Entrepreneurship Over The Life-Cycle: The Role of Human versus Financial Capital Accumulation *

-Preliminary Version-

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Abstract

In this paper we use administrative data on the population of Danish entrepreneurs to provide new facts on the taxonomy of entrepreneurship over the life-cycle. We document that entrepreneurs are on average 38 when opening their first firm and that ex-post successful entrepreneurs are even older at business start. We ask whether these life-cycle patterns are mainly explained by the need of accumulating financial assets or entrepreneurial human capital. We provide reduced form evidence that the entrepreneur's human capital at entry is an important predictor for firm survival and success, much more than his wealth at business foundation. Motivated by these empirical facts we develop an occupational choice model in which agents can accumulate entrepreneurial human capital before becoming entrepreneurs. We bring the model to the data and use it to further disentangle the role of human versus financial capital for business formation as well as for the age composition of new entrepreneurs. Finally, we implement the 2014 Danish policy reform in our framework, which lowered the initial capital requirements for incorporated firms. We show that our model comes much closer in matching the response in new business creation observed in the data, compared to traditional models without human capital.

JEL codes: E21, L26, J24

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1 Introduction

Understanding the determinants of entrepreneurial activity is fundamental to explain the evolution of top income and wealth inequality as well as for the design of several business-oriented policy interventions. Entrepreneurs represent a large fraction of individuals in both the upper tail of the income and wealth distribution. According to Boar and Midrigan (2019), who use data from the 2013 wave of the Survey of Consumer Finances (SCF), 38% of households in the top 1% share of the income distribution can be classified as entrepreneurs. This fraction increases to 48% when considering the wealth distribution.

Anecdotical evidence would suggest that entrepreneurs, especially successful ones, are young individuals with great business ideas who open a start-up early in life. While this might be true for some founders, it does not reflect the average entrepreneur. As Azoulay et al. (2020) document, the average age at founding of 2.7 million business owners in the US over the period 2007-2014 is 41.9. When considering only high-growth sectors, the average age at founding is 45 years.

There are two economically relevant reasons why the majority of business owners start a firm late in life. On one side, as often pointed out, if financial markets work imperfectly and individuals face borrowing constraints, aspiring entrepreneurs need time to accumulate enough financial wealth to overcome collateral constraints and operate their firm at a profitable scale. On the other side, an emerging branch of the literature shows how entrepreneurial human capital, defined as all those inalienable factors embodied in the business owner (organizational skills, social contacts, management abilities etc.), is crucial in explaining business success.[1] Little is known about the accumulation process of entrepreneurial human capital and how this affects business entry. In this paper we ask the following question. How important is human capital, as opposed to financial capital, in determining business creation over an individual's life-cycle?

To answer this question we proceed along two lines. On the empirical side, we have access to a rich and detailed panel data set on the universe of Danish firms created between 2000 and 2019. By identifying the ultimate owners of these firms we are able to match firm level data with individual level information on business owners' characteristics. We observe individuals both before and after their transition into entrepreneurship, which enables us to provide new facts on entry into entrepreneurship over the life-cycle. We document the existence of a positive relationship between the accumulated stock of entrepreneurial human capital at business start

[1] For example, Smith et al. (2019) use US tax data to show that on average around three quarters of pass-through business profits represent returns to owners human capital, rather than compensation for holding productive financial wealth.

and future business outcomes. The average age at founding of first-time entrepreneurs is 37.8 years in our dataset, reaching 39 years for ex-post successful entrepreneurs. We also find that the age distribution at business entry is shifted to the right in skill intensive sectors, where human capital is by far more important than other factors of production in determining business success.

We show that the life-cycle patterns of entry into entrepreneurship remain unchanged after controlling for family wealth at business start, a proxy for how borrowing constrained an individual is.

Next, we investigate the relationship between business performance and entrepreneurial human capital further, using different regression specifications. We find that human capital, as proxied by the entrepreneur's position in the wage distribution the year prior to opening the firm, is a stronger predictor of future firm outcomes compared to the entrepreneur's position in the wealth distribution. Specifically, we find that being in the top decile of the human capital distribution compared to the bottom decile i) decreases the likelihood of exiting within the first 5 years by 7%, while wealth does so by only around 2% ii) increases the probability of hiring somebody within the first 5 years from business registration by 20%, while wealth only by 1.8% iii) conditional on survival, is associated with 13% higher firm productivity, compared to a 5% effect of wealth.

