The Role of Human Capital Specificity in Entrepreneurship

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Abstract

We argue that human capital specificity—the extent to which entrepreneurial human capital can be transferred to wage employment—is the key driver of entrepreneurial entry and exit. We provide evidence of this channel, combining data on the universe of Portuguese entrepreneurs and workers with a quantitative structural model. Our reduced-form analysis introduces a difference-in-differences approach that compares entrepreneurs who return to wage employment relative to those who never entered entrepreneurship. We find that individuals starting from lower relative wage trajectories benefit from entrepreneurship due to partial transferability, seeing average wage gains of 7.7 percent. However, individuals starting from higher relative wage trajectories are negatively impacted by partial transferability, and see average losses of 6.1 percent. We incorporate this evidence into a macroeconomic model of endogenous entrepreneurship with borrowing constraints and partially transferable human capital from entrepreneurship to wage employment. We find that borrowing constraints do not meaningfully impact entrepreneurial entry in this environment. Low-type entrepreneurs, with low optimal scale, enter entrepreneurship regardless of financial constraints due to the value of improving labor market outcomes via entrepreneurship. High-type entrepreneurs delay entry due to the risk of losing human capital, rather than inability to achieve their optimal scale. We conclude that policies which mitigate losses to human capital are more effective in spurring entry of high-type entrepreneurship.

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1 Introduction

Most businesses fail. More than half of firms in a cohort of entrants exit within five years, and even the long-run firm exit hazard stays high (Sterk, Sedláček, and Pugsley, 2021; Karahan, Pugsley, and Şahin, 2024). While entrepreneurial exit is widespread, little is known about its impact on the labor market outcomes of entrepreneurs who return to wage employment, an outside option that is a key determinant of entering entrepreneurship. Understanding this dimension of entrepreneurship is important, since it helps inform the design of policy meant to jump-start high-growth entrepreneurship.

A key tension at hand is that time spent in entrepreneurship allows one to accumulate skills for running a business, but precludes human capital accumulation in paid work. If skills in entrepreneurship are specific, and thus not easily transferred to paid work, human capital specificity could become a large barrier to entry for potential high-growth entrepreneurs, especially those who are younger or more risk averse. In contrast, even partial transferrability could be attractive to workers who are experiencing stagnant wage growth, providing an alternative career to gain more human capital and thus escape earnings stagnation. However, if entrepreneur and worker abilities are positively correlated, then this margin leads to negative selection for the entry of low-productivity entrepreneurs.

In this article, we use administrative data from Portugal to provide a battery of evidence that human capital in entrepreneurship is indeed partially specific in the ways as we discussed above. Then, using a calibrated quantitative life-cycle model of entrepreneurship with human capital specificity and financial frictions, we show that human capital specificity is indeed the key determinant of entrepreneurial entry, and further find that the negative selection channel is more dominant. Furthermore, we predict that because human capital specificity is such a dominant determinant of entry, a complete removal of all financial frictions have a significantly muted effect on entry decisions, increasing entry rates by less than 0.01 percentage points (relative to a baseline entry rate of 0.29%). Conversely, doubling the average wage gains of returning entrepreneurs, through reduced human capital specificity, leads to a significantly large 0.09 percetange points increase in the entry rate.

Our evidence is derived from administrative data on the universe of Portuguese worker histories linked to private firms and their balance sheets. The dataset provides a long panel from 1985 to 2020, allowing us to track individuals across entrepreneurship and wage employment, while observing their demographic and employment characteristics and the evolution of the firm they run prior to exit. To ensure that we are not conflating the wage dynamics of "subsistence entrepreneurs" in our analyses, we study only the dynamics of individuals who ran firms with paid employees, along with a host of technical conditions. We compare the wage dynamics of entrepreneurs before and after entrepreneurship to never-entrepreneurs with similar wage dynamics in the pre-period. We establish four main sets of novel empirical patterns in support of our hypothesis.

First, we show that firms exit after multiple years of declining sales, implying that most exits are driven by negative events, not positive exits such as a sale or acquisition.

Second, we show that entrepreneurs earn 3.7 percent higher wages on average upon return to wage employment, and that these gains peak at 5 years after return. However, we find heterogeneous effects along the pre-entrepreneurship wage distribution: those who enter entrepreneurship from a relatively lower wage trajectory experience a wage gain averaging 7.7 percent, but those who enter from a higher wage trajectory experience a wage loss averaging 6.1 percent. Furthermore, the wage impacts are heterogeneous along the age distribution. Entrepreneurs who enter at a younger age experience higher wage gains, especially if they started from a lower trajectory; however, those who enter from a higher trajectory at a younger age face wage losses.

Third, we relate firm performance during entrepreneurship to their wage gains after returning to paid work. We show that entrepreneurs running firms with higher sales experience higher wage gains upon return. However, entrepreneurs who ran their business longer face larger losses.

Finally, we also document that individuals that enter entrepreneurship with a higher wage profile also tend to run higher performing businesses, with higher value added and survival rates. This suggests that productivity in entrepreneurship and paid work is indeed positively correlated.

Taken together, our evidence is supportive of the hypothesis that experience in entrepreneurship is partially usable in paid work, but that this partial transferrability is beneficial to lower wage earners seeking to escape earnings stagnation. Furthermore, it opens the possibility of negative selection as we discussed earlier.

In the second part of the paper, we quantify the economic relevance of the human capital specificity channel using a macroeconomic life-cycle model with risky human capital accumulation in the vein of Huggett, Ventura, and Yaron (2011), but extended to include entrepreneurship. In this model, individuals are born with heterogeneous abilities in paid work and entrepreneurship. Over their life-cycle, they can choose to be workers or entrepreneurs, and always retain the option to switch between occupations. Furthermore, individuals accumulate human capital over the life-cycle, but can only accumulate human capital specific to their occupation of choice. As such, entry into entrepreneurship preclude accumulation of human capital in paid work, and vice versa. Limited transferrability of human capital across occupations in turn render entrepreneurship a risky decision, but benefit low ability workers who benefit from the upside risk of being an entrepreneur. Finally, we also model financial frictions which restrict the optimal scale of the firm, and thus further impact the entry decision of individuals.

We calibrate the model to our data, and use it to study the impact of human capital specificity on the entry decisions of individuals, as well as the broader implications for firm productivity. Our first analysis doubles the average wage gains individuals make after returning to entrepreneurship, by reducing the degree of human capital specificity. We find that this has a large and significant impact on entrepreneurial activity, increasing the number of entrepreneurs in the steady-state by 52%, while increasing the entry rate by 0.09 percentage points (relative to a baseline of 0.29%). However, we find that this margin is due primarily to negative selection of older workers who face wage stagnation as they enter into middle age. As a result, the average sales of firms decline by around 0.27% in the steady-state.

Our second analysis investigates the degree to which financial frictions restrict entry. In our baseline model, individuals face a no-borrowing constraint and are born with zero wealth, which maximizes the role of financial frictions. Then, we relax the borrowing constraint such that all entrepreneurs can always attain their optimal scale. We find that financial constraints have a relatively muted impact on entry, increasing entry rates by around 0.01 percentage points, leading to a 5% increase in the number of entrepreneurs in steady-state. Moreover, in contrast to the first counterfactual, reducing financial frictions primarily increase entry of younger entrepreneurs. Finally, we find that average firm sales increases by almost 40.8%, suggesting that the main channel of financial frictions is to restrict firm growth.

Overall, our quantitative analysis suggests that the main barrier to entry into entrepreneurship is due to the role of human capital specificity, contrary to the predominant view that financial frictions is the key barrier to entry. The latter predominant view around financial frictions has led to substantial development in both private and public sectors in increasing credit provision for entrepreneurs. For instance, the United States Small Business Administration primarily supports entrepreneurs through reduced capital costs. Our analysis suggests that while financial constraints are indeed a barrier to growth, reducing these constraints alone will not necessarily spur greater entrepreneurial activity, especially among high-growth young potential entrepreneurs. Instead, programs that can provide a wage floor to aspiring entrepreneurs (e.g., job protected leave) are more likely to spur entrepreneurial activity.[1]

Literature. Our paper relates to three broad branches of the literature. First, our paper directly relates to the research on the barriers to entry and growth in entrepreneurship, in particular, in macroeconomics and finance. Unlike the existing literature, which emphasizes

[1] As a actual example, many management consulting firms such as Bain and Company (https://www.bain.com/careers/life-at-bain/benefits/) provide unpaid sabbatical to employees, who can use these sabbatical to start a business.

explicit barriers such as financial frictions (e.g., Buera and Shin, 2013; Midrigan and Xu, 2014) or market frictions (e.g., Hincapié, 2020; Tan and Zeida, 2024), our paper emphasizes the role of implicit barriers in the form of deterioration of outside options when entering entrepreneurship.

Furthermore, the mechanism we emphasize, the role of human capital specificity as a barrier to entry, is similar to the mechanism studied by the broader literature on *physical* investment specificity (e.g., Abel and Eberly, 1996). In that literature, physical investment specificity generates a decline in the put option of entrepreneurship. In direct relation to our work, Tan (2022) argues that entrepreneurial risk is associated with lack of insurance and illiquidity arising from physical investment specificity. In our context, human capital specificity is analogous to physical capital specificity in that entry into entrepreneurship requires investing in business-specific human capital that is (partially) nontransferable to wage employment upon exit. The contribution of our paper is an empirical assessment of the impact of human capital specificity on labor market outcomes.

Second, our paper also contributes to a recent literature focusing on the option to return to wage employment as a determinant of entrepreneurial entry. Vereshchagina and Hopenhayn (2009) present a theoretical framework emphasizing the role of the outside options in reducing the riskiness of entrepreneurship, essentially presenting entry into entrepreneurship as a put option. More recently, Catherine (2022) and Choi (2017) build on the insights of Vereshchagina and Hopenhayn (2009) and construct quantitative models to infer the value of such outside options. Unlike them, we emphasize the endogenous nature of outside options and show that it declines in entrepreneurship, thus creating a barrier to entry. In these regards, our findings are similar to those of Gottlieb, Townsend, and Xu (2022), who show that entry into entrepreneurship could pose a career risk to failed entrepreneurs. Unlike ours, their paper studies a particular case of job protective leave for new mothers (in the form of expanded maternity leave), whereas we study the population of entrepreneurs.

Third, finally, while we focus on entrepreneurship, our paper is broadly related to the firm dynamics literature that examines the role of entry and exit for a variety of macroeconomic outcomes, such as the propagation of business cycles (e.g., Clementi and Palazzo, 2016), aggregate responses to trade shocks (e.g., Lanteri, Medina, and Tan, 2024), or gains to financial development (e.g., Buera and Shin, 2013). Unlike these papers, where outside options are typically purely random or fixed (or exit is purely exogenous), we emphasize that the outside options of running a firm are, in fact, endogenous to the decision to start and run said firm.

Roadmap. The rest of the paper is structured as follows. Section 2 presents a stylized framework for the upcoming empirical analysis. Section 3 introduces our data source and Section 4 presents our main empirical results. Section 5 specifies our quantitative model and Section 6 describes the inference approach for our quantitative analysis. Section 7 presents our model results and counterfactual analyses. Finally, Section 8 concludes.

2 Stylized framework

We now introduce a stylized framework to guide our latter data analysis. The framework considers individuals with heterogeneous average lifetime incomes due to heterogeneous income profiles (HIP, following Guvenen, 2007) resulting from differential ability to accumulate human capital (c.f. Huggett, Ventura, and Yaron, 2011). We extend that basic framework to allow for two types of human capital—specific to wage employment and entrepreneurship—as well as partial transferability of human capital between the two, and derive five testable predictions.

Consider an individual i of age j_i. They accumulate human capital specific to wage employment h_i and to entrepreneurship q_i. Human capital in wage employment accumulates according to the law of motion

$$h_i' = g(h_i, a_{h_i}, j_i). \tag{2.1}$$

Here a_{h_i} is an individual-specific human capital accumulation term in wage employment, and the prime denotes next-period human capital. The function $g(\cdot)$ describes the evolution of human capital in wage employment: it is concave and increasing in h, increasing in a_h, and decreasing in j. Together, these features imply that the human capital profile is hump-shaped like in Huggett, Ventura, and Yaron (2011): individuals with higher a_h experience faster growth early in the life cycle but this growth eventually slows down and the profile reverts to losses by retirement age.

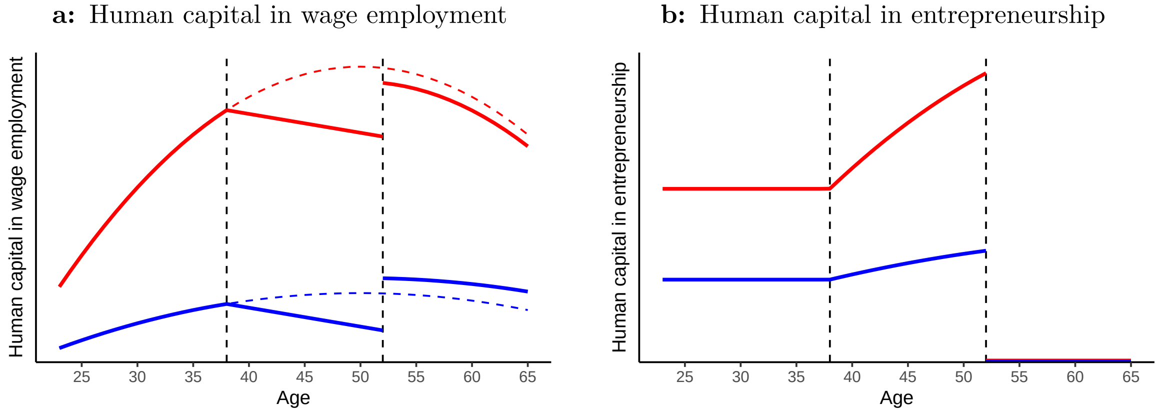
The same individual i can also enter entrepreneurship at any time. When they do, human capital in entrepreneurship accumulates according to the law of motion

$$q_i' = f(q_i, a_{q_i}). \tag{2.2}$$

Analogously to wage employment, a_{q_i} governs the speed of human capital accumulation in entrepreneurship. The function $f(\cdot)$ is increasing and concave in q and increasing in a_q, implying a hump-shaped profile in entrepreneurship. While the individual is running their business, their wage employment-specific human capital erodes at a rate δ_h. Afterwards, when the individual returns to wage employment, only a $(1-\lambda)$ fraction of their entrepreneurship-specific human capital q can be converted to wage employment-specific human capital h, and the rest fully erodes.

