earnings alone could explain entrepreneurship when it is more narrowly defined. Similarly, I find that, over the first 10 years of their firm, French job-creating entrepreneurs earn 49% more than their control group. This premium falls to 20% when accounting for the wages of entrepreneurs who returned to paid employment and adjusting for a 3% opportunity cost of equity. Whether this premium is enough to compensate for entrepreneurial risk is unclear.

My estimation strategy has two steps. First, I use the volatility of wages among my control group of salaried employees to estimate the labor income process entrepreneurs face in paid employment. Second, I use the Simulated Method of Moments (SMM) to estimate the parameters related to entrepreneurship. The three most important are nonpecuniary benefits, initial uncertainty over productivity, and the standard deviation of permanent shocks. Permanent and transitory shocks are disentangled by matching the volatility of value added at different time horizons. The level of nonpecuniary benefits is estimated by targeting the earnings differential between entrepreneurs and their control group, as larger benefits lead individuals with relatively unpromising ideas to become entrepreneurs. Likewise, simulated exit rates are matched with their empirical targets by adjusting initial uncertainty over productivity, as higher uncertainty encourages experimentation, which in turn causes higher exit rates.

The results suggest that nonpecuniary benefits and the option to return to paid employment are equally important in explaining the decision to become an entrepreneur. Indeed, counterfactual experiments show that removing the former (later) would reduce the number of firm creations by 16% (19%), and removing both would reduce firm creations by 45%. Accordingly, the option and expected nonpecuniary benefits over the average entrepreneurial spell have similar values for new entrepreneurs, respectively 74,000€ and 82,000€. By comparison, and taking into account returns to paid employment, individuals who become entrepreneurs earn 89,600€ more than their control group over the following ten years.

On the other hand, only nonpecuniary benefits affect the cross-sectional earnings differential between active entrepreneurs and paid employees. Removing nonpecuniary benefits improves the quality of new firms and, later on, discourages the persistence of relatively unproductive entrepreneurs. Combined, these two effects would cause the earnings differential between active

entrepreneurs and paid employees to double. Removing the option to return to paid employment also improves entrepreneurs' quality at entry, but this improvement is offset by the inability of unsuccessful entrepreneurs to exit later on.

To match cumulative exit rates, the model requires a substantial level of initial uncertainty over permanent productivity ($\log \sigma=0.39$), while matching the volatility of value added requires large permanent productivity shocks ($\log \sigma=0.19$). My estimates therefore imply that, at horizons exceeding four years, permanent shocks generate more risk and option value than initial uncertainty. The average entrepreneurial spell lasts 11 years. Moreover, while removing initial uncertainty has little consequences on entrepreneurial activity, eliminating permanent shocks reduces the average firm's value added by 43%. This shows that permanent shocks explain the growth of successful businesses. A direct piece of evidence of these shocks in the data is that earning inequalities among surviving entrepreneurs increase with firm age, and so does the dispersion of firm size.³ If initial uncertainty were the main source of risk, selection by learning would gradually reduce inequalities among surviving entrepreneurs by eliminating the least efficient ones.

Finally, I run several experiments about policies intended to promote entrepreneurship. I reestimate the model under the assumptions that entrepreneurs either (i) temporarily experience a 20% reduction in wages when returning to paid employment, or (ii) lose 20% of their capital when they close their firm, or (iii) face progressive personal income taxes. I then remove each of these three elements and find them to have only marginal impact. This suggests that policies seeking to reduce labor market frictions, liquidation costs and marginal tax rates would have only limited impact on entrepreneurship.

This paper contributes to the entrepreneurship literature on nonpecuniary benefits and unreported earnings. [Hurst and Pugsley \(2011\)](#) document that over 50% of new US entrepreneurs cite nonpecuniary benefits among their motives. [Pissarides and Weber \(1989\)](#) and [Hurst et al. \(2014\)](#) infer from expenditure data that self-employed workers underreport their income by 25% to 35% in tax forms and household surveys. My approach differs in two ways. First, I measure how large unobserved benefits should be to rationalize observed earnings differentials between

³Speaking of the general population, [Lucas \(2003\)](#) notes that “the fanning out over time of the earnings and consumption distributions within a cohort that [Deaton and Paxson \(1994\)](#) document is striking evidence of a sizeable, uninsurable random walk component in earnings.” [Storesletten et al. \(2004\)](#) make this point quantitatively.

entrepreneurs and paid employees. Second, I focus on job-creating entrepreneurs, who might be less prone to underreporting than self-employed workers running smaller and more informal businesses.⁴ Unlike the previous literature, I also estimate how much nonpecuniary benefits contribute to entrepreneurial entry and persistence.

My paper also builds on [Manso \(2016\)](#)'s insight that entrepreneurs may be motivated by the option value of experimentation. [Hombert et al. \(2017\)](#) and [Gottlieb et al. \(2017\)](#) provide reduced-form evidence that mitigating downside risk spurs entrepreneurial activity. My study makes two new contributions to this literature. First, I show that entrepreneurs face substantial initial uncertainty over their productivity and then experience large permanent shocks, which explains why fallback options encourage entrepreneurship. Second, I estimate the value of the option to return to paid employment and its contribution to entrepreneurship.

[Dillon and Stanton \(2017\)](#) develop a semi-structural model in which risk-neutral individuals can switch to self-employment to learn about their productivity and can return to paid employment. [Humphries \(2017\)](#) develops a life-cycle model without learning but where agents can choose between various forms of self-employment. Relative to these papers, my model is closer to standard life-cycle models of consumption and portfolio choices as it allows for endogenous savings and investment decisions, risk-aversion and permanent productivity shocks, which turn out to be the main source of option value. These additions put the risk-return tradeoffs between entrepreneurship and paid employment at the center of the model.

The paper proceeds as follows. Section 2 presents the data and stylized facts on entrepreneurs' earnings and their firms. Section 3 lays out the model which is estimated in Section 4. Section 5 discusses the results and presents counterfactual experiments. Section 6 provides robustness tests and discusses policy experiments. Section 7 concludes.

2 Stylized Facts

This section presents the data and stylized facts on entrepreneurial earnings and the evolution of young firms. First, I document that entrepreneurs earn a premium over paid employees with

⁴[Schuetze \(2002\)](#) documents that entrepreneurs receiving more payments in cash are more likely to underreport their income. [Hurst et al. \(2014\)](#) report some weak evidence that underreporting decreases with education.

similar characteristics but also face a much larger variance in income. Then, I argue that the age of new entrepreneurs, the life expectancy of their firms and the volatility of their profits suggest that the option value of returning to paid employment is substantial and that entrepreneurs experience large permanent productivity shocks.

2.1 Data and sample

The paper relies on two confidential administrative datasets from the French statistical institute (INSEE): employee earning records and corporate tax files.

Employee earnings – Every year, firms, private organizations and most public administrations are required by law to provide detailed information on each of their employees. These filings are known as *Déclarations Annuelles des Données Sociales* (DADS) and their aggregation constitutes a dataset similar to the US Social Security Master Earnings File. The DADS currently cover the 1976-2013 period and include, in particular, information on wages, working period, hours, and occupation. Among 24 occupations, three identify business owners. INSEE provides the data in two forms: a series of cross sections that cover the entire population and a panel dataset for a representative subsample. The subsample covers $1/25^{th}$ of the population until 2000 and $1/12^{th}$ thereafter, that is approximately $1/20^{th}$ over the 1994-2013 period. In the cross-sectional data, individual identification numbers change from one year to another. As a consequence, individuals can only be followed from one job to the next in the panel data.

Corporate tax files – The second dataset contains income statements and balance sheets collected by the Treasury for the entire universe of French firms between 1994 and 2013. Because this dataset uses the same company identification number as the DADS, I can match business owners with their firm’s accounting data as long as they pay themselves a wage at some point.

Sample – I study firms created between 1994 and 2013 with at least one employee in the year of their creation. I exclude businesses with more than 50 employees or more than 1M euros of equity at their creation, as well as subsidiaries.⁵ Financial and real-estate firms are also excluded, as well as “liberal professions” (lawyers, notaries, doctors ...). Of firms respecting these conditions but having no employee in their first year, only 17% ever hire someone else than their owner.

⁵Corporate tax files are linked to the INSEE survey on financial links (*LiFi*) which can be used to identify firms belonging to the same group.

Firms with at least one employee at creation have on average 3.6 employees at age one. Overall, my main sample contains slightly more than 1 million firms and 4.7 million firm-year observations.

2.2 Income trajectories

Figure 1 reports the evolution of the distribution of earnings of individuals becoming entrepreneurs and that of a control group of paid employees built by matching. Earnings are defined as the sum of wages (net of payroll taxes) and firm's net income.

In Panel A, earnings include wages of entrepreneurs who closed their firm and returned to paid employment. The left plot shows that entrepreneurs earn on average 36% more than the control group over the first ten years. However, this comparison is somewhat misleading because entrepreneurs need to invest equity that could otherwise generate interests on a savings account. When adjusting for a 3% opportunity cost of equity, the earnings differential falls to 20%. I proxy equity as capital employed minus long term liabilities. It is not clear what the appropriate cost of capital is and 3% may very well understate the true cost of equity. Here, my main goal is to provide an indication of how the entrepreneurial premium varies when I control for the opportunity cost of equity. The right plot shows that entrepreneurial entry is followed by a large increase in the dispersion of earnings, which is three times larger than in the control group.

In Panel B, I compare the earnings of active entrepreneurs to that of their control group, but I remove entrepreneurs (and their match) from the data as soon as they close their firm. As better businesses are more likely to survive, survival bias causes the earnings differential to be larger and increase faster than in Panel A, averaging 49% over the first ten years. In spite of the exit of the least efficient firms, the dispersion of earnings among surviving entrepreneurs increases with firm age.

[Insert Figure 1 about here]

These plots are based on a subsample of 11,830 entrepreneurs and 107,701 entrepreneur-year observations. My panel data on wages covers only 1/20th of the population. Moreover, business owners can only be followed before and after their entrepreneurial spell if they receive a wage from their own firm. Otherwise, corporate tax files cannot be linked with employee earnings records.

Naturally, this condition is correlated with success. To reduce selection bias, Figure 1 only takes into account entrepreneurs paying themselves a wage in the first two years of their entrepreneurial spell. I find evidence that this subsample is not very different from other entrepreneurs hiring an employee in the first year. As reported in appendix Table B.1, over the first 10 years, firms run by these entrepreneurs generate only 1,700€ more in earnings. This bias gradually disappears and becomes statistically insignificant by year six. Similarly, I find the difference in exit rates between the two samples to be below one percentage point.

I match each new entrepreneur with a paid employee using pre-entrepreneurial characteristics. Specifically, matches are drawn from the sample of individuals who had the same employment status (working or not) over each of the three years preceding entrepreneurial entry. They must also have the same sex and main occupation. The main occupation is defined at the two-digit level (24 groups) as the one that generated the highest total earnings over the last two years. To pick the best match among paid employees satisfying these conditions, I compute the Mahalanobis distance to the entrepreneur with respect to four variables: age and income over each of the last three years. Table 1 reports the balance quality between the control and treated groups.

[Insert Table 1 about here]

The closest element of comparison for the earnings differential reported in Panel A is the study of Manso (2016) who conducts a similar matching exercise and finds no statistically significant difference in earnings between self-employed individuals and paid employees.⁶ The fact that his study uses self-employed as a proxy for entrepreneurship is the most likely explanation for this difference. By contrast, Levine and Rubinstein (2017) distinguish incorporated entrepreneurs from other self-employed workers and find that the former earn 29% more than they would in paid employment.

⁶Previous longitudinal studies suffer from small sample size. For the US, Manso (2016) uses the National Longitudinal Study of Youth (NLSY79) and have 5,470 self-employed individual-year observations. Dillon and Stanton (2017) uses the Panel Study of Income Dynamics (PSID) in which 1,550 men are entrepreneurs at some point.

2.3 Early years of businesses

Table 2 reports summary statistics for firms with at least one employee in the year of their creation. New entrepreneurs are on average slightly older than 40 when they create their firm and are therefore at least twenty years away from retirement. Yet most firms die within ten years, which indicates that the option value of returning to paid employment may be substantial.

[Insert Table 2 about here]

Two important features of the data suggest that exits may be difficult to explain with a simple model of selection where entrepreneurs learn about their skills or the quality of their idea. First exit rates do not drastically fall as firms get older. Second, the dispersion of firm size, measured by the standard deviation of log value added, increases with age. These facts suggest that permanent productivity shocks could be the main determinant of the evolution of the firm size distribution. If selection was only caused by learning, exits should be concentrated among younger firms. Moreover, the level of heterogeneity should decrease with age as the least efficient entrepreneurs return to paid employment. By contrast, permanent productivity shocks can cause the death of mature businesses and, at the same time, increase heterogeneity among surviving firms. Finally, one last and more direct piece of evidence that entrepreneurs experience large permanent productivity shocks is that the volatility of log value added ($\text{std of } \log \text{VA}_{it+k} - \log \text{VA}_{it}$) increases with horizon (k).

Disentangling permanent and transitory productivity shocks is important for at least two reasons. First, only permanent shocks should significantly increase the entrepreneurial risk premium as business owners can self-insure against transitory shocks through consumption smoothing. Second, just like initial uncertainty, permanent shocks increase the option value of experimentation if entrepreneurs can return to paid employment. One key difference is that initial uncertainty only generates option value in the first business years. On the other hand, permanent shocks create option value among mature nonperforming firms and can therefore encourage their owners to delay their return to paid employment.