Figure 2.1 illustrates these human capital processes through the example of two individuals in red and blue. These two hypothetical individuals work in wage employment from age 23 until 38, then run their businesses between 38 and 52, after which they return to wage employment until they retire. The red individual experiences faster human capital growth both in wage employment and in entrepreneurship than the blue one. The dashed lines on the left panel show their wage employment-specific human capital, had they not started a business. Upon return, the high-growth individual in red comes back at a lower level of human capital than its counterfactual value while the low-growth individual in blue comes

Figure 2.1: Human capital profiles



Notes: Hypothetical wage employment and entrepreneurship-specific human capital processes. Dashed lines show human capital for individuals who never started a business. Solid lines show human capital for individuals who ran a business from age 38 to 52 (vertical dashed lines). *Source:* authors' own illustration.

back higher. The difference is due to (i) the imperfect transferability of human capital from entrepreneurship to wage employment, and (ii) different levels of foregone human capital in wage employment while running a business, due to different abilities of human capital accumulation.

Finally, we assume that the earnings of the individual is proportional to their human capital. Consequently, individuals with a lower ability to accumulate human capital have a flatter earnings profile in wage employment while those with a higher accumulation term experience steeper earnings increases.

With the setup complete, we now spell out five predictions:[2]

1. Individuals with a flatter earnings profile before entering entrepreneurship experience earnings gains after return. Our framework predicts this since low-earning individuals already experience wage stagnation, thus any human capital gain in entrepreneurship benefits them.

2. Conversely, individuals with a steeper earnings profile before entering entrepreneurship

[2]We formally derive these predictions under parametric assumptions for the human capital processes in Appendix A.

experience earnings losses after return. Our framework predicts this since human capital in entrepreneurship is an imperfect substitute for the human capital in wage employment that they forgo.

3. For individuals with a flatter earnings profile before entrepreneurship, the earnings gain is decreasing in the age of entry. This is due to the concave nature of human capital growth.

4. For individuals with a steeper earnings profile before entrepreneurship, the earnings loss is decreasing in the age of entry. Again, this is explained by the concave nature of human capital growth.

5. The overall impact of entrepreneurship on the return option to wage employment is ambiguous.

Having presented our framework, we now turn towards analyzing the data to test these predictions.

3 Data and measurement

3.1 Data source

Data on entrepreneurs' full work histories are rarely available. As Goetz, Hyatt, McEntarfer, and Sandusky (2016, p.435) put it, "[m]ost existing data sources are limited in their ability to depict the interaction between startups and their human assets, including owner, founding team members and early employees." Our dataset allows us to track such interactions.

We use Quadros de Pessoal (QP), a rich linked employer-employee dataset collected by the Portuguese Ministry of Labor and Social Security. This is a nationally mandated survey that each wage-paying firm is legally obligated to complete. We have data on establishments, their affiliations with a particular firm, and detailed information on their workers, covering the period between 1985–2020. We follow individuals' work histories across employers, accompanied by detailed information on wages, occupations, job titles, tenure, age, gender and education. Crucially for our analysis, we have comprehensive information on earnings, which includes the base wage, regular benefits, irregular benefits and overtime pay. We supplement the QP data with administrative data on financial statements for universe of firms in the non-financial sector (Sistema de Contas Integradas das Empresas, or SCIE). This provides us measures of firm performance to analyze the drivers of firm exit.

A key empirical challenge in entrepreneurship research lies in determining how we define and identify entrepreneurs. The standard approach is to define entrepreneurs as those who are self-employed. This approach potentially underestimates a substantive amount of economic activity derived by those who decide to incorporate and become employees of the firm. We follow Queiró (2022) who, also using QP, defines entrepreneurs as top managers of newly established firms. In turn, to identify top managers, we leverage the occupational classification in QP, which is consistent with the International Standard Classification of Occupations (ISCO).[3]

Our main research design involves comparing the wage trajectories of entrepreneurs that return to wage employment, against otherwise equivalent individuals who never entered entrepreneurship. We define the former as "return-entrepreneurs" and the latter as "never-entrepreneurs." We restrict our sample to individuals of post-college working age (age 22 to 65), and further restrict the set of return-entrepreneurs to individuals who started a business between the ages of 25 to 55. This restriction is necessary to (i) create a sample with a sufficiently long pre-entry wage trajectory for our matching algorithm (discussed later), and (ii) to evaluate the post-return wage trajectory. Therefore, our sample for analysis excludes individuals who started a business when they are very young or very old, and who also never exited entrepreneurship.

[3]ISCO provides a multi-layer hierarchy of organization within the firm, starting with directors, chief executives and general managers. Top managers are defined at the highest layer of organizational hierarchy that a particular firm reports.

Our final sample includes a panel of 709 thousand firms matched with 5.6 million workers (Table 1), of which 47 thousand (0.8 percent) are return-entrepreneurs. In turn, 7 percent of firms employ at least one return-entrepreneur in their enterprise. Return-entrepreneurs are widespread in the Portuguese economy, covering all 39 occupations, 30 sectors, and 8 locations in our sample. Furthermore, return-entrepreneurs have different, mostly better, socioeconomic characteristics than never-entrepreneurs. 60 percent of return-entrepreneurs are males with an average age of 41.3, whereas never-entrepreneurs are comprised of 53 percent males with an average age of 40.1 years. On average, 59 percent of the sample have less than a high school education, 24 percent have a high school diploma and 17 percent have a college degree. Return entrepreneurs are 28 percentage points more likely to have graduated from college and earn 31 percent higher wages than never-entrepreneurs.

3.2 Measuring firm performance

As we discussed, the SCIE dataset provides information on firm balance sheets, expenses, and sales. For measuring firm performance, as a baseline, we focus on the dynamics of firm value added, which we compute as the difference between firm sales and cost of goods sold. For additional analyses, we also consider the dynamics of firm labor productivity and total factor productivity (TFP). Labor productivity is computed as the log difference in value added and labor. For TFP, we assume that the firm operates a production function with decreasing returns to labor of the form

$$y = \omega l^{\nu} \tag{3.1}$$

where ω is the total factor productivity (TFP) of the firm, and $0 < \nu < 1$ captures the degree of decreasing returns to scale. Our goal is to measure ω; to that end, we impute ω by assuming that $\nu = 0.8$, consistent with conventional choices on the returns to scale.

3.3 Measuring the effect of entrepreneurship on post-exit wages

Our fundamental goal is to estimate the effect of a stint in entrepreneurship on the post-exit wage trajectory of the entrepreneur. The ideal research design would involve comparing the wage trajectory of two potential entrepreneurs, one who ends up starting a business and another who does not start one but is identical in every other aspect. Because such an ideal counterfactual does not exist, we instead compare the wage trajectories of return-entrepreneurs to that of otherwise "identical" never-entrepreneurs. We explain here, in detail, our construction of the counterfactual wage trajectory.

We begin by decomposing wages into the following factors:

$$\log w_{it} = X_{it}\beta + u_{it}, \tag{3.2}$$

$$u_{it} = \phi_g(j_{it}) + \varepsilon_{it}. \tag{3.3}$$

Here, i denotes the individual and g denotes a group that the individual belongs to. For our purposes, the "group" we will construct are the set of never-entrepreneurs who exhibit similar characteristics to return-entrepreneurs. Furthermore, X_{it} are observable predictors, j_{it} is age, and $\phi_g(\cdot)$ is a function that depends on group characteristics. ε_{it} is the error term, assumed to be uncorrelated with X_{it} and j_{it}.

Our wage equation parses the determinants of wages into two components. The linear term $X_{it}\beta$ assumes that some characteristics affect an individual's wages but do not have heterogeneous effects across groups. Conversely, the function $\phi_g(\cdot)$ assumes that there are characteristics unique to the group that drive the wage profile of individuals. In particular, $\phi_g(\cdot)$ is the empirical counterpart to the human capital accumulation term a_h in our stylized framework. For concreteness, consider a case where return-entrepreneurs are uniquely drawn from the financial sector whereas never-entrepreneurs are uniquely drawn from the manufacturing sector. β then captures the effect that return-entrepreneurs and never-entrepreneurs have differing average wages due solely to the sector they work in, as opposed to fundamental differences between workers and entrepreneurs. Conversely, $\phi_g(\cdot)$ accounts for the effect that, net of the pure composition effect, “entrepreneurial types” have differing wage profiles from “non-entrepreneurial types.”

Our goal is to isolate a set of never-entrepreneurs that resemble return-entrepreneurs. Using the formalization above, this amounts to finding a set of never-entrepreneurs with $\phi_g(\cdot)$ that are similar to return-entrepreneurs. To that end, we first estimate β in Equation 3.2 using the entire population of never-entrepreneurs. The observables X_{it} include gender, education, occupation, and in some extensions sector and location. Denoting this estimate by $\hat{\beta}$, we then construct residualized wages for every individual:

$$\log \tilde{w}_{it}(j_{it}) = \log w_{it} - X_{it}\hat{\beta}. \tag{3.4}$$

Note that, by our definition in Equation 3.2, the residualized wages are now only a function of the group-based wage profiles.

Next, we match entrepreneurs to workers by group. We define a “group” as the set of entrepreneurs with the same age of entry, which we denote by j^{entry}. Note that for a group j^{entry}, we would observe a wage profile prior to entry $\{\tilde{w}_{it}(j_{it})\}_{22 \leq j_{it} < j^{\text{entry}}}$. Then, for each individual return-entrepreneur i in that group, we locate a never-entrepreneur i' who has a wage profile between the ages of 22 and j^{entry} that is similar to that of the return-entrepreneur i. Formally, for each return-entrepreneur i and never-entrepreneur i', we construct the loss function

$$Q = U + V \tag{3.5}$$

where

$$U \equiv \frac{1}{j^{\text{entry}} - 22} \sum_{j=22}^{j^{\text{entry}}} \Delta^2, \tag{3.6}$$

$$V \equiv \frac{1}{j^{\text{entry}} - 22} \sum_{j=22}^{j^{\text{entry}}} \left(\Delta - \frac{1}{j^{\text{entry}} - 22} \sum_{j=22}^{j^{\text{entry}}} \Delta \right)^2, \tag{3.7}$$

$$\Delta \equiv \log \tilde{w}_{i't}(j) - \log \tilde{w}_{it}(j). \tag{3.8}$$

and locate a never-entrepreneur i' that minimizes this loss. Our goal with this loss function is to locate a never-entrepreneur that is (i) close to the entrepreneur in a standard least-squares sense (captured in U), but also (ii) has a wage trajectory that is "parallel" to the entrepreneur's to ensure that the parallel trends assumption holds for our later analysis (captured in V). In a conventional difference-in-differences framework, one would put all the weight on V and ignore U. We include U as part of our matching function since two individuals can have the same wages trajectories but very different average wages. If the level of wages are themselves a determinant of the outside options of entrepreneurs, then matching only on V would violate the parallel trends assumption post-entrepreneurship.

From the group of matched never-entrepreneurs, we then estimate $\phi_g(\cdot)$, which gives us the counterfactual path of wages had the return-entrepreneur never started a business. Then, we compute the following wage gap:

$$\log w_{it}^{\text{gap}} = \log \tilde{w}_{it}(j_{it}) - \hat{\phi}_g(j_{it}). \tag{3.9}$$

Note that, by construction, $\mathbb{E}[\log w_{it}^{\text{gap}} \,|\, j < j^{\text{entry}}] = 0$, and $\mathbb{E}[\log w_{it}^{\text{gap}} \,|\, j > j^{\text{exit}}]$ (j^{exit} being the age at exit) is the average unconditional effect on entrepreneurship on the wages of return-entrepreneurs. Therefore, estimating the effect on entrepreneurship boils down to a before-after estimator of the following form:

$$\log w_{it}^{\text{gap}} = \theta \mathbb{1}(\text{Post}_{it}) + e_{it} \tag{3.10}$$

where the indicator $\mathbb{1}(\text{Post}_{it})$ is 0 for the pre-entry period and 1 after return to wage employment. e_{it} is the error term, and θ estimates the effect of entrepreneurship on the wage trajectory of the individual upon return to wage employment. The empirical analyses in the following section are richer specifications that build on this estimator.

3.4 Characteristics of the pre-period wage gap

3.4.1 Quality of the match

Panel a of Figure 1 plots the average wage gap up to five years prior to entry into entrepreneurship. From a visual inspection, the quality of the match appears to be reasonable with a minimal degree of pre-trends. Panel b of Figure 1 plots a kernel density plot of the distribution of the wage gap in the pre-period. The distribution is roughly symmetric and centered approximately around 0. However, the distribution is highly dispersed, with a standard deviation of around 0.38. This indicates that while the match is reasonably good on average, there is substantial heterogeneity in wages across return-entrepreneurs.

3.4.2 Distribution and persistence of the wage gap

From our estimation framework, a non-zero wage gap is indicative of a return-entrepreneur who either (i) experienced a temporary shock to labor productivity, or (ii) is a permanently different individual relative to the average entrepreneur (i.e., worker fixed effects, or β_i in our stylized framework).

In Table 2, we summarize the persistence of the wage gap in two ways. First, we report the estimate of an AR(1) regression with and without person fixed effects (columns 1 and 2). We find that the wage gaps are partly explained by a persistent (but transitory) shock, and can also be explained by person fixed effects. Second, we further examine our hypothesis that better workers experience faster wage growth, as in our stylized framework. We compute the year-on-year growth rate of the wage gap and regress the growth rates on the worker fixed effects from the earlier AR(1) model, which we denote by $\bar{w}$. Column 3 reports our results, showing that individuals with higher $\bar{w}$ also experience larger wage growth on average.

Taken together, our stylized facts replicate earlier research (e.g., Huggett, Ventura, and Yaron, 2011), and provide grounding for our framework as presented in Section 2. Therefore, when we study the impact of entrepreneurship on the labor market outcomes of individuals, we focus narrowly on a split along the dimensions of the age of entry and $\bar{w}$.

3.4.3 Worker fixed effects and firm performance

We conclude this section by examining whether entrepreneurs' pre-period productivity in wage employment is related to the performance of their firm. Specifically, in Figure 2 we examine the relationship of $\bar{w}$ with the average sales of the firm during the tenure of the individual (Panel a), length of firm survival (Panel b), and the length of firm ownership (Panel c). By and large, we find that entrepreneurs with higher labor productivity also run better performing firms. For instance, a 1 percent increase in $\bar{w}$ goes along a 3.3 percent increase in firm sales. Taken together, these stylized facts suggest some degree of transferability of productivity in wage employment into firm performance. As such, when we turn to our quantitative model, we will emphasize matching this dimension of the data.

4 Empirical results

4.1 Why do entrepreneurs return to wage employment?

Why do entrepreneurs return to wage employment? While the working assumption of most quantitative models is that they do so because of negative shocks to profitability (e.g., as in Hopenhayn, 1992), recent work has proposed that exits might be driven by *positive* shocks to the return option to wage employment (e.g., due to the possibility of selling a firm, as in Bhandari, Martellini, and McGrattan, 2022; Mahone, 2023; Guntin and Kochen, 2024). Our main argument in this subsection is that the *negative shocks* interpretation is indeed a key driver.

To make our argument, we compute the dynamics of firm sales over firm age, conditional on exiting at a given age. To ensure comparability, we residualize these measures of sales on year of entry and year fixed effects. Panel a of Figure 3 plots our results, showing that multiple years of decline in sales precede exit. A theory of only positive exits would preclude such dynamics, since investors would have no motivation to purchase a failing firm.

Our results above emphasize the life cycle of firm sales, but the life cycle of the firm itself does not always coincide with the ownership tenure of an individual owner. For instance, a firm that exits after 10 years could have different owners over the course of its existence. Therefore, in panel b of Figure 3 we now plot average firm sales as a function of years in ownership (rather than firm age). The figure reports a similar qualitative result: entrepreneurs return to wage employment after multiple years of declining sales. Unlike in panel a, however, the decline is less steep, suggesting that many owners exit entrepreneurship prior to a complete deterioration of the business.

4.2 The option to return to wage employment

4.2.1 Average impact of entrepreneurship

We begin by examining the average wage gap of returning entrepreneurs, relative to their pre-period wage gap, which we interpret as the impact of entrepreneurship on the labor market outcomes of individual. In the first column of Table 3, we report our estimate of θ based on Equation 3.10. Here, we find that the average impact is positive; upon return from entrepreneurship, the typical entrepreneur earns about 3.7 percent higher wages relative to their pre-period earnings.

We further examine the dynamic impact of entering entrepreneurship on their labor market outcomes. In Figure 4, we estimate the average wage gap in event time, where $t \leq -1$ is the pre-period and $t \geq 0$ is the post-period. The results are plotted relative to $t = -1$. We see that the gains from entrepreneurship manifest gradually, and peak around five years after re-entry.

Our analysis reveals that entering entrepreneurship has a positive impact on average. We next examine the impact of entrepreneurship along two dimensions, following our stylized framework: along the dimensions of labor productivity and age of entry.

4.2.2 Return option and labor productivity

Following our hypothesis, entrepreneurship should primarily benefit individuals with low labor productivity, whereas it would benefit less or even hurt individuals with higher productivity. To test this, we estimate the following regression:

$$\log w_{it}^{\text{gap}} = \theta \mathbb{1}(\text{Post}_{it}) + \gamma \bar{w}_i + \delta \mathbb{1}(\text{Post}_{it}) \times \bar{w}_i + e_{it}, \tag{4.1}$$

where $\bar{w}_i$ refers to the worker fixed effects we estimated earlier, and δ is the estimate of interest. Our hypothesis amounts to $\delta < 0$. Column 2 of Table 3 shows our result that individuals with higher worker fixed effects indeed benefit less from entrepreneurship. Notably, a one standard of in worker fixed effects amounts to 0.26 log points. In other words, whereas an individual that is one standard deviation below the mean would see a 10.3 percent increase in their wages, an individual one standard deviation above the mean would see a 6.3 percent loss. Our back of the envelope calculation reveals that around 60 percent of individuals would benefit from entrepreneurship, with an average wage gain of 7.7 percent. In contrast, the remaining 40 percent of individuals would see an average wage loss of 6.1 percent.

Whereas the earlier result studies a level effect, our hypothesis further implies that entrepreneurship negatively impacts the growth rate of wages of high-wage individuals. To examine this, we estimate a variant of Equation 4.1 by replacing the dependent variable with the growth rate of the wage gap; furthermore, to avoid the effect of mean-reversion from biasing our estimates, we also control for the average pre-period wage gap. Column 3 of Table 3 reports our results, where we see that a 1 percent increase in the worker fixed effect implies a 0.19 percentage point decrease in the growth rate of wages, consistent with our hypothesis.

A potential concern with our result is that the negative (positive) impact on high (low) productivity workers simply arises from mean reversion. To address this concern, Figure 5 plots an event study split by high and low productivity workers. We see no evidence of mean reversion. If anything, higher productivity were *growing* until entry into entrepreneurship had a negative impact; in contrast, lower productivity were *shrinking* until entry into entrepreneurship had a positive impact.

4.2.3 Return option and age of entry

Our theoretical framework further implies that, controlling for worker fixed effects, the benefits of entrepreneurship should be higher for entrepreneurs who started a business at an older age. To test this, we estimate the following regression:

$$\log w_{it}^{\text{gap}} = \theta \mathbb{1}(\text{Post}_{it}) + \gamma j_i^{\text{entry}} + \delta \mathbb{1}(\text{Post}_{it}) \times j_i^{\text{entry}} + \nu_0 \bar{w}_i + \nu_1 \mathbb{1}(\text{Post}_{it}) \times \bar{w}_i + e_{it}, \quad (4.2)$$

where j_i^{entry} is the age of entry minus 25 (i.e., the age of entry relative to the youngest age of entry). δ is the estimate of interest, and our hypothesis amounts to $\delta > 0$. Column 4 of Table 3 reports the result, showing supporting evidence for our hypothesis. While the point estimate appears small, one should note that the average age of entry is 34.

Our framework further implies two additional results. First, among entrepreneurs with lower labor productivity, we would expect the positive impact of entrepreneurship to accrue more to entrepreneurs who enter at a younger age. Second, among entrepreneurs with higher labor productivity, we would expect the negative impact of entrepreneurship to accrue more to entrepreneurs who enter at an younger age. To test this, we estimate the following regression:

$$\log w_{it}^{\text{gap}} = \theta \mathbb{1}(\text{Post}_{it}) + \gamma j_i^{\text{entry}} + \delta \mathbb{1}(\text{Post}_{it}) \times j_i^{\text{entry}} + e_{it} \tag{4.3}$$

separately for low and high productivity entrepreneurs. To construct "low" and "high" bins, we sort the entrepreneurs into quintiles and define a "low" productivity entrepreneur as an individual with $\bar{w}$ in the first quintile and a "high" productivity entrepreneur as an individual with $\bar{w}$ in the fifth quintile. Columns 5 and 6 of Table 3 report our results, supporting for our hypothesis. In Column 5, we see that $\theta > 0$ while $\delta < 0$, indicating that the benefits of entrepreneurship is decreasing in age of entry. In Column 6, we see that $\theta < 0$ while $\delta > 0$, indicating that the negative impact of entrepreneurship is declining in age of entry.

We show further, dynamic evidence in Figure 6. As panel a shows, conditional on starting from lower wages, young entrants to entrepreneurship (those who started a business below 35) experience wage gains after return; at the same time, older entrants (over 45) experience low to no gains. We repeat the analysis for young vs. old entrants from a higher wage profile in panel b: younger entrants experience wage losses while older entrants face no statistically significant losses.

4.3 Relating to firm outcomes

We now investigate the extent to which human capital accumulated during entrepreneurship is transferable to wage employment. To that end, we study the impact of firm performance on the return option of entrepreneurs.

We conduct our investigation along two dimensions. First, we examine whether entrepreneurs that ran a firm with higher average sales benefit from a larger wage gain upon return from entrepreneurship. Second, we examine how the length of tenure impacts the return option of entrepreneurs. In both cases, we estimate a version of Equation 4.3 where we replace j_i^{entry} with sales or tenure. We additionally control for $\bar{w}$, as we already showed earlier that $\bar{w}$ itself is correlated with both the dependent variable (the wage gap) and the independent variable (sales and tenure).

The overall results are reported in Table 4. Column 1 reports our results for sales, where we see that sales predicts a higher post-period wage gap, holding all else constant. This appears consistent with our hypothesis that human capital is (partially) transferable, and might explain why poorly performing workers appear to benefit from entrepreneurship. Figure 7, panel a shows the trajectory of the wage gap by sales: entrepreneurs running businesses with low sales experience persistent wage gains while those who used to run high-sales businesses face an initial decline in, then plateauing of, their wages.

We further examine this hypothesis by splitting our samples into low and high productivity entrepreneurs as before. Column 2 reports the estimate for low productivity and column 3 for high productivity individuals. Strikingly, column 2 shows that, holding constant firm sales, the treatment effect is negative and statistically weakly different from zero (i.e., $\theta < 0$). In contrast, the effect of firm sales is large: a one percent increase in sales increases the wage gap by 3.9 percent. Conversely, for high labor productivity entrepreneurs, we continue to observe that $\theta < 0$; that is, the impact of entrepreneurship is still negative. Indeed, we see that the main reason why high productivity entrepreneurs do not fare even worse is because of the positive mitigating effect of firm sales; i.e., their skills appear partially transferable.

We next turn to our results on tenure. In Column 4, we find that $\delta < 0$, implying that additional years spent in entrepreneurship worsen the return option of entrepreneurs to wage employment. This is again consistent with our hypothesis that wage employment-specific human capital decays in entrepreneurship, and is not fully replaced by entrepreneurship-specific human capital. Turning to the dynamics, panel b of Figure 7 shows that entrepreneurs who ran their businesses for a shorter time face persistently increasing wage gains, while those who ran their businesses longer experience persistent losses.

4.4 Alternative estimator: synthetic DiD

The matching procedure described above is similar in spirit to the synthetic difference-in-differences (SDID) approach (Arkhangelsky, Athey, Hirshberg, Imbens, and Wager, 2021). Both estimation procedures aim to compare treated unit outcomes (wages of return-entrepreneurs) to counterfactual control units that are otherwise identical from a *dynamic* perspective. Our matching procedure picks a never-entrepreneur with an identical wage profile to each return-entrepreneurs in the sample, and compares their (actual or hypothesized) post-exit outcomes. The SDID estimator, instead of picking one control unit, creates a synthetic comparison unit by choosing individual and time weights—ω_i and λ_t—that matches the pre-entry wage profile of return-entrepreneurs.

Formally, the SDID estimator is

$$(\hat{\theta}^{\text{SDID}}, \hat{\alpha}, \hat{\tau}) = \arg\min_{\theta,\alpha,\tau} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\log w_{it} - \alpha_i - \tau_t - X_{it}\beta - \theta \mathbb{1}(\text{Post}_{it})\right)^2 \hat{\omega}_i \hat{\lambda}_t \tag{4.4}$$

with

$$\hat{\omega} = \arg\min_{\omega} \sum_{t=1}^{T_{\text{pre}}} \left(\omega_0 + \sum_{i=1}^{N_c} \omega_i \log w_{it} - \frac{1}{N_t} \sum_{i=1}^{N_t} \log w_{it}\right)^2 + \zeta^2 T_{\text{pre}} \left\|\omega\right\|_2^2 \qquad \text{and}$$

$$\hat{\lambda} = \arg\min_{\lambda} \sum_{i=1}^{N_c} \left(\lambda_0 + \sum_{t=1}^{T_{\text{pre}}} \lambda_t \log w_{it} - \frac{1}{T_{\text{post}}} \sum_{t=+1}^{T_{\text{post}}} \log w_{it}\right)^2$$

where T_{pre} and T_{post} denote the number of pre- and post-treatment time periods, N_c and N_t denote the number of control and treated units, and ζ is a regularization parameter (see Arkhangelsky, Athey, Hirshberg, Imbens, and Wager, 2021, pp.4091–4093 for details). This estimator resembles our matching approach in a few key ways. While SDID differences out observable and unobservable person- and time-invariant characteristics as part of the procedure, we residualize wages in a first step (Equation 3.4). Given that, our procedure can be thought of choosing a control unit i_c such that $\hat{\omega}_i = 1$ for $i = i_c$ and 0 otherwise, and $\hat{\lambda}_t = 1$ for all t.

The empirical setting here has two key features which render our procedure more appropriate for this application. First, the theoretical underpinnings of SDID require a balanced sample, and so does the related estimation software (Clarke, Pailanir, Athey, and Imbens, 2024)—our sample is not balanced. Second, the fraction of treated units in our sample is very small. Practically speaking, our procedure picks the most suitable comparison unit from a massive pool of candidate control units; SDID would assign a small nonzero weight to most control units which could lead to stability issues. Nonetheless, we show estimates using a version of the SDID estimator as a robustness exercise in Table 5: while the magnitudes are different, our main qualitative results, reassuringly, survive.[4]

4.5 Taking stock

We have shown empirical evidence that entrepreneurship worsens the return option to wage employment. Our results reveal that the typical entrepreneur earns higher wages after return relative to never-entrepreneurs, but the aggregate effect masks a vast amount of heterogeneity. Those who enter entrepreneurship from higher wages experience large wage losses while those who come from a lower wage profile earn gains. These results point to the importance of imperfectly transferable human capital from entrepreneurship to wage employment. Furthermore, the dynamic gains and losses are starker for young entrepreneurs, which could induce delayed entry into entrepreneurship, specifically in the presence of financial frictions. We expand on the interplay of these mechanisms in the second half of this paper.