Though the majority of firms in my sample die before reaching 10 years old, exit rates are much lower than in Manso (2016) who finds that the majority of self-employment spells last less than

two years. The difference is likely due to his broader definition of entrepreneurs. However, the exit rates in my sample are nearly identical to those observed among incorporated firms in Norway (van Praag and Raknerud (2017)). Cabral and Mata (2003) also report that the size dispersion of Portuguese manufacturing firms, measured by the number of employees, keeps increasing with age, even after 20 years old. Finally, the age of business owners is consistent with Levine and Rubinstein (2017) who report an average of 43.6 for incorporated businesses.

3 Model

This section lays out a life-cycle consumption model in which individuals can leave paid employment to become entrepreneurs and run a firm with Cobb-Douglas technology. Entrepreneurs learn about the productivity of their firm through experimentation like in Jovanovic (1982) and can return to paid employment in case of disappointment.

[Insert Figure 2 about here]

Figure 2 illustrates the timing of events and decisions by decomposing a period (year) into sub-periods. First, individuals get a business idea with probability p . Ideas arrive only once in a lifetime but do not have to be implemented right away. Individuals also receive labor income shocks, regardless of whether they are entrepreneurs or paid employees.⁷ The first decision of the agents is to choose between paid employment and entrepreneurship for the rest of the year. Individuals can only become entrepreneurs once. If they choose to run a firm, they also decide how much to invest in capital. What is not invested in their firm is saved at the risk-free rate. Finally, at the end of the year, paid employees and entrepreneurs receive their earnings and decide how much to consume.

In the rest of this section, I describe preferences, how entrepreneurs run their firm and learn about their productivity and the dynamics of labor income in paid employment.

⁷I also solved the model assuming that individuals choose their occupation before their labor income shocks and find its predictions to be quantitatively close, with one exception. If labor income shocks happen after the occupation choice, paid employees must wait for an entire year before becoming entrepreneurs when they receive large negative shocks (are fired). This lag causes wages to drop more sharply in $t - 1$ in the model than in the data. It seems more reasonable to assume that when being fired, individuals can immediately become entrepreneurs if they have a business idea.

3.1 Agent

As is standard in the life-cycle literature, the agent has a period utility function with constant relative risk aversion (CRRA). Specifically, the expected utility of agent i at time t is

$$V_{it} = \mathbb{E}_t \sum_{s=t}^{R-1} \beta^{s-t} \frac{(C_{it} + B_{it})^{1-\gamma}}{1-\gamma} + \beta^{R-t} V_{iR} \quad (1)$$

where C is consumption, B a nonpecuniary benefit received by entrepreneurs, β the discount factor, γ the coefficient of relative risk aversion and V_{iR} the terminal value at retirement age R . Throughout the paper, I use the homotheticity of CRRA preferences to normalize wealth, wages and profits by the national average wage.

3.2 Entrepreneurship

3.2.1 Production

As in the data, firms have different sizes from their creation onwards. This dispersion partially arises from the heterogeneity of talents and project quality among entrepreneurs facing decreasing returns to scale due to a span of control, following the theory of [Lucas \(1978\)](#). Specifically, the net profit of the firm is

$$\Pi_{it} = (1 - \tau) [e^{z_{it}} K_{it}^\alpha - \delta K_{it} - r_D D_{it}] \quad (2)$$

where z_{it} measures the log productivity of capital, δ its depreciation rate, and α the curvature of the production function. The model implicitly assumes that labor is chosen freely after observing productivity, in which case wages represent a constant fraction of value-added.

On the other hand, I assume that entrepreneurs make investment decisions before observing z_{it} in order to take into account short-term business uncertainty and capital adjustment costs. This assumption makes returns on capital uncertain.

Log TFP is the sum of a permanent, random walk component $z_{1,it}$ and a transitory shock $z_{2,it}$.

Specifically, the dynamics of z is

$$\begin{cases} z_{it} = z_{1,it} + z_{2,it} \\ z_{1,it} - z_{1,it-1} \sim \mathcal{N}(0, \sigma_{z,1}^2) \text{ i.i.d.} \\ z_{2,it} \sim \mathcal{N}(0, \sigma_{z,2}^2) \text{ i.i.d.} \end{cases} \quad (3)$$

where innovations to the transitory and permanent components are independent from each other and over time. The structural corporate finance literature often uses an AR(1) to model the stochastic component of log TFP. However a stationary process cannot explain why the size dispersion of young French firms increases with age.

Corporate taxes represent a fraction τ of profits and are negative in case of losses, which proxies the firm's ability to carryback and carryforward. Entrepreneurs can borrow without constraint at a rate r_D . I assume that entrepreneurs are not protected by limited liability, which is consistent with evidence that they pledge their homes as collateral to obtain business loans, as documented in the United-States by [Robb and Robinson \(2014\)](#) and in France by [Schmalz et al. \(2017\)](#). Noting r the risk free rate, I impose $r_D = \frac{r}{1-\tau}$ to prevent entrepreneurs from arbitraging the post-tax difference in interest rates. This guarantees that occupation choices are only driven by the relative merits of paid employment and entrepreneurship. Under these assumptions, the dynamics of wealth W is

$$W_{it+1} - W_{it} = (1 - \tau) (e^{z_{it}} K_{it}^\alpha - \delta K_{it}) + r(W_{it} - K_{it}) - C_{it} \quad (4)$$

3.2.2 Beliefs and learning

To start a business, workers need an entrepreneurial idea. Ideas arrive at an annual rate p , and only once in a lifetime. As in [Jovanovic \(1982\)](#), workers do not observe the profitability of their idea and can only learn about it by starting a business, a decision that they can delay. The quality of the project serves as an initial value for permanent productivity z_1 . Specifically, noting t_0 the

arrival year of the idea, the initial value of z_1 is

$$\begin{cases} z_{1,it_0} = \underbrace{\bar{z}}_{\text{industry mean}} + \underbrace{\nu_{1,i}}_{\text{observed}} + \underbrace{\nu_{2,i}}_{\text{unknown}} \\ \nu_{1,i} \sim \mathcal{N}(0, \sigma_{\nu,1}^2) \\ \nu_{2,i} \sim \mathcal{N}(0, \sigma_{\nu,2}^2) \end{cases} \quad (5)$$

where \bar{z} is an observable industry mean, $\nu_{1,i}$ is a component known from the agent and $\nu_{2,i}$ a source of uncertainty. I assume that the entrepreneur updates his beliefs in a Bayesian fashion. His initial prior regarding the permanent component of productivity z_1 and his initial degree of uncertainty σ_{μ,t_0}^2 are

$$\begin{cases} \mu_{it_0} = \bar{z} + \nu_{1,i} \\ \sigma_{\mu,t_0}^2 = \sigma_{\nu,2}^2 \end{cases} \quad (6)$$

Conditional on maintaining his business, he observes the realized TFP but not its decomposition between the transitory and permanent components. In this case, the dynamics of his prior is

$$\mu_{it+1} - \mu_{it} = \frac{\sigma_{\mu,t}^2 + \sigma_{z,1}^2}{\sigma_{\mu,t}^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2} (z_{it} - \mu_{it}) \quad (7)$$

and the uncertainty regarding μ_i evolves following

$$\sigma_{\mu,t+1}^2 = \frac{(\sigma_{\mu,t}^2 + \sigma_{z,1}^2)\sigma_{z,2}^2}{\sigma_{\mu,t}^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2} \quad (8)$$

3.3 Paid employment

The log of the individual's wage y is divided into three components: a deterministic function of age $f(t)$, an idiosyncratic persistent element $l_{1,it}$ and a transitory one $l_{2,it}$.

$$y_{it} = f(t) + l_{1,it} + l_{2,it} \quad (9)$$

The transitory component l_2 is normally distributed with variance $\sigma_{l_2}^2$, while the persistent component l_1 follows an AR(1) process

$$l_{1,it+1} = \rho l_{1,it} + \epsilon_{l,it} \quad (10)$$

where $\epsilon_{l,t}$ is normally distributed with variance $\sigma_{l_1}^2$. This specification is widespread in the life-cycle literature, which often imposes $\rho = 1$ to improve tractability. Finally, the wealth dynamics of paid employees is

$$W_{it+1} = (1 + r)W_{it} + Y_{it} - C_{it} \quad (11)$$

3.4 Recursive formulation

The problem is solved backward by numerical dynamic programming. More details on the numerical procedure are provided in Appendix A.1. Each year is divided into two sub-problems: one for occupation choice and investment, the second for consumption. Let's use an apostrophe sign ($'$) to denote evolving state variables.

In the consumption sub-problem, the agent maximizes

$$V_{t+\frac{1}{2}}(W, \mu, \sigma_\mu, l_1) = \max_C \left\{ \frac{C^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}V_{t+1}(W', \mu', \sigma'_\mu, l'_1, l'_2) \right\} \quad (12)$$

where $W' = W - C$ while l_1 and l_2 evolve as detailed in Section 3.3. Paid employees who have not got an entrepreneurial idea yet receive one with probability p . In that case, μ' and σ'_μ are defined by Equations (5) and (6). They remain unchanged otherwise.

In the occupation and investment sub-problem, the agent maximizes

$$V_t(W, \mu, \sigma_\mu, l_1, l_2) = \max_K \left\{ \mathbb{E}V_{t+\frac{1}{2}}(W', \mu', \sigma'_\mu, l_1) \right\} \quad (13)$$

where $K = 0$ and $K > 0$ respectively imply paid employment and entrepreneurship. Agents who are not former entrepreneurs and have an idea can choose $K > 0$, in which case W' , μ' and σ'_μ evolves as described in Section 3.2. Note that from the agent's point of view, the distribution of $z_{1,it}$ is $\mathcal{N}(\mu_{it}, \sigma_{\mu,t}^2 + \sigma_{z,1}^2)$. If $K = 0$, then μ' and σ'_μ do not change and W' follows Equation (11). Nobody consumes during this sub-period.

Finally, the terminal value V_R only depends on wealth and is approximated using Merton (1969)'s solution, assuming a residual life expectancy of 20 years.⁸ Specifically, the terminal value is

$$V_R(W) = \left(\frac{1 - e^{-20v}}{v} \right)^\gamma \frac{W^{1-\gamma}}{1-\gamma} \quad (14)$$

where $v = \frac{(1-\beta)-(1-\gamma)r}{\gamma}$.

4 Structural Estimation

This section details the structural estimation of the model. I preset a number of parameters using key statistics from the firm data (depreciation rates, tax rates...) and use my control group of paid employees to estimate the dynamics of wages. Finally, I use SMM to estimate parameters that are more difficult to directly infer from the data, namely nonpecuniary benefits (B), the arrival rate of ideas (p), their average quality (\bar{z}), the dispersion of initial priors ($\sigma_{\nu,1}$), the initial uncertainty over productivity ($\sigma_{\nu,2}$) and the size of permanent ($\sigma_{z,1}$) and transitory ($\sigma_{z,2}$) productivity shocks.

4.1 Calibrated parameters

Table 3 reports all preset parameters. As detailed below, I use my control group to estimate the labor income process and use the firm data to directly infer some business-related parameters. Preferences are taken from the existing literature.

[Insert Table 3 about here]

4.1.1 Labor income process

I assume that the deterministic component of wages $f(t)$ is a cubic polynomial in age, which I estimate by OLS. Specifically, I normalize wages by the national average and regress the log on age, age² and age³. I restrict the employee panel data to individuals who have been matched with entrepreneurs and use all observations between 1992 and 2013.

⁸In Merton's model, the agent can also invest in the stock market portfolio. As this is not the case in my model, I use Merton's solution with an equity premium of zero

I estimate the dynamics of the stochastic component of wages by SMM. I target the standard deviations of log income growth at the 1, 3 and 5-year horizons, which provide moment conditions that exactly identify ρ , $\sigma_{l,1}$ and $\sigma_{l,2}$. I use the identity matrix as the SMM weight matrix and find that these empirical moments imply persistent shocks of size $\sigma_{l,1} = 0.345$ and persistence $\rho = 0.835$ and transitory shocks of size $\sigma_{l,2} = 0.312$. This means that nearly half of income shocks mean-reverts within one-year, while the other half is fairly persistent. To compute these empirical moments, I restrict the control group to males between 25 and 55 years old. The goal of this restriction is to eliminate as much as possible variations in income caused by voluntary changes in working hours or transitions in and out of the labor force.

4.1.2 Business environment

A number of parameters relative to the business environment can be reasonably calibrated using moments from the data.

Cost of capital (r and δ) – In the sample, the median interest-to-debt ratio is close to 5.5%. Assuming an inflation rate of 2%, this translates into a real risk-free rate of $r = 3.5\%$. Likewise, I set the depreciation rate to $\delta = 6.5\%$ to match the median ratio of depreciation-to-capital employed. I choose the medians of these two ratios because their mean is distorted by outliers.

Returns to scale (α) – I set $\alpha = 0.28$, which I estimate by OLS. Specifically, I estimate

$$\ln(\text{Adj. Ebitda}_{it}) = \hat{\alpha} \times \ln\left(\frac{\text{Capital Employed}_{it} + \text{Capital Employed}_{it-1}}{2}\right) + u_i + \varepsilon_{it} \quad (15)$$

where u_i are firm fixed-effects. In a world without frictions, the sample mean of the Adj. Ebitda-to-Capital Employed ratio should be $\frac{\delta+r}{\alpha} \approx 0.35$. This prediction is somewhat consistent with the data: the ratio is close to 0.6 for new firms but then converges towards 0.36.

Corporate taxes (τ) – I set $\tau = 0.14$ to match the mean effective tax rate observed in my sample. France has a progressive corporate tax schedule. In 2017, the share of profits below 38,120 euros is taxed at a limited rate of 15%. The share between 38,120 and 75,000 is taxed at 28%, and the rest at 33.3%. My estimate of τ is below 15% because it takes into account wages paid to entrepreneurs, which are tax deductible.