5 Quantitative model

We now turn to modeling entrepreneurial choice in the presence of human capital specificity. Our goal is to quantify the importance of the human capital specificity channel in shaping

[4] We implement the SDID estimator on our unbalanced sample by adding indicator variables for missing observations and setting log wages to 0 for them. This could introduce biases in estimating the panel weights ω_i and λ_t, so we consider these estimation results as suggestive evidence for the robustness of our matching estimates.

entrepreneurial choices. Better understanding the human capital aspect of entrepreneurial risk guides us to design more effective policies to spur entrepreneurship.

We start by considering households that rank sequences of consumption

$$U\left(\{c_j\}_{j=1}^{J}\right) = \sum_{j=1}^{J} \beta^j \frac{c_j^{1-\gamma}}{1-\gamma} \tag{5.1}$$

where j is the age of the individual since they entered the labor force. Following Huggett, Ventura, and Yaron (2011), we assume that individuals enter the labor force at age 23, retire at age 65, and then live for another 20 years in retirement.

At any point in time in the labor force, an individual either earns income through wage employment ("workers") or by running a business ("entrepreneurs"). All individuals start off their careers as workers, before making a decision whether to transition to entrepreneurship or continue in wage employment. If an individual becomes an entrepreneur, they also have the option to transition back into wage employment. Over the course of their time in the labor force, individuals also decide on how much savings to accumulate, which earn a net rate of return r. Therefore, an individual in the labor force makes two key endogenous decisions: (i) occupational choices and (ii) asset accumulation. In contrast, individuals in retirement do not earn any labor or business income, but simply make consumption-savings decisions around the residual value of their savings accumulated during their time in the labor force.

In general, besides their occupation, each individual is characterized by their levels of human capital in wage employment (h); human capital in entrepreneurship (q); shocks to h and q (s and z, respectively); ability to accumulate human capital in either profession (a_h and a_q, respectively); and net savings (b). We assume that at the age of entry ($j = 1$), all individuals draw a vector (h, q, a_h, a_q). We further assume that ability (a_h, a_q) is fixed throughout the lifetime of the individual, but human capital evolves over time. In the next subsections, we detail these variables, their evolution, and their impact on the consumption-savings decision of the individual.

5.1 Workers

We begin by first presenting the problem of a generic worker. At the beginning of the period, a worker has human capital in wage employment and entrepreneurship h and q. Prior to working, the individual receives an i.i.d. shock to their human capital in wage employment, given by $\tilde{h} = hs$. In turn, the earnings they receive is $w\tilde{h}$, where w is the market wage rate. We assume that human capital in wage employment accumulates as a function of their current post-shock human capital and their current time spent in the labor force. Letting h' denote next period human capital, this implies a law of motion given by

$$h' = \tilde{h} + a_h \left(\tilde{h} f(j)\right)^{\theta_h}, \tag{5.2}$$

where $0 \leq \theta_h \leq 1$ and

$$f(j) = \kappa_1 \left(\frac{1}{1 + \exp\left(\kappa_2 (j - \kappa_3)\right)}\right)^{\kappa_4}. \tag{5.3}$$

Furthermore, we assume that

$$\log s' \sim N\left(\mu_s, \sigma_s\right), \tag{5.4}$$

where we restrict μ_s such that $\mu_s + \frac{1}{2}\sigma_s^2 < 0$. Consequently, human capital on average decays at a rate $1 - \exp\left(\mu_s + \frac{1}{2}\sigma_s^2\right)$. Along with decreasing returns to human capital accumulation (θ_h), the exogenous rate of decay implies a hump-shaped earnings profile for workers. This feature is shared with Huggett, Ventura, and Yaron (2011), who extend the widely used Ben-Porath (1967) human capital production function with a shock process.[5] They further model endogenous investment in human capital where, as a result of assumptions on the returns to working, time spent in human capital accumulation is decreasing in age. Rather than includ-

[5] Another strand of the literature (e.g., Heckman, Lochner, and Taber, 1998) reaches similar conclusions by adding multivariate investment choices to the Ben-Porath (1967) model.

ing an endogenous dimension, we directly impose decreasing human capital accumulation in age through $f(j)$, directly estimated from the data, since our focus is on entrepreneurship.

The worker then decides if they want to continue in wage employment or enter entrepreneurship. If the worker decides to enter entrepreneurship, then human capital in entrepreneurship evolves as $q' = (1 - \delta_q)q + \xi\tilde{h}$. ξ here determines the degree of transferability of human capital in wage employment into entrepreneurship. Furthermore, the workers pay an additional switching cost ψ in units of utils. However, if the individual decides to continue in wage employment, then human capital in entrepreneurship evolves as $q' = (1 - \delta_q)q$. $0 \leq \delta_q \leq 1$ determines the degree to which human capital in entrepreneurship exogenously decays when the individual is not currently running a business.

Finally, the worker also decides how much savings b' to bring in to the next period. Like with the standard incomplete markets literature, we assume a non-negativity constraint $b' \geq 0$.

5.2 Entrepreneurs

Similarly to workers, at the beginning of the period, an entrepreneur has human capital in wage employment and entrepreneurship h and q. Prior to the period starting, the individual receives an i.i.d. shock to their human capital in entrepreneurship, given by $\tilde{q} = qz$. This shock represents unforeseen business productivity shock—similar to the extant literature on entrepreneurship or firm investment dynamics (e.g., Midrigan and Xu, 2014; Tan, 2022; Catherine, 2022)—and generates persistence in productivity shocks.

Revenue to running the business is given by a standard Cobb-Douglas function, $y = \tilde{q}^{\zeta}\left(k^{\alpha}l^{1-\alpha}\right)^{\nu}$, where k and l represent capital rented and labor hired. We assume that capital depreciates at rate δ_k. Under assumptions of perfectly competitive input markets, the user cost of capital is thus $r+\delta_k$, while the cost of labor is w. We further assume that entrepreneurs face a collateral constraint of the form

$$k \leq (1 + \phi)\, b, \tag{5.5}$$

with $\phi \geq 0$ limiting the optimal scale of investment. When $\phi = 0$, individuals need to fully self-finance the business through their own savings; when $\phi \to \infty$, there are no limits to borrowing. In addition to the earnings in entrepreneurship, we also assume entrepreneurs enjoy a non-pecuniary benefit of running their own business, which we denote by ψ. This benefit is invariant over time.

The entrepreneur then decides if they want to continue in entrepreneurship or return to wage employment. At this stage, if they continue in entrepreneurship, human capital in entrepreneurship evolves as

$$q' = \tilde{q} + a_q \left(\tilde{q} f(j)\right)^{\theta_q}, \tag{5.6}$$

This evolution captures the idea of learning-by-doing for entrepreneurs (similar to learning-by-doing in wage employment), and that entrepreneurs with different ability grow their firms at different rates. Like with workers, we restrict $0 \leq \theta_q \leq 1$, so that there is decreasing returns to learning. Furthermore, similar to our assumption for workers, we assume that business productivity shocks follow

$$\log z' \sim N\left(\mu_z, \sigma_z\right), \tag{5.7}$$

where we restrict μ_z to $\mu_z + \frac{1}{2}\sigma_z^2 < 0$. This implies that, on average, human capital in entrepreneurship (and thus measured business productivity) decays at a rate $1 - \exp\left(\mu_z + \frac{1}{2}\sigma_z^2\right)$. This, along with decreasing returns to human capital accumulation, also implies a hump-shaped profile to business productivity and income, thus reflecting our empirical findings.

In contrast, human capital in wage employment evolves as

$$h' = (1 - \delta_h)h, \tag{5.8}$$

where $\delta_h \geq 0$ represents decay in human capital when the individual no longer engaged in wage employment. If the entrepreneur returns to wage employment, human capital in entrepreneurship evolves as $q' = 0$, where we simply assume that once individuals return to wage employment, they lose all human capital accumulated in entrepreneurship.

Human capital in wage employment, for a return-entrepreneur, evolves as

$$h' = (1 - \delta_h)h + (1 - \lambda)\tilde{q}, \tag{5.9}$$

with $\lambda \leq 1$. The second term controls the specificity of human capital across occupations, where in particular, $\lambda = 1$ implies that human capital in entrepreneurship cannot be transferred back to wage employment. At this point, we note that overall specificity of human capital arises from two potential dimensions: (i) the decay in human capital δ_h, and (ii) the degree of specificity λ.

Finally, the entrepreneur also decides how much savings b' to bring in to the next period; we again assume a non-negativity constraint $b' \geq 0$.

5.3 Bellman equations

We now present the Bellman equations to formalize the individuals' decision problems. Starting with the worker's problem, and denoting the decision to enter entrepreneurship by the indicator variable $o \in \{0, 1\}$, we have

$$V_j^w(h, q, s, b) = \max_{b', o} U(c) + \beta \Big(o \left(-\psi + \int_{z'} V_{j+1}^e(h', q', z', b') dF_{z'} \right) + (1 - o) \int_{s'} V_{j+1}^w(h', q', s', b') dF_{s'} \Big) \tag{5.10}$$

s.t.

$$\tilde{h} = hs$$

$$h' = \tilde{h} + a_h \left(\tilde{h} f(j) \right)^{\theta_h}$$

$$q' = \begin{cases} (1 + \delta_q)\, q + \xi \tilde{h} & \text{if } o = 1 \\ (1 + \delta_q)\, q & \text{if } o = 0 \end{cases}$$

$$\log s' \sim N(\mu_s, \sigma_s)$$

$$\log z' \sim N(\mu_z, \sigma_z)$$

$$b' = (1 + r)b + w\tilde{h} - c \geq 0$$

For an entrepreneur, we have

$$
\begin{aligned}
V_j^e(h,q,z,b) = \max_{b',o} \psi + U(c) + \beta\Big(o\int_{z'} V_{j+1}^e(h',q',z',b')dF_{z'} \\
+ (1-o)\int_{s'} V_{j+1}^w(h',q',s',b',\xi')dF_{s'}\Big) \qquad (5.11)
\end{aligned}
$$

$$
\begin{aligned}
&\text{s.t.} \\
&\tilde{q} = qz \\
&q' = \begin{cases} \tilde{q} + a_q\left(\tilde{q}f(j)\right)^{\theta_q} & \text{if } o=1 \\ 0 & \text{if } o=0 \end{cases} \\
&h' = \begin{cases} (1-\delta_h)h & \text{if } o=1 \\ (1-\delta_h)h + (1-\lambda)\tilde{q} & \text{if } o=0 \end{cases} \\
&\log z' \sim N\left(\mu_z, \sigma_z\right) \\
&\log s' \sim N\left(\mu_s, \sigma_s\right) \\
&b' = \tilde{q}\left(k^\alpha l^{1-\alpha}\right)^\nu - (r+\delta_k)k - wl + (1+r)b - c \geq 0 \\
&k \leq (1+\phi)\,b, \quad \phi \geq 0 \qquad (5.12)
\end{aligned}
$$

These two Bellman equations fully capture the main model mechanism of wage employment vs. entrepreneurship-specific human capital, and the imperfect transferability between them.

5.3.1 Initial conditions

We assume that individuals are born endowed with a starting level of human capital specific to both wage employment $\bar{h}$ and entrepreneurship $\bar{q}$. Furthermore, they are born with a permanent ability to accumulate both types of human capital, a_h and a_q. Here, for simplicity, we restrict $a_q = a_h = a$. The initial endowment is drawn from the joint distribution

$\left(\log \bar{h}, \log \bar{q}, \log a\right) \sim N(\mu, \Sigma)$. Specifically, we assume that

$$\Sigma = \begin{pmatrix} \sigma_h^2 & \rho_{hq}\sigma_h\sigma_q & \rho_{ha}\sigma_h\sigma_a \\ \rho_{hq}\sigma_h\sigma_q & \sigma_q^2 & 0 \\ \rho_{ha}\sigma_h\sigma_a & 0 & \sigma_a^2 \end{pmatrix}. \tag{5.13}$$

In words, this restriction implies that

1. initial human capital in wage employment and entrepreneurship are correlated,
2. initial human capital and rate of human capital accumulation are correlated, and
3. all other initial variable pairs are uncorrelated.

6 Calibration

We divide our parameters into three sets for calibration. First, standard parameters determining preferences (γ and β) and production (α, ν, δ_k) are taken directly from the literature. The values are reported in the last panel of Table 6. Second, parameters that only influence the earnings process of workers are directly estimated from the data, using the subpopulation of never-entrepreneurs. Since these individuals are never affected by time in entrepreneurship, their earning process helps identify the independent evolution of worker earnings. Finally, parameters that influence the earnings processes of individuals that enter and/or return from entrepreneurship are jointly estimated using an indirect inference approach by matching model-implied moments with data moments. This section describes our calibration approach for the last two sets of parameters.

6.1 Externally estimated parameters

We group these parameters into three subsets. The first, (μ_s, σ_s), determines the evolution of wages as driven exogenous shocks. The second, $(\theta_h, \kappa_1, \kappa_2, \kappa_3, \kappa_4)$, determines the deterministic evolution of wages for some set of given initial conditions. The third,

$(\mu_h, \mu_{a_h}, \sigma_h, \sigma_{a_h}, \sigma_{ha_h})$, determines the joint distribution of initial human capital in wage employment and ability. We estimate these parameters borrowing largely from the approach of Huggett, Ventura, and Yaron (2011).

6.1.1 Shocks to human capital in wage employment

We identify the parameters of the shock process (μ_s, σ_s) using the earnings profiles of older never-entrepreneurs. Our strategy relies on the observation that, in the context of the model, earnings in later ages are predominantly driven by shocks to the human capital process. Specifically, looking to the human capital accumulation process in Equation 5.10, the age profile of wage employment-specific human capital h flattens out at later ages, and deviations are purely driven by shocks s.

Formally, our approach can be summarized as follows. Let $\hat{e}_j \equiv e_j + \epsilon_j$ denote log earnings of an individual at age j as observed in the data. e_j denotes the earnings as implied by our model, whereas ϵ_j denotes measurement error. After substituting in the law of motion of human capital, first-differences in $\hat{e}_j$ can be written as

$$\hat{e}_j - \hat{e}_{j-1} = \log\left(s_j\left(h_{j-1}s_{j-1} + a_h\left(h_{j-1}s_{j-1}f(j-1)\right)^{\theta_h}\right)\right) - \log\left(h_{j-1}s_{j-1}\right) + \log\epsilon_j - \log\epsilon_{j-1}. \tag{6.1}$$

Notice that $f(j) \to 0$ as $j \to 65$. Therefore, for older workers, the above relation reduces to

$$\hat{e}_j - \hat{e}_{j-1} \approx \log s_j + \log\epsilon_j - \log\epsilon_{j-1}, \tag{6.2}$$

Building on this logic, further define $\Delta e_{j,n} \equiv \hat{e}_{j+n} - \hat{e}_j$. This implies that $\Delta e_{j,n} \approx \sum_{i=1}^{n} s_{j+i} + \log\epsilon_{j+n} - \log\epsilon_j$. Leveraging this logic, this implies the following moment condition:

$$\text{var}(\Delta e_{j,n}) = n\sigma_s^2 + 2\sigma_\varepsilon^2, \tag{6.3}$$

that is, the growth rate of earnings is driven by shocks as opposed to human capital accumulation.

However, as the above equation clearly states, simply using σ_s to match $\mathrm{var}(\Delta e_{j,n})$ would overstate the size of the shocks. Therefore, to pin down the degree of measurement error, we further use a second moment condition

$$\mathrm{cov}(\Delta e_{j,n}, \Delta e_{j,m}) = m\sigma_s^2 + \sigma_\varepsilon^2 \quad \text{for } m < n, \tag{6.4}$$

where we see that $2\,\mathrm{cov}(\Delta e_{j,n}, \Delta e_{j,m}) - \mathrm{var}(\Delta e_{j,n}) = (2m-n)\sigma_s^2$ subtracts out the measurement error. Therefore, these two pairs of equation allows us to identify σ_s. For implementation, we calculate the sample analog of these moments as $1/N_j \sum_{i=1}^{N_j} \left(\Delta e_{j,n}^i - \overline{\Delta e_{j,n}}\right)^2$ and $1/N_j \sum_{i=1}^{N_j} \left(\Delta e_{j,n}^i - \overline{\Delta e_{j,n}}\right)\left(\Delta e_{j,m}^i - \overline{\Delta e_{j,m}}\right)$ for each j, using earnings data on never-entrepreneurs above age 55. Then we estimate the variance parameters using two-step optimal GMM.

Finally, we calibrate μ_s to match the observed earnings decline above age 55 in the data, leveraging the fact that $\mathbb{E}\left[\exp(\Delta e_{j,1})\right] \approx (1+g)\exp(\mu_s + \sigma_s^2)$, where g stands for the real earnings growth rate.[6] The first panel of Table 6 collects the parameter values.

6.1.2 Accumulation & initial conditions for human capital in wage employment

The second step is to calibrate the parameters describing the technology for wage employment-specific human capital accumulation and its initial conditions. We do so by minimizing the distance between simulated and observed human capital processes. For the former, we simulate wage employment-specific human capital for $N_{\mathrm{sim}} = 10,000$ workers for a given set of parameters $\Theta \equiv (\theta_h, \kappa_1, \kappa_2, \kappa_3, \kappa_4, \mu_h, \mu a_h, \sigma_h, \sigma_{a_h}, \sigma_{ha_h})$. For the latter, we residualize log hourly earnings by age and calendar years for never-entrepreneurs earning above the minimum wage: by definition, this residualized measure coincides with $\tilde{h}$ since we demean

[6] The real earnings growth rate g is 2.2 percent in Portuguese aggregate data. The average earnings decline at old age $\exp(\Delta e_{j,1})$ is -4.9 percent, which we calculate using OLS of log real wages on age dummies, demographic characteristics, and calendar year fixed effects.

earnings for every age group in each year. We then use the following minimum distance estimator on the (smoothed) first three moments:

$$\widehat{\Theta} = \arg\min_{\widehat{\Theta}} \left(\mathbf{m}^{\text{sim}} - \mathbf{m}^{\text{data}}\right)' \left(\mathbf{m}^{\text{sim}} - \mathbf{m}^{\text{data}}\right) \tag{6.5}$$

where

$$\mathbf{m}^{\text{p}} = \left[\text{mean}_i\left(\tilde{h}^{\text{p}}_{i,j}\right), \;\; \text{var}_i\left(\tilde{h}^{\text{p}}_{i,j}\right), \;\; \text{mean}_i\left(\tilde{h}^{\text{p}}_{i,j}\right) - \text{median}_i\left(\tilde{h}^{\text{p}}_{i,j}\right)\right]_{j=23}^{65}, \quad \text{p} \in \{\text{sim, data}\} \tag{6.6}$$

denotes the first three moments of the human capital profile over age j.[7] Figure 8 shows the fit of the model: the first two moments fit the data well while the third implies less skewness in our simulation than in the data, which is expected given our log normal shock parametrization. The second panel of Table 6 displays the values themselves.

6.2 Internally estimated parameters

The parameters governing the entrepreneurial processes cannot be directly estimated because entry and exit into entrepreneurship are selected. Therefore, these parameters are calibrated using indirect inference, where we use our model to match specific moments that inform specific parameters. Broadly speaking, there are two sets of parameters.

6.2.1 Entrepreneurial human capital shocks, accumulation & initial conditions

This set of parameters directly determines the profitability of entrepreneurship. Therefore, we calibrate the relevant model parameters by leveraging summary statistics on entrepreneurial sales. The third panel of Table 6 summarizes the statistics from the data, our corresponding model statistics, and reports the calibrated parameter values.

[7] In practice, we smooth the simulated and data moments using a flexible polynomial of age: $[1 \;\; j \;\; j^2 \;\; \log j]$.

6.2.2 Transferability parameters

The last step is to calibrate the parameters governing human capital transferability between entrepreneurship and wage employment. We choose these parameter values so that the dynamics implied by the model simulations resemble the empirical patterns presented in the first half of the paper. Specifically, we calculate the simulated wage changes after returning to wage employment, relative to before entering entrepreneurship, and compare them to our difference-in-differences and event study results. We also take into account the fraction of entrepreneurs over the life cycle. The fourth panel of Table 6 shows the calibrated values.

7 Quantitative results

We now use our calibrated model to answer our motivating question: how important is entrepreneurial human capital specificity as a determinant of entry, survival, and growth? Furthermore, how important is human capital specificity relative to financial frictions?

We approach answering this question in two ways. First, we reduce the degree of human capital specificity relative to our baseline such that the average impact of entrepreneurship on wages is 3.7 percentage points larger than our baseline. Recall that in our empirical analysis, we found that entrepreneurship leads to a 3.7 percent wage improvement on average (Table 3). Therefore, this counterfactual allows us to analyze the impact of a 3.7 percent improvement in future wages on entrepreneurial activity. From our calibration, we find that this implies a 41.5 percent reduction in λ.

Second, we contrast the impact of reduced specificity against an alternative economy where firms are never financially constrained. This contrasts our key friction relative to financial frictions, which is commonly thought to be the dominant source of entrepreneurial entry and growth.

Table 7 summarizes our analysis, where the first column reports the outcomes of interest from our baseline model for comparison, the second column reports the impact of reducing

λ, and the last column reports the impact of muting financial frictions.

7.1 Impact on wages

The top panel of Table 7 reports the impact of entrepreneurship on the wages of returning entrepreneurs. The first row reports the average impact where, as discussed earlier, we target a 3.7 percentage point increase relative to the baseline for the counterfactual where we reduce λ. We observe that these gains reflect an improvement to the average gains made by individuals who benefited from entrepreneurship (5.3 percentage points, second row), but conditional on a loss, larger losses suffered by individuals who were hurt by entry into entrepreneurship (1.9 percentage points, third row). Moreover, this suggests that reducing human capital specificity also increases the dispersion of outcomes; indeed, we find that the standard deviation of (log) human capital in entrepreneurship increases from 0.916 log points to 0.958 log points. As we will see later, this happens because reducing specificity increases the average tenure of an entrepreneur; but since entrepreneurial human capital is risky, this leads to a fanning out of entrepreneurial human capital. Appendix Figure OA.1 shows that this increase in dispersion is driven by an increase in the dispersion within age groups.

The last column reports the impact of reducing financial frictions on wages. Since our financial frictions only directly affect the optimal scale of the firm but does not change the human capital accumulation process, we do not expect a meaningful impact on wages. However, while we indeed find that financial frictions do not have a meaningful impact on average, it amplifies the dispersion in outcomes. Average gains increase by 0.1 percentage points, while average losses increase by 0.6 percentage points, relative to the baseline. This happens because reducing financial frictions increases the net present value of running a business, and thus increases the average tenure of an entrepreneur. Therefore, as with reducing human capital specificity, lowering financial frictions also lead to a larger dispersion in entrepreneurial human capital (in this case, by 0.004 log points). Appendix Figure OA.1 shows that this increase in dispersion is also driven by an increase in the dispersion within age groups.

7.2 Impact on entrepreneurial activity

The bottom panel of Table 7 reports the counterfactual impact on various measures of entrepreneurial activity and success. In the first row, we see that reducing specificity increases the fraction of individuals who are entrepreneurs, across all age groups, by 0.21 percentage points in the case of reducing human capital specificity, and 0.02 percentage points when we entirely mute financial frictions. Panel A of Figure 9 plots the fraction of individuals who are entrepreneurs for each age group, and we see that this increase is largely present across all age groups but particularly prominent for older age groups, around age 48.

The next two rows show that the increase in entrepreneurial activity is driven by both an increase in the entry rate and the average survival rate. Reducing human capital specificity increases the entry rate by 0.09 percentage points, while muting financial frictions increases the entry rate by 0.01 percentage points. These two channels also increase the average tenure by 0.54 and 0.04 years, respectively. Furthermore, Panel B of Figure 9 shows that the impact on entry peaks around the age of 41, which then translates into peak entrepreneurial rates around age 48.

Our analysis reveals two results that appear counterintuitive. First, we find that both frictions appear to primarily dampen entry into entrepreneurship by *older* entrepreneurs. This is unexpected since young potential entrants are most impacted by both frictions: low initial wealth implies financial frictions should disproportionally hurt younger entrepreneurs, while exclusion from human capital accumulation in wage employment would also affect younger individuals, given that the bulk of human capital accumulation in wage employment occurs when young. Second, the quantitative results suggest that financial frictions have a much more muted impact than human capital specificity on entrepreneurial activity. Importantly, note that the quantitative role of financial frictions in our model already represents an upper bound to the cost of financial frictions—since our baseline model has no borrowing—, and we initialize the distribution of workers with zero asset holdings. Conversely, with our analysis on human capital specificity, we discipline the analysis using our empirical findings. Given the large focus on financial frictions in entrepreneurship, as well as the multitude of governmental programs designed to spur entrepreneurship through subsidized loans, this might appear surprising.

In fact, both results are derived from the same channel. In our baseline model, the modal entrant enters entrepreneurship at the age of 44, consistent with empirical facts from Portugal, our setting, as well as earlier work using data from the United States (e.g., Azoulay, Jones, Kim, and Miranda, 2020). Crucially, these individuals enter entrepreneurship as a means to escape a stagnating wage path induced by a slowdown in human capital accumulation in wage employment. This effect is made clear by Panels C and D of Figure 9. The average entrepreneurial human capital of a 44 year old entrant is almost 80 percent lower relative to younger entrants in their 20s. Furthermore, the average human capital in wage employment of entrants is also substantially lower among entrants in their 40s. In turn, we see that the age of entry peaks around the time when human capital accumulation in paid work starts to slow down and eventually plateau (i.e., between the ages of 40 and 50). As a result, because the main reason for starting a business is to escape a declining or plateauing wage path, reductions in the barrier to entry primarily stimulate entry by older individuals.

7.3 The role of financial frictions

7.3.1 Financial frictions and optimal scale

We emphasize that our results do not imply that individuals are not financially constrained, or that financial constraints would be irrelevant. Panels A and B of Figure 10 plot, respectively, the fraction of entrants and existing entrepreneurs who are at the borrowing constraint, as a function of their age group. Unsurprisingly, we see that young entrepreneurs are most constrained, and the fraction starts declining as individuals age. As individuals accumulate more assets over time, one would expect the fraction of constrained entrepreneurs to decline. However, we see that the magnitude is still quite large, with around 40 percent of entrepreneurs being constrained at the age of 40.

In turn, as Panel C of Figure 10 shows, these financial constraints have a large impact on the monetary benefits of running a business. Across all age groups, reducing financial constraints unambiguously increases the average sales of firms. Averaging across all age groups, we find that lowering borrowing constraints increase average sales by 40.8 percent (Table 7). However, lowering financial constraints also lead to a negative selection of individuals into entrepreneurship, leading to a 6.1 percent decrease in the average human capital in entrepreneurship (last row, Table 7). This outcome is similar to the effect of lowering entry barriers by lowering human capital specificity, but the latter is quantitatively more important, lowering average human capital in entrepreneurship by 20.8 percent.

7.3.2 Financial frictions and entry

Most arguments for the evidence of financial frictions as a barrier to entry rely on standard econometric analysis showing that increases in wealth lead to increases in entry propensities; non-exhaustive examples of this voluminous literature include the seminal work by Evans and Jovanovic (1989) and Hurst and Lusardi (2004). The basic logic is straightforward. Under the null hypothesis that an individual is not financially constrained, wealth should have no predictive power for entry, since the optimal scale of the firm—and, thus, the net present value of a business—is not tied to individual wealth. Therefore, a positive relationship between wealth and entry propensities would indicate the presence of financial constraints as a barrier to entry. More recent papers (e.g., Adelino, Schoar, and Severino, 2015) typically amount to refining the earlier work by Evans and Jovanovic (1989).

Panel D of Figure 10 plots the regression coefficient of entry on log bond holdings for each age group for all counterfactuals. Focusing on the broad patterns in the baseline model, and looking first at individuals before the age of 40, we see that entry is positively correlated with assets, mirroring the high number of constrained entrants when they are young. However, we also see that the correlation falls to zero past the age of 30, even as the fraction of constrained entrants and entrepreneurs remain high. Furthermore, past the age of 40, the correlation between wealth and entry turns *negative*, even as the number of constrained entrants starts increasing. Even more surprisingly, we also observe that this pattern is replicated almost exactly one-for-one in the counterfactual without financial frictions.