4.1.3 Preferences

Preference parameters are taken from the literature. I set the discount factor to $\beta = 0.96$, following the structural estimation of the life-cycle consumption model with labor income risk by [Gourinchas and Parker \(2002\)](#) and [Guvenen and Smith \(2014\)](#).

I set the coefficient of relative risk aversion to $\gamma = 1$, in which case the agent has log utility preferences. Estimates of γ in the laboratory often suggest values slightly below 1 ([Holt and Laury \(2002\)](#), [Harrison and Rutström \(2008\)](#)). In particular, [Andersen et al. \(2008\)](#) use experimental data to elicit risk aversion in the context of the life-cycle problem of their participants and find $\gamma = 0.74$. [Gourinchas and Parker \(2002\)](#) estimate γ to be between 0.5 and 1.4. [Chetty \(2006\)](#) argues that empirical evidence on the elasticity of labor supply impose a level of γ below 2.

4.2 Identification

Ideally, we want the model to match moments that *(i)* are informative about the seven estimated parameters and *(ii)* should matter for entrepreneurs. The latter include, in particular, expected earnings, riskiness and investment horizon. This section discusses the choice of these moments and [Figure 3](#) illustrates key comparative statics used for identification. To construct this figure, I set all parameters to their SMM estimates and then vary each of them holding the others constant. For each parameter, I report the evolution of the moment that is likely to be the most informative.

[Insert [Figure 3](#) about here]

Some comparative statics are straightforward. For example, a higher arrival rate of ideas (p) lowers the average age of entrepreneurs as business opportunities appear sooner. Matching age is important because the option value of returning to paid employment depends on how close entrepreneurs are to retirement. Moreover, the value of experimentation depends on investment horizon: younger workers are more likely to experiment with less promising ideas since many years of profits would offset the cost of experimentation in case of success.

Likewise, the average EBIT informs us about the average quality of entrepreneurial ideas (\bar{z}). Matching EBIT, rather than EBITDA for example, simplifies the interpretation of my results by making them much less dependent on the calibration of the depreciation rate and returns

to scale.⁹ I adjust EBIT to reintegrate wages paid to entrepreneurs, taking into account that wages are not subject to corporate taxes. Specifically, I define adjusted EBIT as $\text{Adj. EBIT}_{it} = \text{EBIT}_{it} + \text{Wage}_{it}/(1 - \text{Tax Rate}_{it})$.

Permanent and transitory shocks are disentangled by matching the volatility of log value added at different time horizons: one and three years. As shown in Panel C, volatility is independent of horizon when shocks are purely transitory ($\sigma_{z,1}=0$). Conversely, increasing the size of permanent shocks causes volatility to be greater at the 3-year horizon. For each firm age, I compute the empirical volatility at horizon k as the standard deviation of the residuals of an OLS regression where the dependent variable is the change in log value added between t and $t + k$ and the explanatory variables are a set of 3-digit industry and year dummies.

The dispersion in log value-added that is not accounted for by productivity shocks is attributed to the variance of initial permanent productivity. This variance is decomposed into an observed ($\sigma_{\nu,1}^2$) and an unobserved ($\sigma_{\nu,2}^2$) component, which represents initial uncertainty. As illustrated in Panel B, these two components can be teased out by noting that higher initial uncertainty encourages experimentation, which in turn increases exit rates. Previous papers by [Manso \(2016\)](#) and [Dillon and Stanton \(2017\)](#) also interpret high exit rates over the first years of entrepreneurial spells as evidence of experimentation. If initial uncertainty is high enough to match exit rates but the simulated standard deviation of log value added is still smaller than its empirical target, the gap is filled by increasing the observed component of initial productivity ($\sigma_{\nu,1}^2$), as illustrated in Panel G.

Finally, I estimate nonpecuniary benefits by targeting the average earnings differential between entrepreneurs and their control group over the first ten years following entry, taking into account entrepreneurs who returned to paid employment. This moment is the integral between the top and bottom curves in Panel A.1. of Figure 1, divided by 10. As shown in Panel A of Figure 3, nonpecuniary benefits reduce the average earnings differential by encouraging entry and keeping inefficient businesses alive. To compute the simulated earnings differential, I construct a simulated control group by mimicking the matching procedure used for the empirical data. I start by

⁹ α and δ determine how much capital is used to produce one unit of EBITDA, and how much is destroyed in process. Hence, if these parameters are not correctly calibrated, the model can match the empirical EBITDA and yet overstate or understate the empirical EBIT.

simulating the life of 10^5 paid employees. Then, I match each new entrepreneur to one of these paid employees of the same age by computing the euclidean distance with respect to the last three years of wages.

With the exception of the earnings differential, all moments are targeted for each firm age between 1 and 10. Therefore, the SMM procedure tries to match firm life-cycle patterns, which also provide useful information for identification. In particular, an increase in the dispersion of firm size is a sign of permanent shocks. The first year (age zero) is not targeted because it rarely reflects a complete year of business. For the same reason, I exclude exiting firms when computing simulated and empirical moments. Before computing the moments, I winsorize all variables but age by industry-year at the 1st and 99th percentiles.

The SMM procedure seeks the vector of parameters $\theta = \langle B, p, \bar{z}, \sigma_{\nu,1}, \sigma_{\nu,2}, \sigma_{z,1}, \sigma_{z,2} \rangle$ that minimizes

$$(\mathbf{m} - \widehat{\mathbf{m}}(\theta))' \mathbf{W} (\mathbf{m} - \widehat{\mathbf{m}}(\theta)) \quad (16)$$

where $\widehat{\mathbf{m}}(\theta)$ is the vector of 61 simulated moments generated by the model, and \mathbf{m} its empirical counterpart. The weighting matrix \mathbf{W} is defined as follows. First, I compute the empirical average of each set of moments. I then take the square of its inverse and use it as diagonal elements of \mathbf{W} . For example, Ebit at age 1 and 10 have the same weight, which is determined by the average Ebit over the ten first years. Unlike other moments, the entrepreneurial premium is targeted only once, so I multiply its weight by 10. Off diagonal elements of \mathbf{W} are set to zero.¹⁰

4.3 Estimation results

Column (1) of Table 4 reports parameters estimated by SMM in my baseline specification. I estimate that nonpecuniary benefits represent 42.5% of the average national wage. This represents 6,700 euros per year over my sample period and sums up to 74,000 euros over the average length of entrepreneurial spells. Nonpecuniary benefits also represent less than 15% of profits and therefore fall under existing estimates of earnings underreporting (Pissarides and Weber (1989), Hurst et

¹⁰A common choice for the weight matrix in the inverse of the covariance matrix of the empirical moments. All my moments have low standard errors, but some of them have standard errors by magnitudes smaller than others. In particular, the empirical premium is measured using a much smaller number of observations. As a result, using the inverse of the covariance matrix would put a disproportionate weight on them.

al. (2014), [Astebro and Chen \(2014\)](#)). However previous studies consider the entire self-employed population which largely consists of smaller and more informal businesses. Underreporting might be more pervasive in these samples than among job-creating entrepreneurs. [Schuetze \(2002\)](#) documents that entrepreneurs receiving more payments in cash are more likely to underreport their income and [Hurst et al. \(2014\)](#) report some weak evidence that underreporting decreases with education.

Overall, entrepreneurs face a substantial amount of risk. First, productivity shocks are fairly large with a standard deviation of $\sqrt{\sigma_{z,1}^2 + \sigma_{z,2}^2} \approx 0.33$. Hence, even if entrepreneurs observed their permanent productivity and had no debt, the standard deviation of returns to capital would be twice that of the S&P500. While these shocks are mostly transitory, a one standard deviation shock to the permanent component would raise EBITDA by roughly 20%.

[Insert Table 4 about here]

Moreover, new entrants face substantial uncertainty regarding their initial permanent log productivity ($\sigma_{\nu,2} = 0.395$). For a given level of capital, an entrepreneur whose initial permanent productivity is above his belief by $\sigma_{\nu,2}$ would generate an EBITDA 50% above his expectation. Nonetheless, four years of permanent shocks ($\sqrt{4} \times \sigma_{z,1} = 0.39$) produce as much dispersion in productivity than initial uncertainty. Given that a firm’s simulated life expectancy at birth is 11 years, permanent shocks generate more risk and option value than initial uncertainty.

Finally, old firms are slightly less risky than young ones. From the entrepreneur’s point of view, the standard deviation of his next log TFP is $\sqrt{\sigma_{\mu,t}^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2}$. This standard deviation equals 0.52 for new firms and rapidly converges to 0.38. Indeed, Equation (8) implies that uncertainty regarding the permanent component of TFP converges towards $\lim_{t \rightarrow \infty} \sigma_{\mu,t} = 0.19$. Uncertainty remains substantial because transitory shocks generate too much noise for entrepreneurs to immediately observe permanent changes in productivity.

4.4 SMM Fitness

As reported in Figure 4, the model matches the data well. Its biggest weakness is its tendency to overestimate EBIT growth. As a result, the average simulated EBIT is slightly below its empirical target in the first six years and above it thereafter. One possible set of explanations lie

in institutional frictions that the model ignores. For example, stringent labor regulation discourages French firms to grow above 49 employees (Garicano et al. (2016)). Moreover, France has a progressive corporate tax schedule. In the sample, the average corporate tax rate is 14%, but the marginal rate reaches 33% above 75,000 euros of profits. Firms with more than 7.6M euros in sales cannot benefit from reduced tax rates at all. Economic frictions such as financial constraints and imperfect bayesian updating could also slow down the growth of EBIT by delaying the exit of unsuccessful firms and investment in the successful ones.

[Insert Figure 4 about here]

An important question is how my results might be affected by overestimating profits in the second decade of the firm’s life. Given the discount and survival rates, a risk-neutral agent would value business earnings in the first decade three times more than in the second. A risk-averse agent would put even less weight on late profits as they occur in good states of the world where the marginal utility of money is low.

To better understand the model and the identification of key parameters, I also estimate it under the assumptions that (i) there are no nonpecuniary benefits ($B = 0$), or (ii) no permanent productivity shocks ($\sigma_{z,1} = 0$) or (iii) no initial uncertainty ($\sigma_{\nu,2} = 0$). The model fitness under these different assumptions is reported in appendix Figure C.1. Of particular interest are the moments that cannot be matched when a parameter is set to zero. For example, without nonpecuniary benefits, the model cannot match at all the dispersion of log value-added because small and inefficient firms do not exist or are very rare. The only way to increase the dispersion is to extend the right tail of the distribution by increasing $\sigma_{\nu,1}$, but this cannot be done without blowing up the mean EBIT. This result indicates that the dispersion of value added is a source of identification for B .¹¹ Without permanent productivity shocks, the model cannot simultaneously match the volatility of log value added at the one-year and three-year horizons. More interestingly, the model predicts that the dispersion of log value-added should decrease with firm age because selection by learning eliminates the least productive firms, which causes heterogeneity among survivors to decrease. On the other hand, the model can match the data relatively well when initial uncertainty is set to zero, which suggests that this parameter is not key in understanding the data.

¹¹This also explains why the standard error for my estimate of B is very small, as the empirical dispersion of firm size is precisely estimated.

5 Discussion

This section discusses my main results. First, I show that the model correctly predicts the income trajectories of entrepreneurs and their control group before and after the creation of their firm. Second, I compute the certainty equivalent of the option to return to paid employment. Finally, I run counterfactual experiments to quantify the importance of key model ingredients.

5.1 Simulated income trajectories

Figure 5 reports the income trajectories of new entrepreneurs and their control group, in the model and in the data. Earnings include wages of entrepreneurs who returned to paid employment. Overall, the model captures relatively well (i) who become entrepreneurs and (ii) the subsequent earnings differential.

[Insert Figure 5 about here]

With regard to selection into entrepreneurship, simulated data replicate the decline in labor income that leads to entrepreneurial entry as well as the average income of new entrants. In the model, the decline of wages in the years leading to the entrepreneurial spell triggers the decision to start a firm by lowering the agent's opportunity cost. There is no ex-ante guarantee that the model would reproduce these patterns. First, the deterministic component of wages, $f(t)$, is increasing around 40 years old. Second, labor income inequalities are substantial in the model: the within-cohort standard deviation of log persistent income is $\sqrt{\sigma_{i,1}^2/(1-\rho^2)} = 0.63$. Entrepreneurs could therefore be drawn from a pool with a different level of income.

As a consequence of the excessive growth of Ebit reported in Panel C of Figure 4, the model slightly underestimates the premium over the first six years, and overstates it thereafter.

Finally, the structural model allows me to quantify biases in my matching strategy. My algorithm takes into account wages over the last three years but ignores negative (positive) labor income shocks received in year 0 that could have triggered (prevented) entrepreneurial entry. Because of this selection bias, the control group's earnings overstate what entrepreneurs would earn in paid employment. In simulated data, I can keep track of the true potential wage of entrepreneurs and find its mean to be 12% lower than that of the control group (see appendix Figure C.2).

5.2 Option value of exit

In this section, I define the option value of returning to paid employment as the amount of money required to keep entrepreneurs' expected utility unchanged when removing this option, that is its certainty equivalent. Dropping indexes to simplify the notation, the option value is solution to the following equation:

$$V_t(W + \text{Option Value}, \mu, \sigma_\mu, l_1 - \infty) = V_t(W, \mu, \sigma_\mu, l_1) \quad (17)$$

in which the entrepreneur is prevented from finding a paid job by imposing an infinite stigma on the persistent component of labor income. Because expected utility is strictly increasing in wealth and labor income, this equation has a unique solution and can be solved numerically by dichotomy.