The main reason for this outcome is because the primary determinant of entry into entrepreneurship is human capital specificity, where individuals trade off the upside risk of gaining more human capital through entrepreneurship and the downside risk of losing human capital due to specificity. For younger individuals, this risk deters entry since they still have a long career ahead of them. A negative shock to their human capital due to entrepreneurship would have large a negative impact in a net present value sense. As a result, only wealthier individuals, with a lower effective risk aversion, are willing to enter entrepreneurship. However, this positive relationship does not reflect financial constraints for running a business.

Conversely, older individuals on the margin of entering entrepreneurship primarily weigh the benefits of using entrepreneurship as an escape from wage stagnation. Therefore, they value the upside risk more than the downside risk. In particular, poorer individuals value the upside risk more, since they are already stuck in a low wage state. As a result, the entry propensity becomes decreasing in wealth. Appendix Figure OA.2 illustrates this through the value of entry for a young vs. an old individual as a function of assets.

8 Conclusion

Our article presents two key contributions. First, we provide new evidence on the wage dynamics of entrepreneurs who return to wage employment relative to those who never entered entrepreneurship. A key finding we uncover is that entrepreneurs with lower pre-entry wages benefit from entrepreneurship, while those with higher wages prior to entry are hurt by entrepreneurship. We argue that the empirical evidence is consistent with the notion that human capital accumulated in entrepreneurship is partially—but, crucially, not fully—transferrable back to wage employment

Second, using our calibrated quantitative model, we uncover that the bulk of entrepreneurial activity is driven by workers using entrepreneurship as a means to escape stagnation in wage growth. As a result, financial constraints do not meaningfully impact entrepreneurial activity on the extensive margin, because the benefits of entrepreneurship to the majority of individuals accrue from the partial transferability of human capital, not from the direct monetary benefits of running the business. As such, governmental policies that emphasize a reduction in borrowing frictions might not be successful in spurring high-growth entrepreneurship, since financial constraints were not a barrier to entry to begin with. Overall, our results shows that detailed analysis regarding the degree of human capital specificity of entrepreneurship is important, as it heavily shapes the entry decision of entrepreneurs, and in turn shapes the degree to which financial constraints are a barrier to successful entrepreneurship.

We note one limitation of our analysis, namely, that our modeling of financial frictions only restrict firms from achieving their optimal scale. Recent work has shown that financial frictions could also impede the ability of firms to accumulate intangible capital (e.g, reduced R&D spending as in Ottonello and Winberry, 2024). Because intangible capital can impact the growth trajectory of the firm, it could have a much larger impact on the monetary value of entrepreneurship. In turn, this would lead to a larger role for financial frictions on the extensive margin. As these analysis are beyond the scope of our article, we leave these questions open for future research.

9 Figures and tables

9.1 Tables

Table 1: Summary statistics

	All	Return-entrep.	Never-entrep.
Num. observations			
Workers	5,604,455	47,623	5,556,832
Firms	709,462	48,172	661,290
Occupations	39	39	39
Sectors	30	30	30
Locations	8	8	8
Statistics (means)			
Male (percent)	53.4	59.7	53.4
Age (years)	40.1	41.3	40.1
Education			
Less than high school (percent)	59.2	30.8	59.4
High school (percent)	24.1	24.7	24.1
College (percent)	16.6	44.5	16.5
Monthly wage (EUR)	764	997	763
Entrep. experience (years)	3.1	3.1	–

Notes: Return-entrepreneurs are paid workers with an observed entrepreneurial history. Never-entrepreneurs are paid workers who are not observed to have started a business in sample. The firm count for return-entrepreneurs shows the number of firms that employ at least one return-entrepreneur. Occupations and sectors are measured on the 2-digit level. Locations are NUTS II statistical regions. Educational groups are based on 1-digit educational categories (less than high school: did not finish 12th grade; high school: finished 12th grade but did not earn a bachelor's degree; college: earned a bachelor's degree and may have acquired higher levels of education). Monthly wages for return-entrepreneurs are measured after returning to wage employment. *Source:* QP–SCIE, authors' calculations.

Table 2: Properties of pre-period wage gap

Dependent variable:	$\log w_{it}$	$\log w_{it}$	$\log \frac{w_{it}}{w_{i,t-1}}$
	(1)	(2)	(3)
ρ	0.78	0.343	
$\sigma(\epsilon)$	0.287	0.232	
$\sigma(\bar{w})$		0.258	
η			0.123

Notes: Columns 1 and 2 report the results of an AR(1) regression with and without firm fixed effects, respectively. ρ refers to the estimated auto-correlation parameter, $\sigma(\epsilon)$ the standard deviation of the residuals, and $\sigma(\bar{w})$ the standard deviation of the fixed effects. Column 3 reports the results of a regression of the growth rate of wages (in log differences) on the estimated $\bar{w}$. η refers to the estimated parameter. *Source:* QP–SCIE, authors' calculations.

Table 3: Main results

Dependent variable:	$\log w_{it}^{\text{gap}}$	$\log w_{it}^{\text{gap}}$	$\log \frac{w_{it}^{\text{gap}}}{w_{i,t-1}^{\text{gap}}}$	$\log w_{it}^{\text{gap}}$	$\log w_{it}^{\text{gap}}$	$\log w_{it}^{\text{gap}}$
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Pooled	Pooled	Pooled	"Low"	"High"
$\mathbb{1}$(Post)	0.037***	0.020***	-0.019***	0.065***	0.18***	-0.074***
	(0.0033)	(0.0030)	(0.0025)	(0.0058)	(0.014)	(0.014)
$\mathbb{1}$(Post) $\times$ $\bar{w}$		-0.32***	-0.19***			
		(0.013)	(0.011)			
$\mathbb{1}$(Post) $\times$ age of entry				-0.0029***	-0.0048***	0.0053***
				(0.00057)	(0.0012)	(0.0012)
Observations	91022	76520	57780	91022	14454	16512

Notes: Column 1 reports the estimate per Equation 3.10. Column 2 reports the estimate per Equation 4.1. Column 3 reports the results using the growth in wage gap as a dependent variable. Column 4 reports the estimate per Equation 4.3. Columns 5 and 6 report results split by "low" and "high" type entrepreneurs, respectively. *Source:* QP–SCIE, authors' calculations.

Table 4: Firm performance results

Dependent variable:	$\log w_{it}^{\text{gap}}$			
	(1)	(2)	(3)	(4)
	Pooled	"Low"	"High"	Pooled
$\mathbb{1}$(Post)	-0.15***	-0.029*	-0.45***	0.041***
	(0.0079)	(0.016)	(0.023)	(0.0045)
$\mathbb{1}$(Post) $\times$ sales	0.032***	0.039***	0.058***	
	(0.0014)	(0.0035)	(0.0034)	
$\mathbb{1}$(Post) $\times$ tenure				-0.0077***
				(0.0014)
Observations	70257	13986	14056	76520

Notes: Columns 1 reports results using the full sample. Columns 2 and 3 report results using the split "low" and "high" sample, respectively. Column 4 reports the results using *tenure* as the interaction variable. *Source:* QP–SCIE, authors' calculations.

Table 5: Robustness to synthetic DiD

Dependent variable:	$\log w_{it}$		
	(1)	(2)	(3)
	Pooled	"Low"	"High"
$\mathbb{1}$(Post)	0.067	0.249	-0.078
	(–)	(–)	(–)
Observations	30362	30362	30362

Notes: Synthetic DiD estimates per Equation 4.4. Due to computational limitations, the regressions are estimated on a 1 percent sample of entrepreneur and never-entrepreneur wage histories. Columns 2 and 3 report results split by "low" and "high" type entrepreneurs, respectively. Statistical inference based on clustered bootstrap standard errors in progress. *Source:* QP–SCIE, authors' calculations.

Table 6: Calibrated parameters

a: Shocks to wage employment-specific human capital

Parameter	Value
μ_s	-0.077
σ_s	0.102
σ_ε	0.237

b: Accumulation & initial conditions for human capital in wage employment

Parameter	Value
θ_h	0.719
$(\kappa_1, \kappa_2, \kappa_3, \kappa_4)$	[1.604, 0.006, 8.128, 30]
μ_{ha_h}	[−0.238, 1.090]
Σ_{ha_h}	$\begin{bmatrix} 0.266 & 0.062 \\ 0.062 & 0.018 \end{bmatrix}$

c: Shocks, accumulation & initial conditions for entrepreneurial human capital

Parameter	Target	Data	Model
μ_q	Fraction of entrepreneurs	0.45%	0.40%
ψ	Fraction of serial entrepreneurs	1.2%	0%
σ_q	St.d. of average sales	2.19	4.34
ρ_{hq}	Elas. of average sales to mean earnings in wage emp.	3.3%	2.7%
θ_q	AR(1) of sales	0.70	0.64
μ_s	Average sales growth from entry to exit	0.104	0.458
σ_s	St.d. of sales growth	0.676	0.283

d: Human capital transferability parameters

Parameter	Description	Value
λ	HC transferability from entrepreneurship to wage employment	0.980
ξ	HC transferability from wage employment to entrepreneurship	0
δ_h	Depreciation rate of wage emp. HC in entrep.	0.117

e: Externally set parameters

Parameter	Description	Value
α	Capital share	1/3
ν	Returns to scale in production	3/4
δ_k	Capital depreciation rate	0.067
γ	Risk aversion	2
β	Discount factor	0.96
ϕ	Collateral constraint	0.

Notes: Calibrated parameter values. On the third panel, sales are measured as log turnover. The second column describes the summary statistic used to calibrate each model parameter in the raw data. See text for details. *Source:* QP–SCIE, authors' calculations.

Table 7: Impact on wages and outcomes

	Baseline	Reducing specificity	Reducing FF
		Impact on wages	
Average (%)	4.9	8.4	4.7
Average gains (%)	10.8	16.1	10.9
Average losses (%)	11.0	12.9	11.6
		Impact on entrepreneurship	
% entrep.	0.40	0.61	0.42
Entry rate (%)	0.29	0.38	0.30
Average tenure (years)	1.65	2.19	1.69
St.d. tenure (years)	1.37	1.75	1.43
Avg. sales (% rel. to baseline)	–	-0.27	40.8
HC (h) of entrants (% rel.)	–	1.7	-3.1
HC (q) of entrants (% rel.)	–	-20.8	-6.0

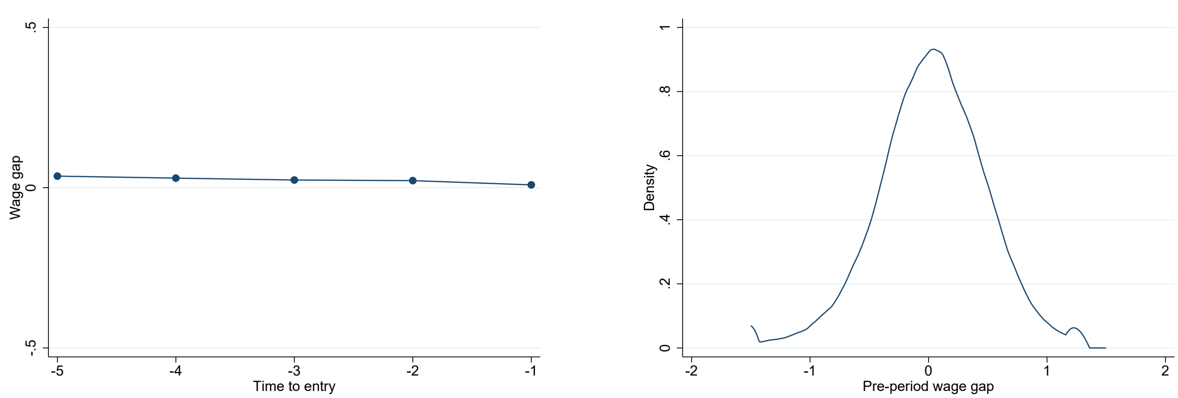
Notes: Moments corresponding to three model estimates: baseline, counterfactual with increased human capital transferability λ, and counterfactual with reduced financial frictions (looser collateral constraint ϕ). Top row shows the aggregate fraction of entrepreneurs across ages. High/low productivity refers to individuals with earnings above/below median in the pre-period. *Source:* QP–SCIE, authors' calculations.

9.2 Figures

Figure 1: Match quality and distribution of pre-period wage gaps

a: Average wage gap in pre-period

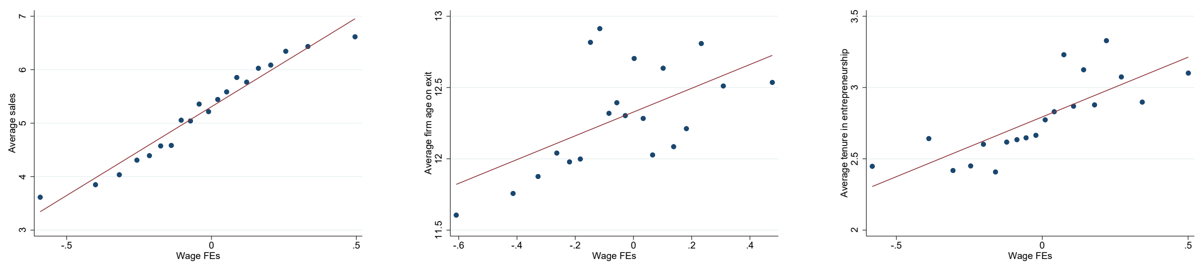
b: Distribution of wage gap in pre-period



Notes: Panel a plots the average wage gap in the years prior to entry into entrepreneurship. The vertical axis spans one standard deviation of the wage gap. Panel b plots the distribution of the wage gap in the pre-period. *Source:* QP–SCIE, authors' calculations.