[Insert Figure 6 about here]

As reported in Figure 6, the mean option value of new entrants exceeds five average national wage. This represents 82,000 euros and is equivalent to 12 years of nonpecuniary benefits. Though the option's value significantly decreases over time, it remains sizable among older firms because of permanent productivity shocks.

5.3 Counterfactual experiments

To further understand the model, I run counterfactual experiments in which I shut down some mechanisms and study how they affect the entrepreneurial sector and premium. Panel A of Table 5 reports the change in the number of entries, firms and their value added relative to the baseline model. Panel B reports the premium received by entrepreneurs over the first 10 years following the creation of their firm.

[Insert Table 5 about here]

Permanent TFP shocks – In Column (2), I eliminate permanent productivity shocks by setting $\sigma_{z,1} = 0$. In this specification, the potential growth of successful firms is considerably

reduced, which explains why the average value added falls by 42.7%. The scarcity of very successful entrepreneurs also reduces the earnings differential between entrepreneurs and paid employees.

Initial Uncertainty – In Column (3), I assume that individuals perfectly observe the initial heterogeneity in permanent productivity. Specifically, I set initial uncertainty to zero ($\sigma_{\nu,2}^2 \leftarrow 0$) and adjust the dispersion of the observed component of initial productivity such that the total initial variance remains the same ($\sigma_{\nu,1}^2 \leftarrow \sigma_{\nu,1}^2 + \sigma_{\nu,2}^2$). In this counterfactual experiments, individuals have less incentive to experiment with entrepreneurship, but this reduces the number of new firms by only 5%. Moreover, the decrease in exit rates offsets this effect such that the number of firms does not change. The mean value added barely moves. Overall, initial uncertainty has no first-order effect.

Nonpecuniary benefits – As shown in Column (4), removing nonpecuniary benefits reduces the number of firm creations by 19% and the total number of firms by 31%. The average firm is substantially better and the earnings differential between active entrepreneurs and their control group nearly doubles, jumping from 60.6% to 118.4%. These findings illustrate the importance of nonpecuniary benefits in explaining the entry and persistence of apparently inefficient entrepreneurs.

Exit option – In Column (5), I assume that entrepreneurs cannot return to paid employment when they fail. As a result, entries are reduced by 19%. Interestingly, the earnings differential between active entrepreneurs and their control group barely changes because two opposing effects offset each others. On the one hand, new entrepreneurs are of better quality. On the other hand, unlucky entrepreneurs experiencing large negative productivity shocks have to keep running their firms.

Nonpecuniary benefits & Exit option – Finally, Column (6) combines the assumptions of Columns (5) and (6). Removing nonpecuniary benefits and the option to return to paid employment at the same time reduces the number of firm creations by 45%. The combined effect is stronger than the sum of individual effects because initial expectations regarding permanent productivity are normally distributed (see Equation (6)). Removing nonpecuniary benefits *or* the option to return to paid employment only discourages individuals to become entrepreneurs if their beliefs fall in the left tail of the distribution, where density is low. Removing both moves the threshold further right, where density is much higher, and therefore discourages much more

individuals to become entrepreneurs.

5.4 Attitude towards entrepreneurial risk

This section shows that, in simulated data, a large fraction of entrepreneurs would be better off with higher uncertainty over productivity or if permanent shocks were larger. This is especially the case for new entrants and entrepreneurs about to close their firm, that is marginal entrepreneurs. Because of the option to return to paid employment, marginal entrepreneurs are protected against downside risk, which implies that uncertainty and permanent productivity shocks only bring upside potential. These findings nuance the notion that entrepreneurs need to be rewarded for bearing idiosyncratic risk, which in turn explains why the model can match the data with relatively small nonpecuniary benefits.

From the entrepreneur’s point of view, the next log TFP follows

$$z_{it} \sim \mathcal{N}(\mu_{it}, \sigma_{\mu,t}^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2). \quad (18)$$

and its variance can therefore be decomposed into three components: prior uncertainty ($\sigma_{\mu,t}^2$), permanent ($\sigma_{z,1}^2$) and transitory ($\sigma_{z,2}^2$) shocks. To test whether an entrepreneur is averse to a source of risk, I compute the change in expected utility that would follow an increase of the associated component of variance by $\Delta = 0.01$. I assume this change to be unexpected and to last only one year. I also reduce z by $\frac{\Delta}{2}$ to keep expected productivity $\mathbb{E}[e^z]$ unchanged. This adjustment is transitory for changes in $\sigma_{z,2}^2$, permanent otherwise, and known from entrepreneurs who correct their priors (μ) accordingly.

[Insert Table 6 about here]

I say that entrepreneurs are averse to a component of variance if it reduces their expected utility. As reported in Table 6, nearly one entrepreneur out of two would have higher expected utility if permanent shocks or uncertainty regarding current productivity were higher. This fraction is even larger for new entrants and entrepreneurs about to close their firm.

Note that entrepreneurs whose profits far exceed what they would make as paid employees do not need to be compensated for risk to run their firm. Risk increases the observed premium

by driving away marginal entrepreneurs. However, the attitude towards risk of new entrants and entrepreneurs on the verge of closing their businesses suggests that marginal entrepreneurs are not averse to $\sigma_{\mu,t}^2$ and $\sigma_{z,1}^2$.

6 Robustness tests and Policy experiments

6.1 Robustness tests

This section reports how my structural estimates change when the model is enriched to take into account labor market frictions, liquidation costs and personal income taxes. I also discuss how my results vary when I assume different levels of relative risk aversion.

Labor market stigma – Difficulties to find a new job when returning to the labor market should reduce both entry and exit rates. In Column (2) of Table 4, I assume that entrepreneurs receive an additional shock of -0.2 to the persistent component of their wage (l_1) upon closing their firm. This shock dissipates as in Equation (10). To support this calibration of the labor market stigma, appendix Figure C.3 reports the income trajectories of entrepreneurs who close their firm within three years. Upon returning to paid employment, these entrepreneurs earn 21% less than their control group, a difference which becomes statistically insignificant five years later. As this friction makes it costly to exit, matching empirical exit rates requires a higher level of initial uncertainty. For the same reason, the model requires slightly smaller nonpecuniary benefits to explain the persistence of inefficient businesses.

Liquidation costs – Another cost of returning to paid employment may come from the inability to recover the full value of capital. As reported in Column (3), I find that introducing a fixed liquidation cost equal to 0.5 national average wage affects my results in the same way as the labor market stigma does.¹² I calibrate this liquidation cost such that it represents 20% of the average capital of firms in their penultimate year in my baseline specification.¹³

¹²Ideally, the liquidation cost should be a fraction of the firm’s capital but this would reduce the tractability of the model since capital would become a state variable.

¹³There is little evidence on what liquidation costs are for small businesses. My calibration tries to follow liquidation/bankruptcy costs estimated in the literature, generally in slightly different contexts. Glover (2016) finds an observed default cost of 25% of firm value. Davydenko et al. (2012) estimate default cost to be 21.7% of market value. Andrade and Kaplan (1998) estimate distress cost to be between 10 and 23%. Hennessy and Whited (2007) structurally estimate bankruptcy costs equal to 15% of capital for “small” compustat firms.

Personal income tax – Because it is akin to change of scale, a proportional income tax has no effect in a model with CRRA utility. On the other hand, progressive taxes increase incentives to undertake risky projects by providing insurance (Domar and Musgrave (1944)) but can also discourage individuals motivated by the option value of experimentation and unwilling to share risk with the government. Column (4) of Table 4 reports how structurally estimated parameters change when progressive income taxes are introduced in the model. I use the following tax schedule, which seeks to replicate French personal taxes in 2017

$$\text{Marginal Tax Rate}_{it} = \begin{cases} 0\% & \text{if } \text{Income}_{it} < 0.36 \\ 14\% & \text{if } 0.36 \leq \text{Income}_{it} < 1.00 \\ 30\% & \text{if } 1.00 \leq \text{Income}_{it} < 2.69 \\ 41\% & \text{if } 2.69 \leq \text{Income}_{it} < 5.70 \\ 45\% & \text{if } 5.70 \leq \text{Income}_{it} \end{cases} \quad (19)$$

I find that estimated nonpecuniary benefits are now one fourth smaller. However, this change mostly reflects the fact that taxes reduce pecuniary earnings in a similar way.

Risk Aversion – I also reestimate all parameters for different coefficients of relative risk aversion, specifically $\gamma = 0.5$, $\gamma = 1.5$ and $\gamma = 2$. Appendix Table B.2 shows that parameter estimates are not overly sensitive to my assumption regarding regarding γ .

Counterfactual experiments – I replicate the counterfactual experiments reported in Table 5 and report the results in appendix Table B.3. Most of my conclusions are robust across specifications and for different levels of relative risk aversion between 0.5 and 2. Nonpecuniary benefits are slightly less important when the model assumes that entrepreneurs face frictions when they return to paid employment. But my conclusion that the entrepreneurial premium would be much larger without nonpecuniary benefits still holds. When entrepreneurs have difficulties returning to paid employment, the model needs higher initial uncertainty to explain empirical exit rates, which slightly reinforces the role of initial uncertainty in explaining entrepreneurial entry.

Option value – Finally, I recompute the option value of returning to paid employment for each robustness test and report the results in appendix Figure C.4. As the option provides insurance to entrepreneurs, moving from $\gamma = 1$ to $\gamma = 2$ increases the option value of new entrepreneurs by

roughly 20%. Introducing taxation reduces it by 20%, which is close to the average tax rate and therefore just reflects a change in scale. Interestingly, the option value is higher when the model is estimated with a labor market stigma or a liquidation cost. This can be explained by the fact that estimated initial uncertainty is larger in these specifications.

6.2 Policy experiments

In this section, I use the model to investigate how policy makers can promote entrepreneurship. Specifically, I look at the partial equilibrium effect of policies seeking *(i)* to facilitate returns to the labor market, *(ii)* to reduce liquidation costs and *(iii)* changing the personal income tax schedule. To evaluate the effects of removing the labor market stigma, I use parameters estimated assuming that such stigma exists and reported in Column (3) of Table 4. Similarly, I use parameters respectively reported in Columns (4) and (5) to evaluate the effect of removing liquidation costs and changing the tax schedule. Table 7 reports the effects of these policies.

[Insert Table 7 about here]

Removing labor market stigma – Facilitating returns to paid employment increases the number of entrepreneurial entries by 7.5% but reduces the total number of firms by 1.6% because entrepreneurs can now return to paid employment more easily. The average quality of firms improves a little bit, but the overall effect is limited.

Removing liquidation costs – Eliminating liquidation costs has an effect smaller but similar to removing labor market stigma. This is not surprising given that these two policies reduce the cost of exit and that, in my calibration, the stigma is slightly more expensive than the liquidation cost.

Capping marginal tax rate at 30% – Capping the marginal tax rate has very little effect on entries, exits or the quality of firms. This policy would only reduce taxes for income above 2.7 national average wage, which is slightly more than the earnings of entrepreneurs running 10 year old businesses. Hence, the policy focuses on successful entrepreneurs and states of the world where the marginal utility of money is small due to risk aversion. Note that this result could change if some entrepreneurs were close to risk neutral or if the distribution of TFP was highly skewed.

Moving to a proportional income tax – The effect of a progressive tax is ambiguous as it provides risk sharing but also reduces the option value of entrepreneurs. I find that moving to a proportional income tax would reduce the number of inefficient entrepreneurs as the government would stop subsidizing workers who switch to entrepreneurship to enjoy nonpecuniary benefits at the cost of lower pecuniary - and therefore taxable – earnings.

Overall, my policy experiments suggest that promoting entrepreneurship is difficult. By contrast, [Hombert et al. \(2017\)](#) find that a 2002 French reform providing generous downside insurance for unemployed individuals starting a business immediately increases firm creation by 25%. However, they also find this effect to be entirely confined to firms with zero employee at creation.

7 Conclusion

In this paper, I study whether job-creating entrepreneurs are motivated by nonpecuniary benefits or the option value of experimentation. I find both to be equally important in explaining why individuals become entrepreneurs and that removing both would reduce the number of firm creations by half. Nonpecuniary benefits are also crucial to explain the cross-sectional difference in earnings between entrepreneurs and paid employees. An important byproduct of my structural estimation is that entrepreneurs experience large permanent productivity shocks which generate a lot of option value if entrepreneurs can return to paid employment and are important to explain the evolution of the firm size distribution.

My model focuses on two trade-offs faced by potential entrepreneurs: whether to work as paid employees or strike out on their own, and, conditional on going it alone, whether to invest in their own firm or in the risk-free asset. However, other studies focus on the relative performances of entrepreneurial investment and public equity indices and underline that entrepreneurs are severely underdiversified ([Moskowitz and Vissing-Jorgensen \(2002\)](#)). Though entrepreneurial investment generates higher returns than public equity, it is unclear whether that premium is large enough to compensate entrepreneurs for bearing more idiosyncratic risk ([Kartashova \(2014\)](#)). Future research could answer this question by expanding the model presented in this paper to allow entrepreneurs to invest in the stock market portfolio.

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8 Tables and figures

Table 1: Matching Quality

Note: This table reports the balance between the sample of entrepreneurs and the control group. Each new entrepreneur is matched with an individual having the same previous occupation, sex and labor force participation status over the last three years. The final match minimizes the Mahalanobis distance in terms of age and earnings for each of the three years preceding the entrepreneurial spell.