Figure 2: Labor productivity and firm performance

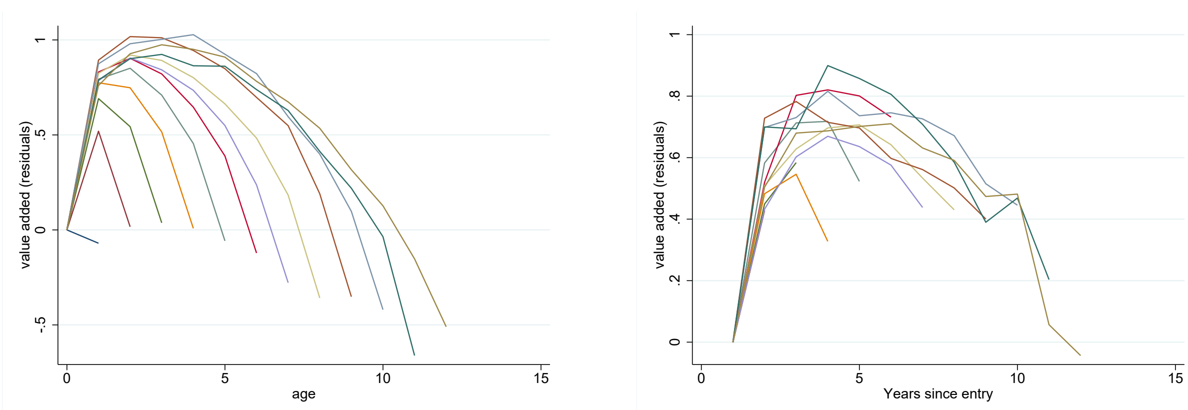
a: Average sales **b:** Average firm age on exit **c:** Average tenure



Notes: Panel a plots the average sales of the firm during the tenure of the entrepreneur as a function of $\bar{w}$. Panel b plots the average age of the firm on exit as a function of $\bar{w}$. Panel c plots the average tenure of an entrepreneur as a function of $\bar{w}$. *Source:* QP–SCIE, authors' calculations.

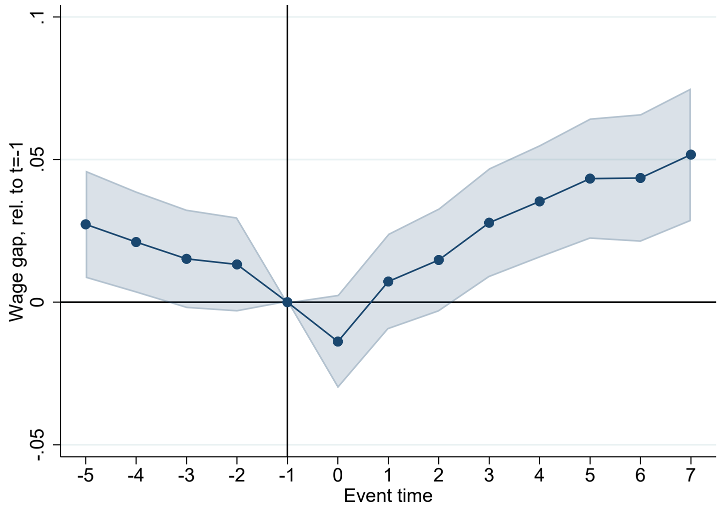
Figure 3: Dynamics of firm performance prior to exit

a: Over life cycle of firm **b:** Over tenure of entrepreneur



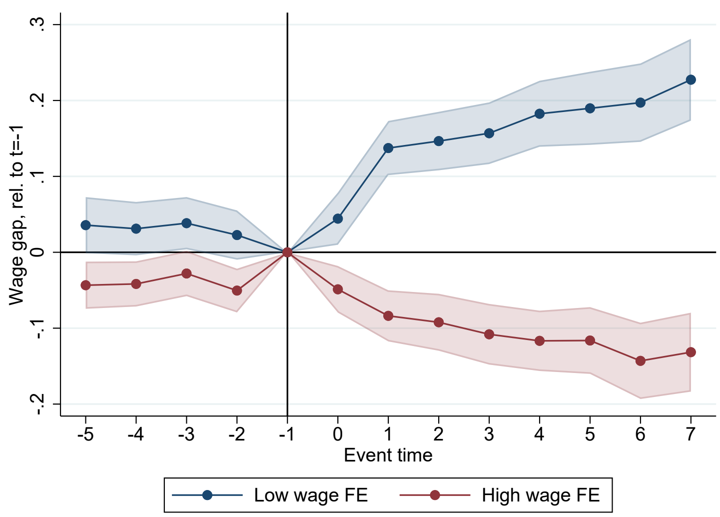
Notes: Panel a: *age* denotes firm age prior to exit. Panel b: *tenure* denotes number of years of tenure prior to exit. The last data point on each line is the age / years of tenure at exit. Both panels plot average firm sales relative to the first year. *Source:* QP–SCIE, authors' calculations.

Figure 4: Wage gap event study



Notes: Event time in years on horizontal axis: $t = -1$ refers to last period before entrepreneurship, $t = 0$ to first period afterwards. The values are normalized to the average wage gap at $t = -1$. Shaded areas represent 95 percent confidence bounds. *Source:* QP–SCIE, authors' calculations.

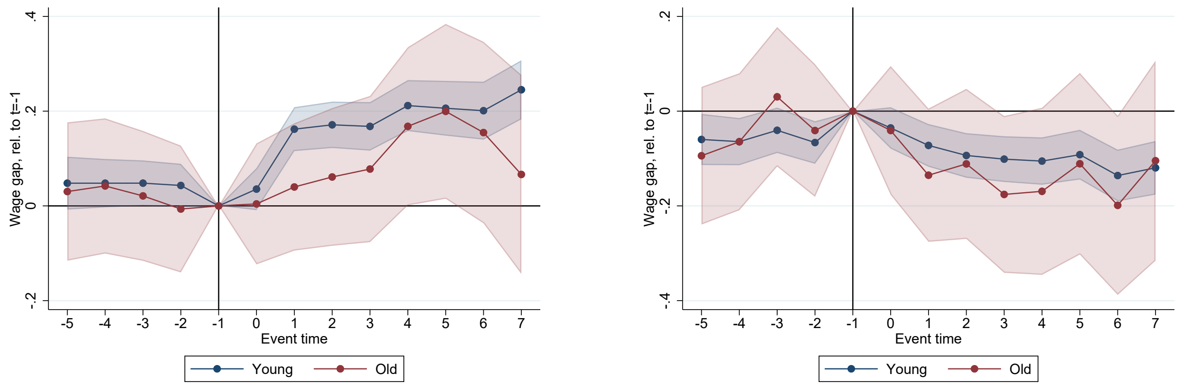
Figure 5: Wage gap event study by pre-entrepreneurship wage trajectory



Notes: Event time in years on horizontal axis: $t = -1$ refers to last period before entrepreneurship, $t = 0$ to first period afterwards. The values are normalized to the average wage gap at $t = -1$. The figure plots the wage gap split by low and high wage FE entrepreneurs. "Low" refers to entrepreneurs in the first quintile of $\bar{w}$. "High" refers to entrepreneurs in the fifth quintile of $\bar{w}$. Shaded areas represent 95 percent confidence bounds. *Source:* QP–SCIE, authors' calculations.

Figure 6: Wage gap event study by age

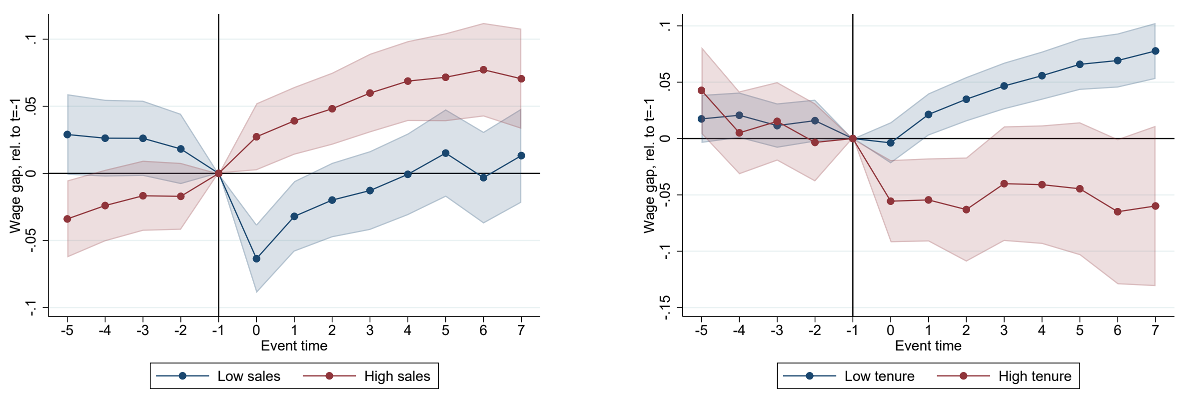
a: Low wage FE **b:** High wage FE



Notes: Event time in years on horizontal axis: $t = -1$ refers to last period before entrepreneurship, $t = 0$ to first period afterwards. The values are normalized to the average wage gap at $t = -1$. The figure plots the wage gap split by age across low and high wage FE entrepreneurs. "Young" refers to entrepreneurs starting a business at 35 or less, "old" to starting a business after 45. "Low" refers to entrepreneurs in the first quintile of $\bar{w}$, "high" to entrepreneurs in the fifth quintile of $\bar{w}$. Shaded areas represent 95 percent confidence bounds. *Source:* QP–SCIE, authors' calculations.

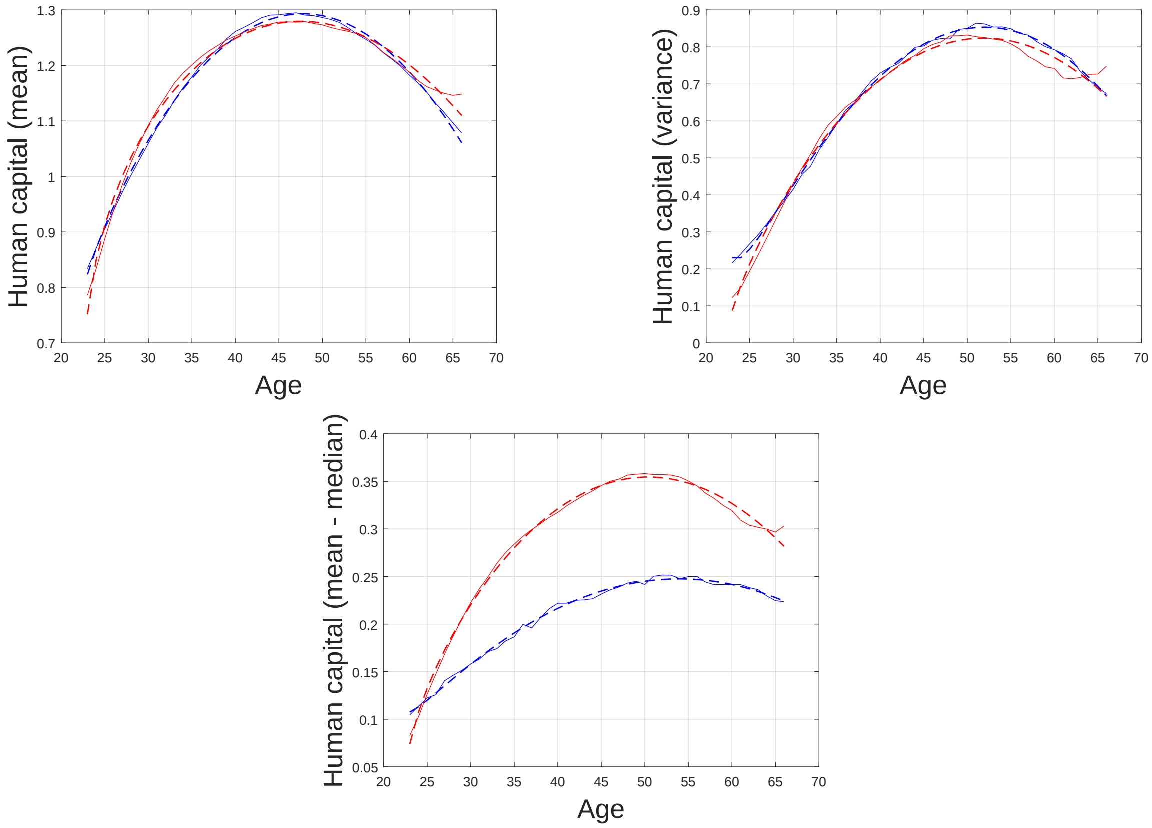
Figure 7: Wage gap event study by firm performance

a: Sales **b:** Tenure



Notes: Event time in years on horizontal axis: $t = -1$ refers to last period before entrepreneurship, $t = 0$ to first period afterwards. The values are normalized to the average wage gap at $t = -1$. The figure plots the wage gap split by low and high sales and tenure in entrepreneurship. Low (high) sales refer to below (above) the median. Low (high) tenure refers to less than (above) 5 years of running a business. Shaded areas represent 95 percent confidence bounds. *Source:* QP–SCIE, authors' calculations.

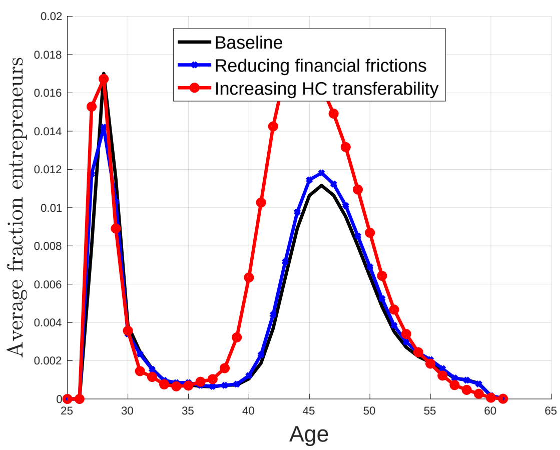
Figure 8: SMM model fit, second calibration step



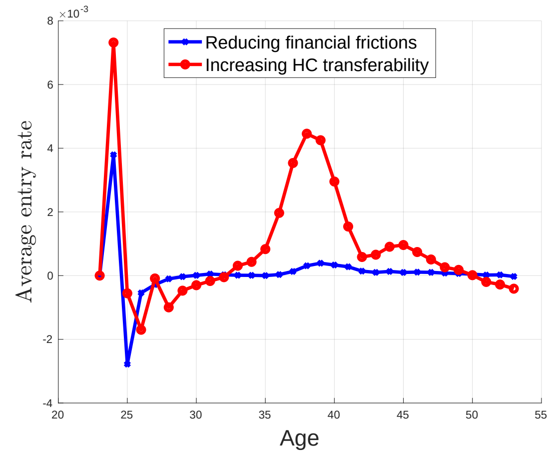
Notes: Blue lines correspond to simulated profiles of first three moments of human capital from the baseline model. Red lines correspond to observed profiles of first three moments of human capital from the data. Solid lines show the raw moments, dashed lines show a fitted polynomial. See the text for details. *Source:* QP–SCIE, authors' calculations.