	Mean		Covariance matrices											
	Entrepreneurs	Control group	Entrepreneurs				Control group							
Age _{t₀}	40.49	40.35	78.5				72.6							
Income _{t₀-1}	1.439	1.447	3.48	2.13					3.61	1.99				
Income _{t₀-2}	1.588	1.598	4.02	1.74	2.01					4.03	1.71	1.90		
Income _{t₀-3}	1.610	1.626	4.457	1.61	1.78	2.05					4.69	1.58	1.72	1.87

Table 2: Firm Characteristics by Age

Note: This table reports summary statistics for firms with at least one employee at creation between 1994 and 2013. Ebit is normalized by the average national wage. The volatility of value added is estimated by computing the standard deviation of the residuals of an OLS regression in which the dependent variable is the change in log value added and the explanatory variables are a set of year, sector and firm age dummies. All variables but the entrepreneur's age are winsorized at the 1st and 99th percentiles by firm age-year-sector groups. Incomplete business years are excluded.

	Firm Age											
	1	2	3	4	5	6	7	8	9	10	11	12
Cumulative Death rate	0.10	0.18	0.25	0.31	0.37	0.42	0.45	0.48	0.52	0.55	0.58	0.60
Ebit + Entrepreneur's wage (mean)	1.96	2.42	2.70	2.97	3.22	3.35	3.42	3.53	3.65	3.53	3.73	3.84
Std of log Value Added	1.00	0.99	1.01	1.02	1.03	1.05	1.06	1.07	1.08	1.09	1.11	1.11
1-Year Volatility of Value Added	0.46	0.41	0.39	0.39	0.38	0.37	0.36	0.36	0.35	0.36	0.36	0.36
3-Year Volatility of Value Added	0.64	0.59	0.57	0.55	0.54	0.53	0.53	0.51	0.50	0.51	0.55	0.53
Age of Entrepreneur (mean)	41.2	42.3	43.3	44.2	45.0	45.0	46.6	47.4	47.9	48.3	49.5	50.3
Employees (mean)	3.60	3.89	4.17	4.38	4.60	4.76	4.91	5.01	5.09	5.11	5.14	5.17
Observations (in thousands)	951	773	625	511	424	353	291	237	192	153	117	85

Table 3: Calibrated Parameters

Note: This table reports all calibrated parameters. In Panel A, I use the control group to predict log wage as a cubic polynomial in age. In Panel B, I estimate the parameters governing the stochastic component of wages. First, I compute the empirical standard deviations of log wage growth at the 1, 3 and 5 year horizons among the control group, restricted to males between 25 and 55. I then use these moments to pin down the three parameters of the labor income dynamics by SMM. Panel C reports the calibration of preference and economic environment parameters. Preferences are based on existing estimates. The corporate tax rate matches the sample empirical mean. The business loan and depreciation rates match the sample medians. Returns to scale are estimated by regressing $\ln(\text{EBITDA} + \text{Owner's Wage})$ on $\ln(\text{Capital Employed})$ with firm fixed effects.

Panel A: Life-cycle profile of log wage		
<i>OLS estimates:</i>		
f_1	Effect of age on log wage	.3452
f_2	Effect of age ² /10	-.0560
f_3	Effect of age ³ /1000	.0321
f_0	Intercept	-6.0085
Panel B: Labor income risk		
<i>Estimated parameters:</i>		
ρ	Persistence	.835
σ_{l_1}	Std of persistent shocks	.345
σ_{l_2}	Std of transitory shocks	.312
<i>Moment conditions:</i>		
	1-Year horizon std of log income growth	.570
	3-Year horizon	.724
	5-Year horizon	.814
Panel C: Preferences & Environment		
<i>Preferences:</i>		
γ	Risk aversion	1
β	Discount factor	.960
<i>Environment:</i>		
τ	Corporate tax rate	.140
r	Risk-free rate	.030
r_D	Business loan rate	.035
δ	Depreciation rate	.065
α	Returns to scale	.280

Table 4: Parameters Estimated by SMM

Note: This table reports the results of my SMM estimations. Column (1) corresponds to the baseline specification in which entrepreneurs can go back to paid employment without frictions. Nonpecuniary benefits are normalized by the mean national wage, which averages 15,800 euros over the sample period (1994-2013). All specifications target the same empirical moments, which are reported in Figure 4, along with their simulated counterparts in the baseline specification. In Column (2), I assume that entrepreneurs receive a persistent shock of -0.2 to their log labor income when they return to paid employment. In Column (3), entrepreneurs who close their firm must pay a fixed liquidation cost of 0.5 average national wage ($\approx 7,900$ euros). In Column (4), agents face a progressive personal income tax (see Equation (19)). The SMM procedure and the computation of bootstrapped standard errors are detailed in Appendix A.2.

		Alternative Specifications			
		(1)	(2)	(3)	(4)
		Baseline	Labor Market Stigma	Liquidation Cost	Progressive Income Tax
B	Nonpecuniary benefit	.425 (.001)	.323 (.002)	.380 (.002)	.324 (.001)
$\sigma_{\nu,1}$	Dispersion of priors	.704 (.002)	.617 (.002)	.584 (.003)	.773 (.002)
$\sigma_{\nu,2}$	Initial uncertainty	.395 (.002)	.541 (.002)	.541 (.002)	.351 (.002)
$\sigma_{z,1}$	Std of permanent shocks	.195 (.000)	.191 (.000)	.193 (.000)	.183 (.000)
$\sigma_{z,2}$	Std of transitory shocks	.268 (.000)	.277 (.000)	.270 (.000)	.281 (.000)
p	Arrival rate of ideas	.013 (.000)	.024 (.000)	.027 (.000)	.027 (.000)
\bar{z}	Mean log productivity	-.317 (.001)	-.341 (.001)	-.288 (.001)	-.352 (.001)

Table 5: Counterfactual Experiments

Note: This table reports the effects of removing key model ingredients. In each counterfactual experiment, I simulate the model using estimated parameters reported in Column (1) of Table 4. Panel A reports the relative changes on the number of firm creations, the number of firms, and their mean and total value-added. Panel B reports the average percentage earnings differential between entrepreneurs and a control group of paid employees. This control group is built by matching using age wages over the three years preceding the entrepreneurial spell. The line “All entrepreneurs” takes into account those who returned to paid employment, whereas “Active entrepreneurs” ignores entrepreneurs after their return to paid employment. In Column (2), permanent productivity shocks are set to zero. In Column (3), I assume that entrepreneurs perfectly know their abilities before starting their firm. In Column (4), nonpecuniary benefits are set to zero. In Column (5), I assume that entrepreneurs cannot return to paid employment. Finally, Column (6) combines the assumptions of Columns (4) and (5).

	Removed Element					
(1)	(2)	(3)	(4)	(5)	(6)	
Baseline	Permanent TFP Shocks	Initial Uncertainty	Nonpecuniary Benefits	Exit Option	(4) & (5) Combined	
<i>Panel A: Changes in Entrepreneurial Sector</i>						
Firm creations	-2.3%	-5.0%	-16.0%	-19.0%	-45.2%	
Firms	-9.5%	-0.0%	-30.6%	+7.7%	-39.1%	
Mean Value Added	-42.7%	+1.2%	+28.1%	-13.5%	+20.0%	
Total Value Added	-48.2%	+1.2%	-11.1%	-6.9%	-26.9%	
<i>Panel B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	37.3%	23.3%	43.6%	52.6%	59.5%	121.1%
Active entrepreneurs	60.6%	35.1%	63.1%	118.4%	59.5%	121.1%

Table 6: Share of Entrepreneurs Averse to Productivity Risk

Note: This table reports the share of entrepreneurs who would have lower expected utility if (i) the variance of permanent productivity shocks ($\sigma_{z,1}^2$), (ii) that of transitory shocks ($\sigma_{z,2}^2$) or (iii) the uncertainty over their current productivity level (σ_μ^2) were higher. For each of these three sources of risk, I compute what the expected utility of each entrepreneur would be after and unexpected $\Delta = 0.01$ increase in either $\sigma_{z,1}^2$, $\sigma_{z,2}^2$ or σ_μ^2 for one year. In each case, I adjust the current expectation of profitability μ such that the path of Z remains the same in expectation.

Source of risk:	Age of Firm				Year Before	
	0	1-5	5-10	>10	Exit	All
σ_μ^2 Prior uncertainty	.227	.407	.539	.568	.009	.477
$\sigma_{z,1}^2$ Permanent shocks	.272	.484	.639	.744	.025	.594
$\sigma_{z,2}^2$ Transitory shocks	1.00	1.00	1.00	1.00	1.00	1.00

Table 7: Policy Experiments

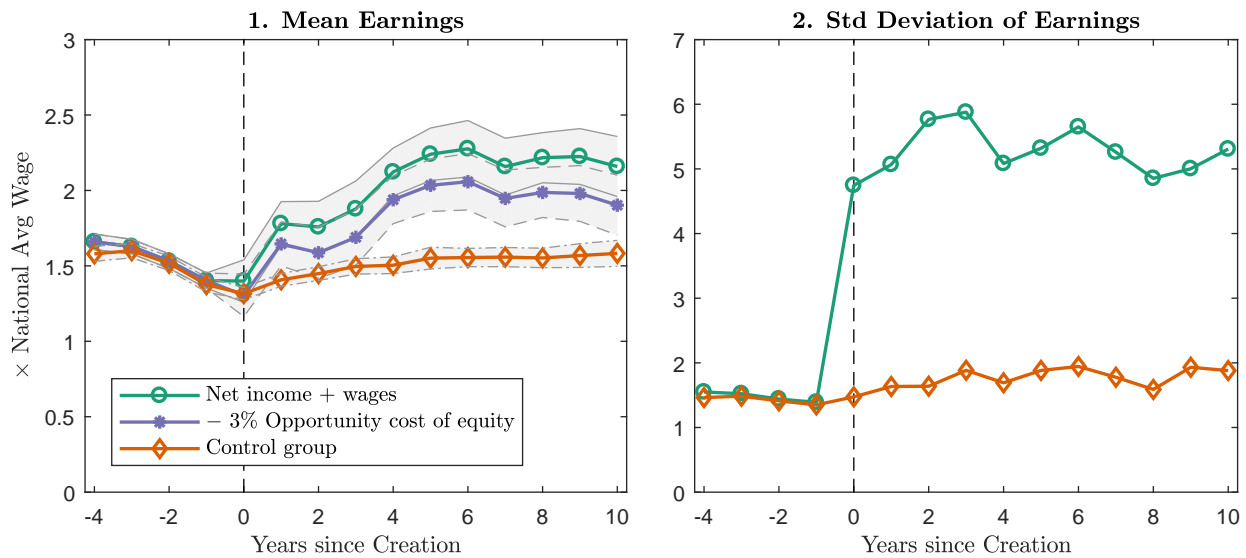
Note: This table reports how policy experiments affect the entrepreneurial sector in simulated data. In Columns (1) and (2), I report the effect of eliminating labor market frictions and liquidation costs faced by entrepreneurs when they close their firms. I use parameters reported in Columns (3) and (4) of Table 4 and estimated while taking these frictions into account. In Columns (3) and (4), I report the effect capping the marginal income tax rate at 30% or moving to a proportional income tax. The initial income tax schedule is detailed in Equation (19). In both cases, I use parameter reported in Column (5) of Table 4 and estimated while taking into account progressive income taxes.

	(1)	(2)	(3)	(4)
	Removing Labor Market Frictions	Removing Liquidation Costs	Capping Marginal Tax Rate at 30%	Moving to a Proportional Income Tax
Number of entries	+7.5%	+5.6%	+0.2%	-1.4%
Number of firms	-1.6%	-0.8%	+0.1%	-7.0%
Mean Value Added	+2.2%	+0.7%	+0.3%	+5.6%
Total Value Added	+0.6%	-0.1%	+0.4%	-1.7%

Figure 1: Evolution of Earnings around Entrepreneurial Entry

Note: These graphs report the evolution of the income distribution among workers becoming entrepreneurs at time 0 and a control group of paid employees constructed by matching. The mean income of entrepreneurs is defined as the sum of wages (net of payroll taxes) and firm’s net income. In Panel A, it includes entrepreneurs who returned to paid employment. By contrast, Panel B only reports income of entrepreneurs as long as they are still running their business. The matching algorithm takes into account sex, last occupation, age and wages received over each of the three years preceding the entrepreneurial spell. Shaded areas represent 95% confidence intervals estimated by block bootstrap.

A. Including Entrepreneurs Retuning to Paid Employment



B. Conditional on Still Running a Business

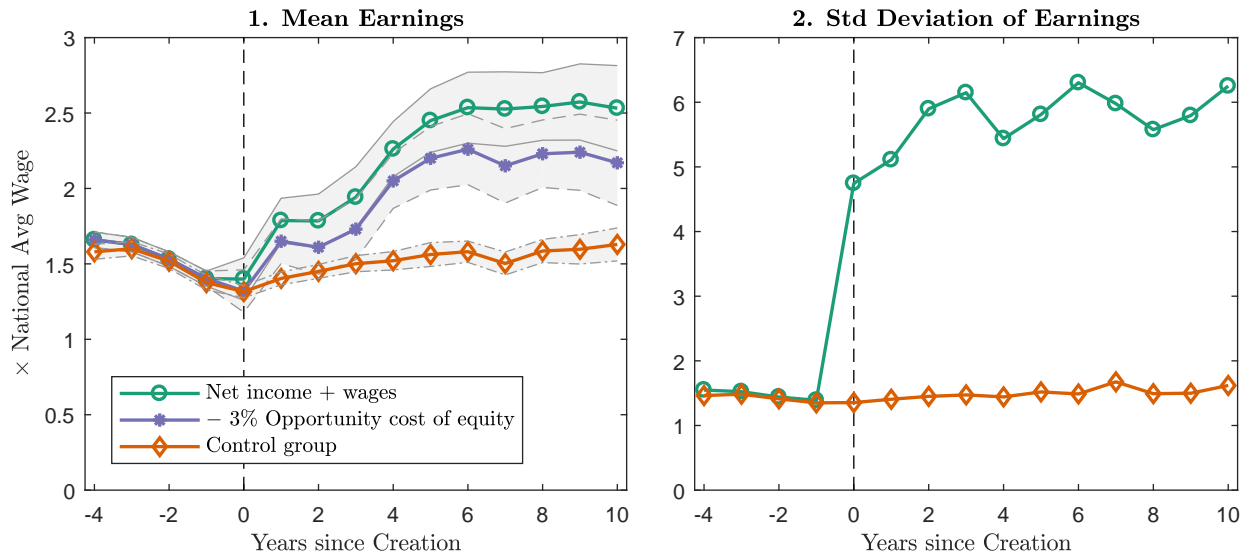


Figure 2: Model Timeline

Note: This figure illustrates the timing of events and decisions in the model by decomposing a period (year) into sub-periods.