Figure 9: Entrepreneurial activity over the life cycle

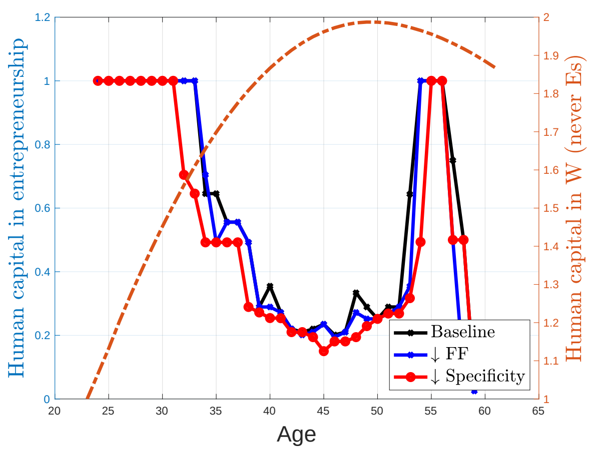
a: Fraction of entrepreneurs



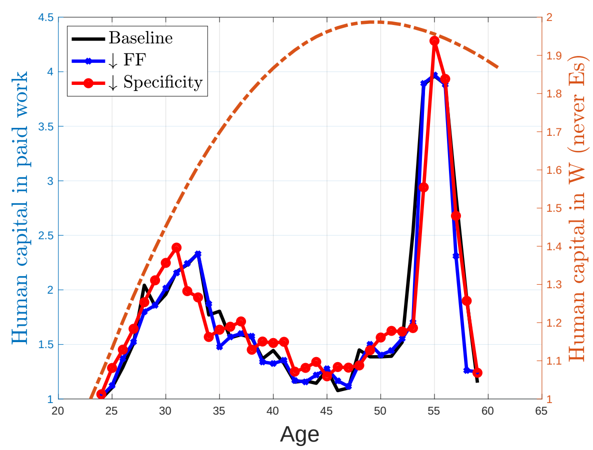
b: Entry rate



c: Entrant human capital in entrepreneurship

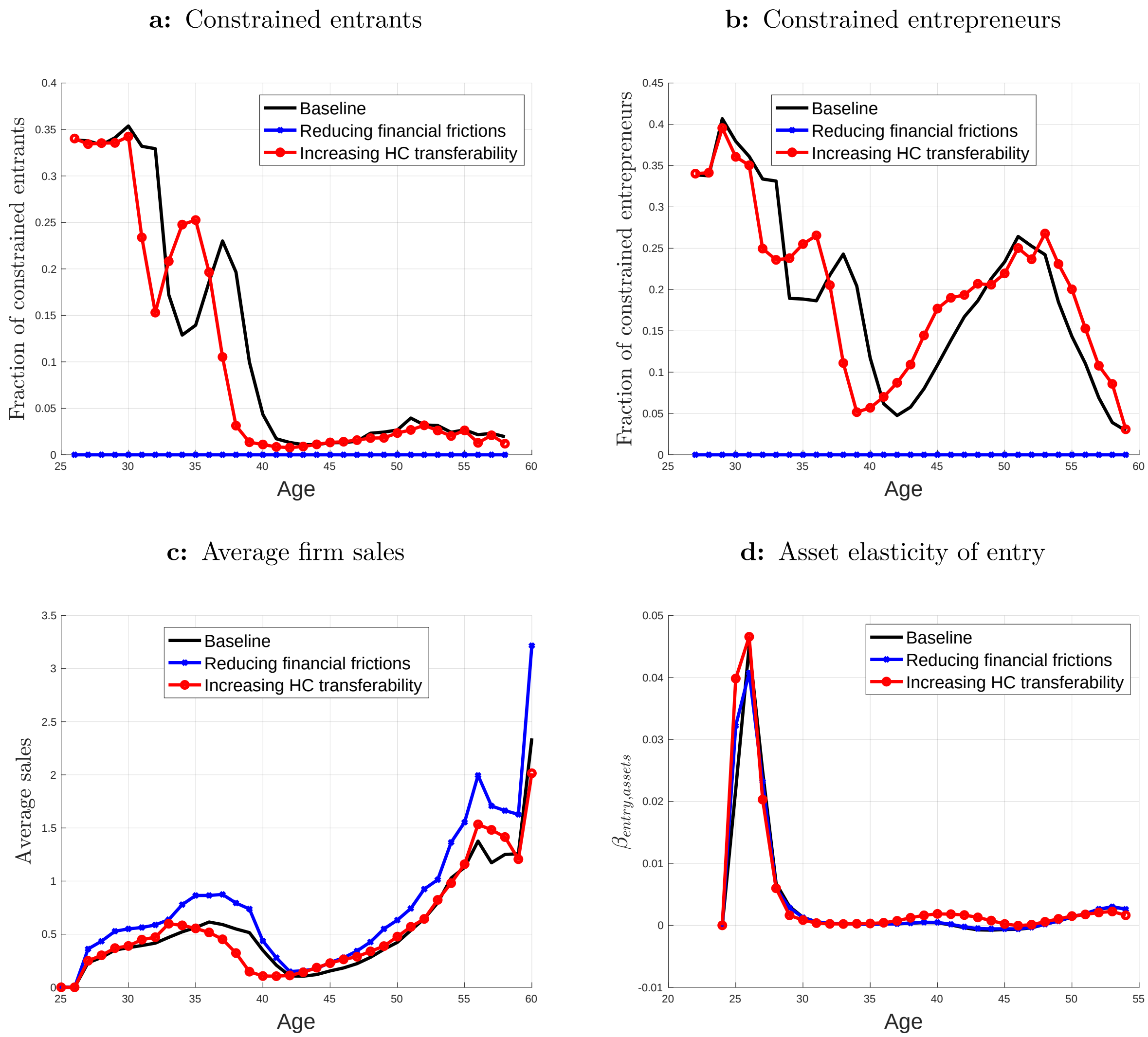


d: Entrant human capital in wage employment



Notes: Panel A plots the percentage of the labor force that are entrepreneurs, by age group. Panel B plots the entry rate into entrepreneurship by age group. The entry rate is reported relative to the baseline. Panel C plots the average entrepreneurial human capital of entrants, by age of entry. Panel D plots the average human capital in wage employment of entrants, by age of entry. For both Panels C and D, values are plotted relative to the human capital of entrants in the baseline in age 24. Brown dot-dashed line in Panels C and D refer to the average human capital in wage employment of never entrepreneurs, and replicates Panel A of Figure 8. Black lines correspond to estimates from the baseline model. Blue lines correspond to estimates from a counterfactual model with reduced financial frictions ($\phi = \infty$). Red lines correspond to estimates from a counterfactual model with reduced human capital specificity ($\downarrow \lambda$). *Source:* QP–SCIE, authors' calculations.

Figure 10: The role of financial constraints



Notes: Black lines correspond to estimates from the baseline model. Blue lines correspond to estimates from a counterfactual model with reduced financial frictions (looser collateral constraint ϕ). Red lines corresponds to estimates from a counterfactual model with increased human capital transferability λ. *Source:* QP–SCIE, authors' calculations.

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Online Appendix

A Predictions from stylized framework

Our stylized framework in Section 2 implies a number of testable predictions. The main text offers an intuitive reasoning based on a graphical representation of generic human capital accumulation processes, given by Equations 2.1 and 2.2. Here we formally derive these predictions under a set of parametric assumptions for the human capital processes.

Consider the following parametrization for accumulating wage employment-specific human capital, given by Equation 2.1:

$$h_i' = \left(1 + a_{h_i}^{j_i}\right) h_i. \tag{OA.1}$$

Similarly, assume that the accumulation of entrepreneurial human capital is given by

$$q_i' = \left(1 + a_{q_i}^{j_i}\right) q_i. \tag{OA.2}$$

Finally, as in the main text, assume that (i) while running a business, unused wage employment-specific human capital erodes at the rate δ_h, and (ii) only a fraction $(1-\lambda)$ of entrepreneurial human capital can be transferred back to wage employment upon return.

Now consider an individual who at age j decides to start a business, runs it for t years, then returns to wage employment. Assume that their wage employment-specific human capital is $\bar{h}$ when they enter entrepreneurship, and their starting entrepreneneurial human capital is $\bar{q}$. During their tenure in entrepreneurship, they accumulate $\prod_{s=1}^{t}\left(1 + a_q^{j+s}\right)\bar{q}$ amount of entrepreneurial human capital, while their unused wage employment-specific human capital stock erodes to $(1-\delta_h)^t\bar{h}$. Therefore, upon return their wage employment-specific human capital is $(1-\delta_h)^t\bar{h} + (1-\lambda)\prod_{s=1}^{t}\left(1 + a_q^{j+s}\right)\bar{q}$. Had this individual not started a business, their human capital would have kept accumulating to $\prod_{s=1}^{t}\left(1 + a_h^{j+s}\right)\bar{h}$.

These parametrizations yield the following predictions:

1. Individuals with a flatter earnings profile before entering entrepreneurship experience earnings gains after return. That is, there is a threshold human capital accumulation term $\underline{a}_h$ so that $(1-\delta_h)^t\bar{h} + (1-\lambda)\prod_{s=1}^{t}\left(1+a_q^{j+s}\right)\bar{q} > \prod_{s=1}^{t}\left(1+\underline{a}_h^{j+s}\right)\bar{h}$.

2. Conversely, individuals with a steeper earnings profile before entering entrepreneurship experience earnings losses after return. That is, there is a threshold human capital accumulation term $\bar{a}_h$ so that $(1-\delta_h)^t\bar{h} + (1-\lambda)\prod_{s=1}^{t}\left(1+a_q^{j+s}\right)\bar{q} < \prod_{s=1}^{t}\left(1+\bar{a}_h^{j+s}\right)\bar{h}$.

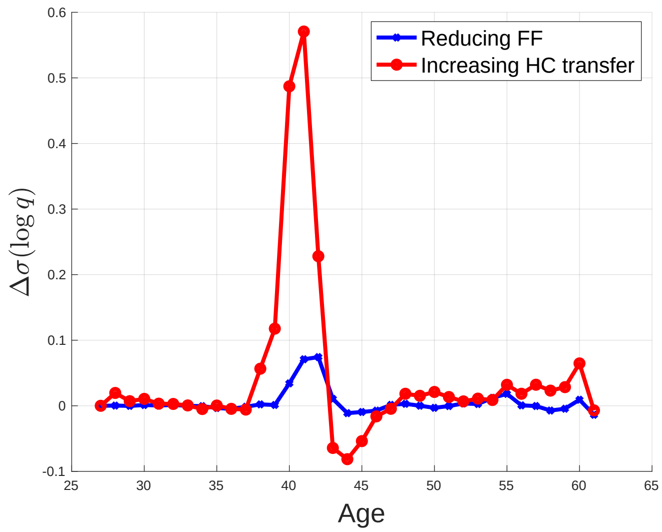
3. For individuals with a flatter earnings profile before entrepreneurship, the earnings gain is decreasing in the age of entry. That is, $\prod_{s=1}^{t}\left(1+\underline{a}_h^{j+s}\right)\bar{h} < \prod_{s=1}^{t}\left(1+\underline{a}_h^{j'+s}\right)\bar{h}$ for $j < j'$.

4. For individuals with a steeper earnings profile before entrepreneurship, the earnings loss is decreasing in the age of entry. That is, $\prod_{s=1}^{t}\left(1+\bar{a}_h^{j+s}\right)\bar{h} < \prod_{s=1}^{t}\left(1+\bar{a}_h^{j'+s}\right)\bar{h}$ for $j < j'$.

5. The overall impact of entrepreneurship on the return option to wage employment is ambiguous.

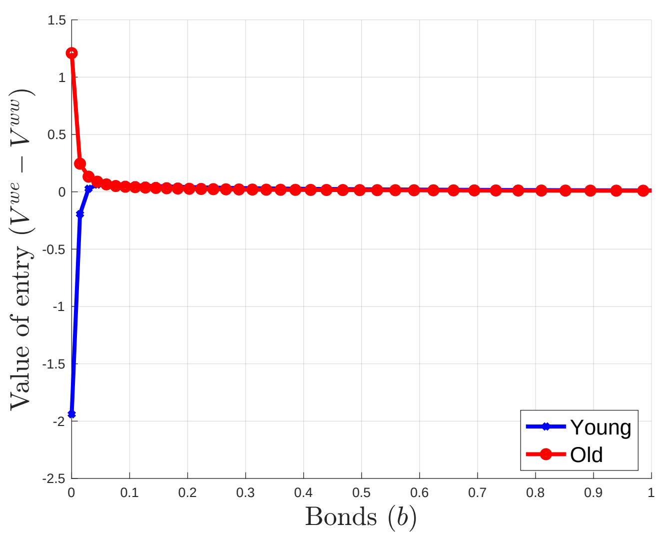
B Additional figures

Appendix Figure OA.1: Dispersion of $\log q$, by age



Notes: This figure plots the standard deviation of human capital in entrepreneurship ($\log q$) for each age group of entrepreneurs. The values are plotted as the difference relative to the baseline (0 = no change). Blue line corresponds to estimates from a counterfactual model with reduced financial frictions (looser collateral constraint ϕ). Red line corresponds to estimates from a counterfactual model with increased human capital transferability λ. *Source:* QP–SCIE, authors' calculations.

Appendix Figure OA.2: Value of entry



Notes: This figure plots the value of entry into entrepreneurship for a young (blue) vs. an old (red) individual in wage employment, as a function of assets b. *Source:* QP–SCIE, authors' calculations.