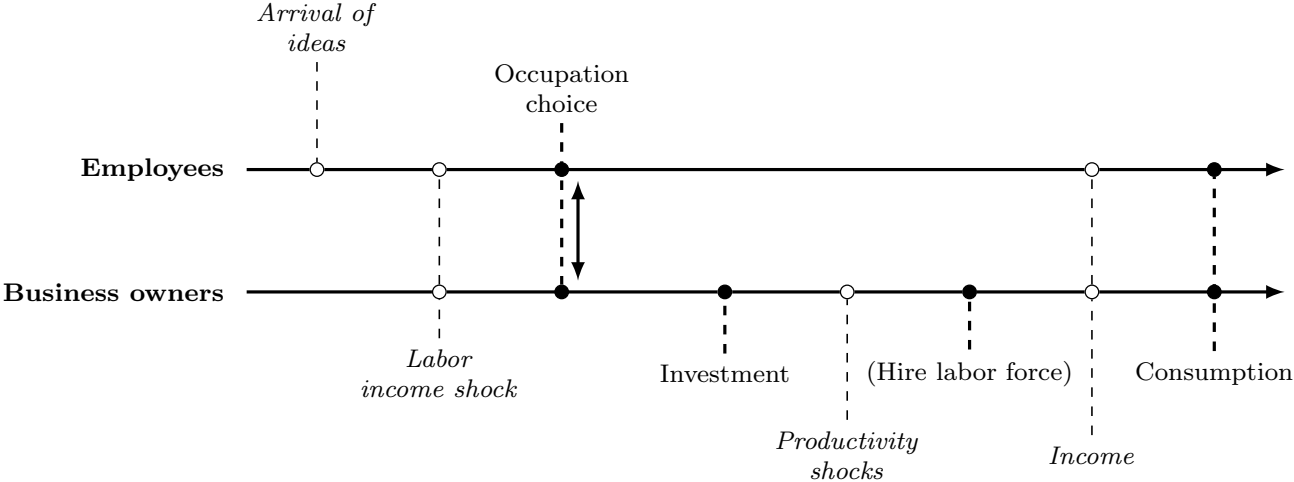


Figure 3: Elements of Identification

Note: These plots display the relationships between estimated parameters and their primary source of identification. I start by setting all parameters to their baseline estimates, reported in Column (1) of Table 4 and represented by vertical dashed lines. Then, I move each parameter around its estimated value holding the others constant. I then report the evolution of the simulated moment(s) that is likely to be the most informative. In Panel A, the premium is the mean yearly earnings difference between entrepreneurs and their control group over the first ten years, normalized by the average national wage. In Panels B to G, moments are reported for 5-year old firms but the SMM targets all of them for each firm age from 1 to 10.

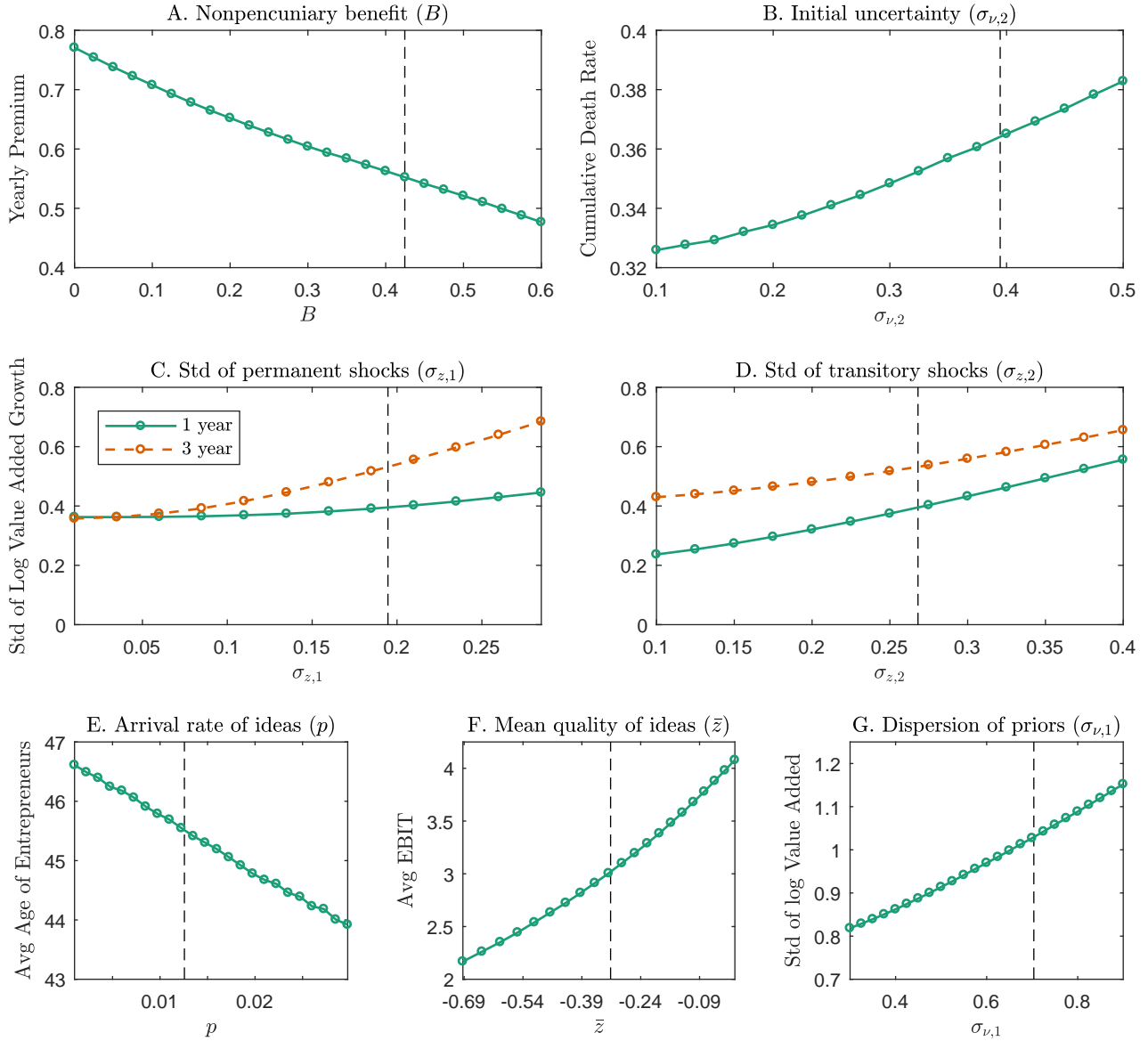


Figure 4: Baseline SMM Fitness

Note: These plots report all empirical moments targeted in my structural estimation as well as their simulated counterparts in my baseline estimation. Estimated parameters used in the simulation are reported in Column (1) of Table 4. The mean adjusted Ebit include wages received by the business owner. The average premium is the mean yearly earnings difference between entrepreneurs and their control group over the first ten years. This premium and adjusted Ebit are reported as a fraction of the average national wage.

A. Mean Yearly Premium over the first 10 years

Data: 0.567 — Model: 0.567

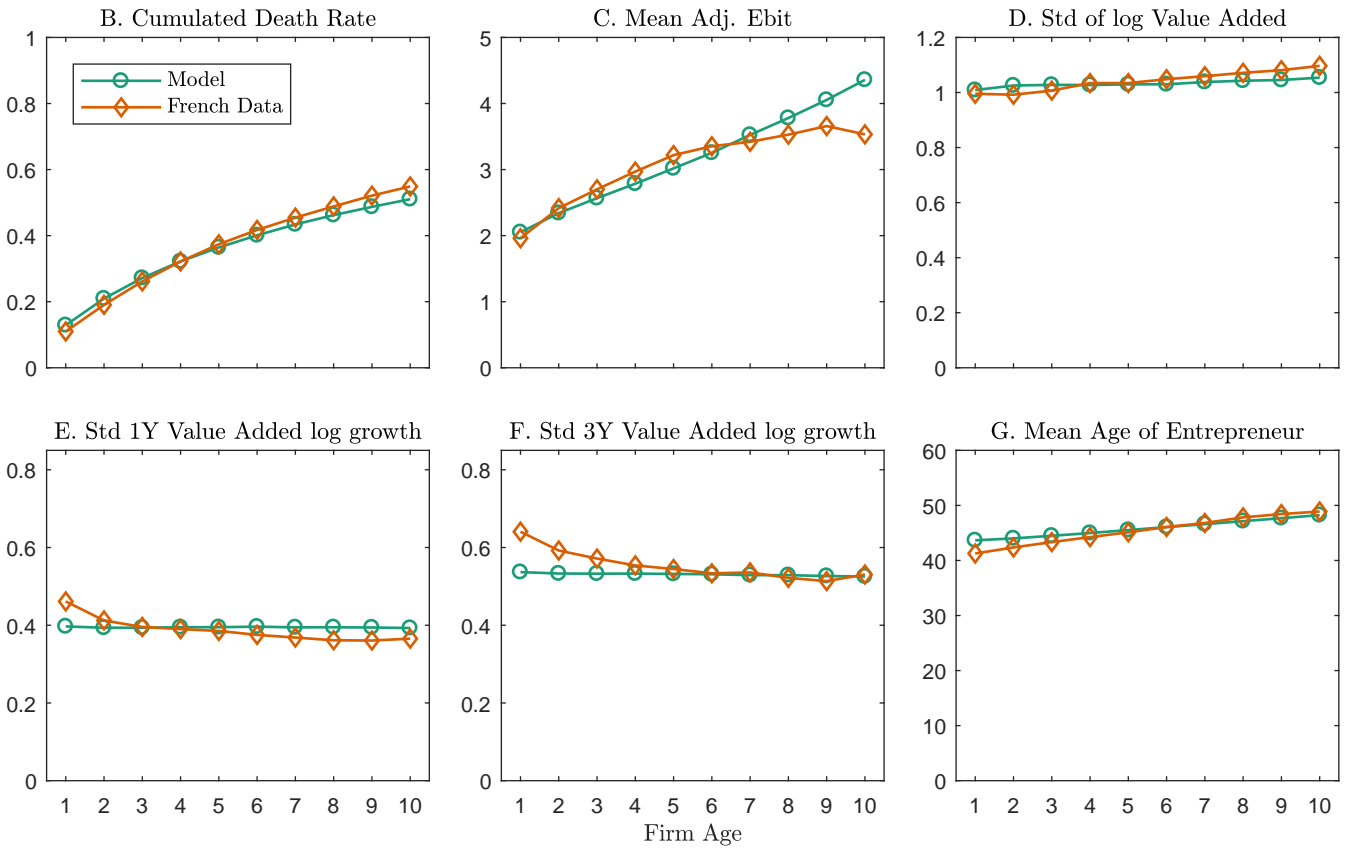


Figure 5: Predicted and Observed Income Trajectories

Note: This graph reports the mean income of individuals becoming entrepreneurs at time 0 and that of a control group constructed by matching. The income of entrepreneurs is defined as the sum of wages (net of payroll taxes) and firm net income. It includes entrepreneurs who returned to paid employment. The left plot reports simulated data from the baseline model using estimated parameters reported in Column (1) of Table 4. The right plot reports the empirical counterpart. For empirical data, the matching algorithm takes into account sex, last occupation, age and wages received over each of the three years preceding the entrepreneurial spell. For simulated data, the matching procedure is only based on age and the last three years of wages. Shaded areas represent 95% confidence intervals estimated by bootstrap.

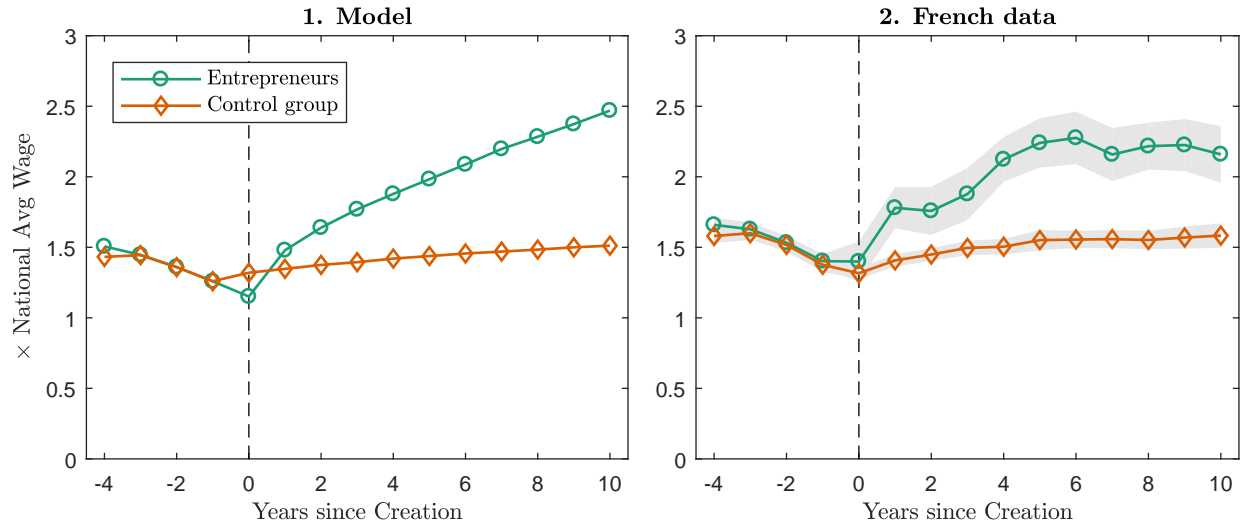
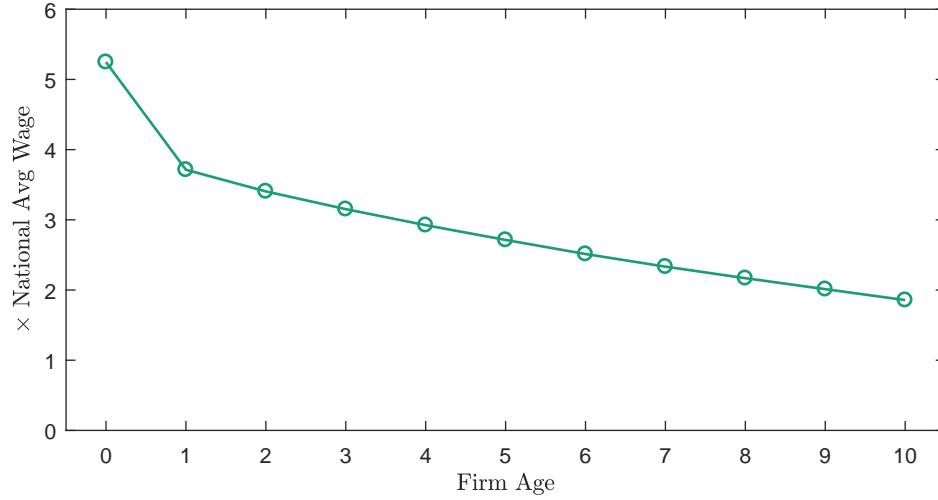


Figure 6: Option Value of Returning to Paid Employment

Note: This figure reports the certainty equivalent of the option value of returning to paid employment. The certainty equivalent is estimated numerically by solving Equation (17) and is normalized by the average national wage. I simulate the baseline model using estimated parameters reported in Column (1) of Table 4, compute the option value for each entrepreneur and report its mean by firm age.



APPENDIX

A Model

A.1 Numerical solution

Discretization – The 5 state space and 2 control variables of the problem are discretized as follows. Financial wealth (W) is normalized by the average national wage and takes values between 0.01 and 500. The grid is uniformly distributed between the logs of these two bounds with a mesh size of $\Delta(w) = 0.1$. The agent’s belief regarding the log of his permanent productivity (μ) takes 51 uniformly distributed values between -2 and 5. The agent never chooses to become/remain an entrepreneur if $\mu < -2$. Uncertainty regarding permanent productivity is a deterministic function of firm age, which is discretized using 41 points between 0 and 40. I add three negative points to that grid: -3 denotes a former entrepreneur, while -2 and -1 respectively represent paid employees without and with an entrepreneurial idea. The persistent component of wages is discretized with 21 points uniformly distributed between -3 and 3 standard deviations using [Tauchen \(1986\)](#)’s method. The transitory component is similarly discretized with 11 points.

Consumption is determined by the choice of the next following value of wealth. Capital is discretized with 41 points as a fraction of the maximum investment the agent can make: k_{\max} . This maximum takes the minimum of two values. The first one is the optimal capital for a risk-neutral and unconstrained agent. The second one is the largest investment that the true agent can make without taking the risk of being unable to consume at the end of the period, which would result in a utility of $-\infty$. Hence, the agent must have enough wealth to meet his liabilities if $Z = 0$. Therefore, the value of k_{\max} is:

$$K_{\max}(W, \mu, \sigma_{\mu}) = \min \left\{ \left(\frac{\alpha \mathbb{E}[Z]}{\delta + r_D} \right)^{\frac{1}{1-\alpha}}, \frac{1 + (1 - \tau)r_D}{(r_D + \delta)(1 - \tau)} W \right\} \quad (20)$$

where $\mathbb{E}[Z]$ is the expected value of Z from the agent's point of view, that is $\mathbb{E}[Z] = e^{\mu + \frac{\sigma_\mu^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2}{2}}$.

Resolution of the Bellman equation – The model is solved backward by dynamic programming. Each year is split into two sub-periods.

2. In the second sub-period, the agent chooses her consumption, then receive labor income shocks and entrepreneurial ideas (on the first day of the following year). Using an apostrophe sign (') to denote evolving state variables, the Bellman equation for this subperiod is:

$$\left\{ \begin{array}{l} V_{t+\frac{1}{2}}(W, \mu, a, l_1) = \max_C \left\{ \frac{C^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}V_{t+1}(W', a', \sigma'_\mu, l'_1, l'_2) \right\} \\ \text{with} \quad W' = W - C \\ \quad \quad \quad l'_1 \sim \mathcal{N}(\rho l_1, \sigma_{l,1}^2) \\ \quad \quad \quad l'_2 \sim \mathcal{N}(0, \sigma_{l,2}^2) \\ \text{and if } a = -2 \text{ and with probability } p: \\ \quad \quad \quad a' = a + 1 \\ \quad \quad \quad \mu' \sim \mathcal{N}(\bar{z}, \sigma_{v,1}^2) \\ \text{else:} \quad \quad \mu' = \mu \\ \quad \quad \quad a' = a \end{array} \right. \quad (21)$$

where a is firm age, C is chosen so that W' is on the grid and $a = -2$ indicates that the agent has not yet got an entrepreneurial idea.

1. In the first sub-period, the agent chooses his occupation and how much to invest in his firm

if he chooses to become an entrepreneur. The Bellman equation for this subperiod is:

$$\left\{ \begin{array}{l}
 V_t(W, \mu, a, l_1, l_2) = \max_K \left\{ \mathbb{E}V_{t+\frac{1}{2}}(W', \mu', a', l_1) \right\} \\
 \text{with, if } K > 0: \quad W' = W + (1 - \tau)(e^z K^\alpha - \delta K) + r(W - K) \\
 \quad \quad \quad \mu' = \mu + \frac{\sigma_\mu^2 + \sigma_{z,1}^2}{\sigma_\mu^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2} (z - \mu) \\
 \quad \quad \quad a' = a + 1 \\
 \quad \quad \quad z \sim \mathcal{N}(\mu, \sigma_\mu^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2) \\
 \text{and, if } K = 0: \quad W' = (1 + r)W + e^{f(t)+l_1+l_2} \\
 \quad \quad \quad \text{if } a \geq 0, a' = -3 \text{ else } a' = a \\
 \quad \quad \quad \mu' = \mu \\
 \text{s.t.} \quad \quad \quad K = 0 \text{ if } a = -3 \text{ or } a = -2
 \end{array} \right. \quad (22)$$

where σ_μ is a deterministic function of firm age a (see Equation (8)). I discretize z using 41 points on the interval $\mu \pm 3 \times \sqrt{\sigma_\mu^2 + \sigma_{z,1}^2 + \sigma_{z,2}^2}$. As there is no reason to expect W' and μ' to be on the grid, I estimate the continuation value $V_{t+\frac{1}{2}}(W', \mu', a', l_1)$ by interpolation. I interpolate the value function as follows. First, I multiply V_t by $1 - \gamma$ if $\gamma > 0$ and take the log. I interpolate the resulting function with respect to log wealth and μ' . Finally, I take the exponential of the result and divide it by $1 - \gamma$ if $\gamma > 1$. I find the optimal K in two steps. First, I assume that the agent chooses to become entrepreneur (if he can) and solve for the optimal $K > 0$. Under this assumption, l_2 is no longer a state variable, which reduces the computational cost of solving for K^* . I compute the optimal continuation value for $K^* > 0$ and compare it to the continuation value for $K = 0$. The agent chooses entrepreneurship if the former is above the latter.

Simulation – I save the optimal policies from 25 to 65 years old and then simulate the model. I initialize wealth at $W = 0.1$ and generate a random distribution for the persistent component of labor income using its stationary distribution, that is $\mathcal{N}\left(0, \frac{\sigma_{l,1}^2}{1-\rho^2}\right)$. The simulation follows the timeline of Figure 2. Stochastic processes are not discretized and optimal policies therefore need to be interpolated. This is relatively straightforward for investment and consumption but not for

the occupation choice, which is a binary decision. While solving the Bellman equation, I save the ratio of the continuation values of entrepreneurship and paid employment. If $\gamma > 1$ ($\gamma \leq 1$), the agent is better off as an entrepreneur if this ratio is below (above) one. I use linear interpolation to estimate this ratio for the current coordinates of the agent.

A.2 SMM procedure

Global optimization routine – The SMM solves Equation (16) with respect to seven parameters: $B, \sigma_{\nu,1}, \sigma_{\nu,2}, \sigma_{z,1}, \sigma_{z,2}, p, \bar{z}$. This is done using the following procedure.

1. I start by delimiting the parameter space by assuming that $B \in [0; 2]$, $\sigma_{\nu,1} \in [0; 1]$, $\sigma_{\nu,2} \in [0; 1]$, $\sigma_{z,1} \in [0; 0.3]$, $\sigma_{z,2} \in [0; 0.4]$, $p \in [0; 0.1]$ and $\bar{z} \in [-0.5; 0.5]$.
2. I draw a low-discrepancy (Halton) sequence of N points θ_i within that space. Then, from $i = 1$ to $i = N$, I run the following procedure:
 - (a) If $i > 1$, then $\tilde{\theta}_i = \theta_i x^i + (1 - x^i)\theta^*$, otherwise $\tilde{\theta}_i = \theta_i$.
 - (b) Using $\tilde{\theta}_i$ as a starting point, run a local optimization to minimize the SMM objective function. I use MATLAB's implementation of the Nelder-Mead simplex algorithm.
 - (c) If the result of the optimization is below θ^* , then replace θ^* with the new best.
 - (d) If $i < N$, go back to (a). Otherwise, θ^* is the solution and the algorithm stops.

The idea of the algorithm is to run local optimizations using a large numbers of starting points. As the algorithm progresses, new starting points get closer and closer to the best solution found so far. The speed of convergence depends on x , which I set to 0.95. I allow 250 evaluations of the objective function during local estimation steps and set $N = 100$. This means that the model is solved approximately 25,000 times by SMM. Solving the model takes approximately 2 minutes on a high-end graphic card (Nvidia Tesla K80). In practice, I find that $N = 10$ is sufficient to get estimates very close to the final solution. Almost all local minimization steps converge to the same region and exceptions return much higher error functions. This makes me confident that the procedure converges to the global minimum.

Standard errors – Standard errors are estimated as the square roots of the diagonal elements of matrix Q , which is defined as:

$$Q = [J^T \mathbf{\Omega}^{-1} J]^{-1} \quad (23)$$

where $\mathbf{\Omega}$ is the empirical variance-covariance matrix of targeted moments and J the Jacobian matrix of the simulated moments with respect to estimated parameters. The variance-covariance matrix is estimated by block bootstrap with replacement on the actual data. Specifically, I randomly resample firms/entrepreneurs (using firm IDs) and paid employees (using individual's IDs) and preserve the entire time series of each firm/entrepreneur or paid employee. The Jacobian matrix is approximated around the SMM estimate using forward finite differences with a spacing of 0.01.

B Additional tables

Table B.1: Earnings and Exit rate Differences between Samples

Note: This table reports earnings and exit rates for firm that hired at least one employee in the first year. In Panel A, the sample is restricted to firms who paid their owner a wage in the first two years whereas Panel B takes into account the full sample.

	Age of firm									
	1	2	3	4	5	6	7	8	9	10
Panel A: At least one employee at creation and early wage to entrepreneur										
Net Income + Owner's Wage (k€)	12.9	16.6	19.5	23.3	25.9	28.3	27.9	26.6	30.4	32.6
	(1.0)	(1.0)	(1.1)	(1.2)	(1.2)	(1.3)	(1.4)	(1.4)	(1.5)	(1.6)
Exit rate (%)	5.8	8.1	8.6	7.9	7.3	6.6	6.1	6.1	6.2	5.9
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Panel B: At least one employee at creation										
Net Income + Owner's Wage (k€)	10.1	13.3	16.8	20.1	23.5	26.0	26.2	28.2	30.4	32.5
	(0.4)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)	(0.5)	(0.6)	(0.6)	(0.7)
Exit rate (%)	7.3	9.7	9.3	8.7	8.2	7.4	6.9	6.8	6.9	6.5
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)

Table B.2: Sensitivity of Parameter Estimates to Risk Aversion*Note:* This table reports the sensitivity of my baseline parameter estimates to the coefficient of relative risk aversion.

		(1)	(2)	(3)	(4)
		$\gamma = 0.5$	$\gamma = 1$	$\gamma = 1.5$	$\gamma = 2$
B	Nonpecuniary benefit	.375 (.002)	.425 (.001)	.425 (.002)	.425 (.002)
$\sigma_{\nu,1}$	Dispersion of priors	.773 (.001)	.704 (.002)	.683 (.002)	.679 (.002)
$\sigma_{\nu,2}$	Initial uncertainty	.314 (.002)	.395 (.002)	.450 (.002)	.403 (.001)
$\sigma_{z,1}$	Std of permanent shocks	.185 (.000)	.195 (.000)	.185 (.000)	.194 (.000)
$\sigma_{z,2}$	Std of transitory shocks	.281 (.000)	.268 (.000)	.282 (.000)	.272 (.000)
p	Arrival rate of ideas	.028 (.000)	.013 (.000)	.026 (.000)	.018 (.000)
\bar{z}	Mean log productivity	-.340 (.001)	-.317 (.001)	-.307 (.001)	-.312 (.002)

Table B.3: Counterfactual Experiments – Robustness Checks

Note: This table reports the same counterfactual experiments as Table 5. In Panels I to III, I assume different model specifications, for which estimated parameters are reported in Table 4.

	(1) Baseline	Removed Element				(6) (4) & (5) Combined
		(2) Permanent TFP Shocks	(3) Initial Uncertainty	(4) Nonpecuniary Benefits	(5) Exit Option	
Panel I: Labor Market Stigma						
<i>I.A: Changes in Entrepreneurial Sector</i>						
Firm creations		-4.0%	-15.3%	-12.7%	-17.0%	-37.9%
Firms		-9.9%	-1.6%	-26.1%	+5.0%	-39.9%
Mean Value Added		-42.5%	+3.6%	+21.9%	-19.5%	-1.0%
Total Value Added		-48.2%	+1.9%	-9.9%	-15.5%	-40.9%
<i>I.B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	37.2%	23.3%	57.8%	47.9%	57.7%	104.8%
Active entrepreneurs	67.7%	35.1%	74.5%	107.6%	57.7%	104.8%
Panel II: Liquidation Costs						
<i>II.A: Changes in Entrepreneurial Sector</i>						
Firm creations		-3.1%	-13.9%	-11.2%	-18.9%	-41.5%
Firms		-9.7%	-0.7%	-26.8%	+7.9%	-41.9%
Mean Value Added		-43.0%	+1.9%	+23.2%	-21.2%	+1.1%
Total Value Added		-48.5%	+1.1%	-9.9%	-14.9%	-41.2%
<i>II.B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	36.9%	23.2%	50.6%	44.4%	53.9%	107.7%
Active entrepreneurs	65.5%	40.5%	69.3%	108.9%	53.9%	107.7%
Panel III: Progressive Income Tax						
<i>III.A: Changes in Entrepreneurial Sector</i>						
Firm creations		-2.3%	-4.6%	-19.4%	-21.7%	-46.7%
Firms		-6.7%	+0.1%	-30.6%	+4.3%	-38.5%
Mean Value Added		-41.6%	+0.6%	+28.8%	-10.1%	+21.2%
Total Value Added		-45.5%	+0.7%	-10.6%	-6.3%	-25.5%
<i>III.B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	37.3%	24.4%	42.2%	56.3%	65.6%	127.9%
Active entrepreneurs	61.2%	37.5%	61.9%	111.2%	65.6%	127.9%

Table B.3 *continued*

In Panels IV to VI, I assume different levels of relative risk aversion, for which estimated parameters are reported in Table B.2.

	Removed Element					(6) (4) & (5) Combined
	(1) Baseline	(2) Permanent TFP Shocks	(3) Initial Uncertainty	(4) Nonpecuniary Benefits	(5) Exit Option	
Panel IV: Relative Risk Aversion of $\gamma = 0.5$						
<i>IV.A: Changes in Entrepreneurial Sector</i>						
Firm creations		-2.3%	-3.1%	-18.8%	-20.7%	-45.0%
Firms		-11.4%	-0.0%	-26.8%	+9.2%	-26.6%
Mean Value Added		-41.1%	+0.5%	+25.0%	-11.9%	+12.7%
Total Value Added		-47.8%	+0.4%	-8.5%	-3.7%	-17.3%
<i>IV.B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	37.0%	24.7%	40.6%	53.8%	60.6%	108.1%
Active entrepreneurs	59.9%	38.5%	60.5%	103.1%	60.6%	108.1%
Panel V: Relative Risk Aversion of $\gamma = 1.5$						
<i>V.A: Changes in Entrepreneurial Sector</i>						
Firm creations		-2.1%	-6.8%	-13.4%	-21.1%	-46.0%
Firms		-6.2%	-0.0%	-31.2%	+3.8%	-38.7%
Mean Value Added		-40.4%	+2.2%	+28.0%	-13.5%	+18.9%
Total Value Added		-44.0%	+2.2%	-11.9%	-10.2%	-39.0%
<i>V.B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	37.4%	23.9%	45.5%	50.4%	64.7%	136.3%
Active entrepreneurs	61.7%	37.0%	65.0%	113.7%	64.7%	136.3%
Panel VI: Relative Risk Aversion of $\gamma = 2$						
<i>VI.A: Changes in Entrepreneurial Sector</i>						
Firm creations		-2.8%	-6.3%	-14.0%	-22.1%	-47.1%
Firms		-5.4%	+0.0%	-31.9%	-1.4%	-55.6%
Mean Value Added		-43.7%	+1.7%	+26.7%	-12.8%	+19.3%
Total Value Added		-46.8%	+1.7%	-13.7%	-14.1%	-47.1%
<i>VI.B: Entrepreneurial Premium over first 10 years</i>						
All entrepreneurs	37.3%	24.4%	42.2%	52.6%	70.5%	151.9%
Active entrepreneurs	61.2%	37.5%	61.9%	115.4%	70.5%	151.9%

C Additional figures

Figure C.1: SMM Fitness without key parameters

Note: This figure reports all empirical moments targeted in my structural estimation as well as their simulated counterparts in the model either without nonpecuniary benefits ($B = 0$), or without permanent productivity shocks ($\sigma_{z,1} = 0$), or without initial uncertainty ($\sigma_{\nu,2} = 0$). In each case, I reestimate the model by SMM using the same set of empirical moments.

A. Mean yearly Premium over first 10 years

Data: 0.567 — Model: 0.567

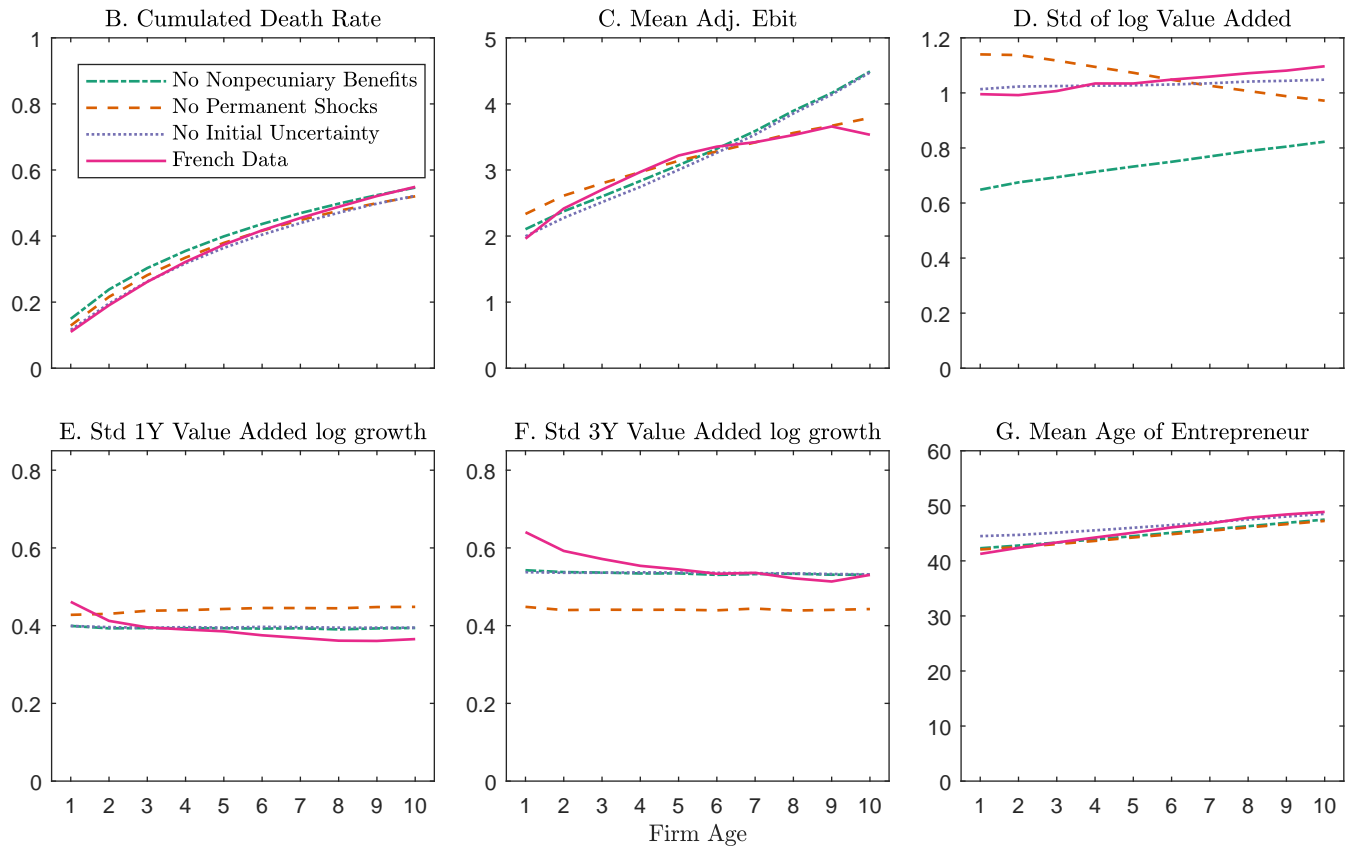


Figure C.2: Bias of Matching Method in Simulated Data

Note: This graph reports the mean income of individuals becoming entrepreneurs, that of a control group constructed by matching, and the true wage that entrepreneurs would have received as paid employees. The model is simulated using estimated parameters reported in Column (1) of Table 4. The simulated matching procedure is based on the last three years of wages.

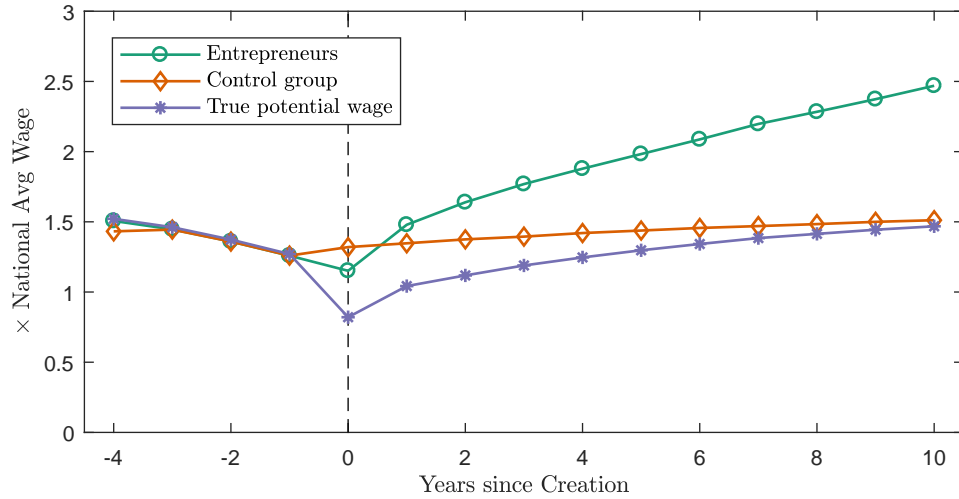


Figure C.3: Income Trajectories for Short Entrepreneurial Spells (<3 years)

Note: This graph reports the income trajectories of entrepreneurs closing their firms in the first three years and that of a control group built by matching. The mean income of entrepreneurs is defined as the sum of wages and net income. The matching algorithm takes into account sex, pre-entrepreneurial occupation and wages received over the last three years.

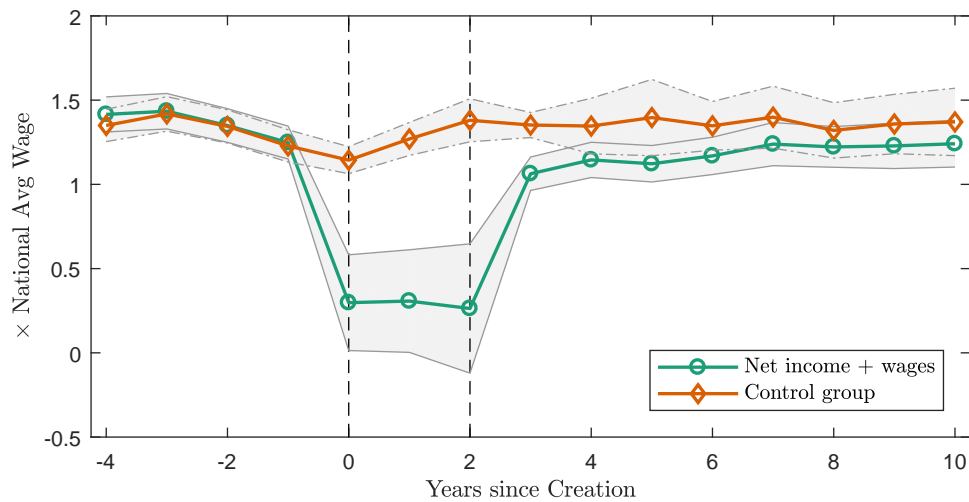


Figure C.4: Option Value – Robustness Tests

Note: This figure reports the option value of returning to paid employment under different model assumptions. The option value is estimated numerically by solving Equation (17) and normalized by the average national wage. I simulate the baseline model using parameters estimated by SMM, compute the option value for each entrepreneur and report the mean by firm age. Panel A reports mean option values for different level of relative risk aversion using parameters reported in Table B.2. Panel B uses parameters reported in Table 4.