Our second contribution is to develop a novel structural framework that allows us to study the main mechanisms of entrepreneurial activity over the life-cycle and their implications for macroeconomic aggregates. From the large literature on human capital accumulation in paid employed jobs we borrow the idea that entrepreneurial skills are the result of career choices made during different stages of life.[2] We nest an endogenous human capital accumulation channel in an occupational choice model in the tradition of Cagetti and De Nardi (2006) and Buera (2009). Our model of entrepreneurship features a realistic life-cycle structure and allows agents to accumulate entrepreneurial human capital using a learning-by-doing (LBD) technology. Individuals are endowed with different innate abilities as paid employed workers and entrepreneurs, which follow an exogenous stochastic process. In each period they make an occupational choice between being a worker or an entrepreneur. In both occupations individuals accumulate entrepreneurial skills, although with different learning-by-doing technologies. The stock of accumulated human capital directly affects the productivity of the business, in turn impacting the profits of the firm and the optimal firm size. Entrepreneurs face collateral con-

[2] See, for example, Huggett et al. (2011) and Blandin and Peterman (2019a)

straints, in the sense that they can only borrow up to a fraction of their wealth. These model ingredients generate a non-trivial sorting of individuals across occupations depending on their asset holdings, exogenous abilities and accumulated stock of human capital.

We bring the model to the data and use it to further disentangle and quantify the role of financial versus human capital accumulation as a fundamental driver for business creation. We study how the share of entrepreneurs in the economy, the age composition of new entrepreneurs and the productivity distribution at business start are all affected by the presence of collateral constraints. We do so through a counterfactual analysis in which we completely eliminate financial frictions. We find that eliminating collateral constraints enables more individuals to start a firm, but that these new entrepreneurs are much less productive and have less human capital when compared to entrepreneurs of the same age class under the baseline economy. In this sense, financial frictions act as a selection mechanism on the type of individuals that start a business. Second, we evaluate how human capital accumulation interacts with financial frictions in affecting business formation. To this end, we solve a model in the tradition of Cagetti and De Nardi (2006) with no human capital accumulation and calibrate it to match the same aggregate moments of our model economy. We then evaluate the differential response across our baseline framework and the traditional model in business formation and age composition of new entrepreneurs when the collateral constraint is loosened. We compare the responses from the two model economies with the data. We exploit the 2014 Danish policy reform on incorporated businesses, which lowered the initial capital requirements for incorporated firms and introduced a new legal type of incorporated firm which could be started for free. We show that i) the reform successfully increased the number of new business registrations but only modestly spurred entrepreneurship ii) a model with endogenous human capital accumulation comes close to matching the elasticity of new transitions into entrepreneurship to changes in financing conditions, while traditional models overestimate the positive effect of making access to credit easier on business formation. The remainder of the paper proceeds as follows. The next section relates our paper to other work in the literature. Section 2.1 presents and discusses the dataset in some detail as it is a newly assembled and cleaned dataset to study entrepreneurship. Section 2.2 presents some stylized facts, while section 2.3 documents our empirical findings using different regression specifications. Section 3 outlines the model economy and section 4 explains how we bring the model to the data. Section 5 performs the first counterfactual analysis, while section 6 investigates the role of endogenous human capital accumulation. The final section concludes.

1.1 Related Literature

Our paper relates to several strands of literature. It builds on the work studying the effects of entrepreneurship on macroeconomic aggregates started with the seminal paper by Quadrini (2000). Subsequently, Cagetti and De Nardi (2006) and Buera (2009) have developed a theoretical framework to study the interaction of entrepreneurial decisions and borrowing constraints, the former with a focus on its consequence for wealth inequality. More recently, Bruggemann (2021) analyzes an optimal labor income tax problem with entrepreneurs that supply labor endogenously. The paper most close in spirit to ours is Bhandari and McGrattan (2020). The authors build on the occupational choice model of Cagetti and De Nardi (2006) to highlight the importance of accounting for sweat equity when designing business and corporate taxes. The concept of sweat equity and entrepreneurial human capital share some similarities but differ in two major respects. In Bhandari and McGrattan (2020) entrepreneurs can invest time in creating sweat equity which increases the firm's productivity. Typical activities that would rise sweat equity are marketing and networking activities that build customer bases and client lists. In this sense the notion of sweat equity is closer to the concept of intangible capital and is firm specific, rather than individual specific as human capital. Second, the authors do not investigate the role of sweat equity for business creation nor study how it affects transitions into entrepreneurship, which is the focus here.

Several papers have investigated how different personal traits impact entrepreneurial outcomes. For example, Queiró (2018) uses Portuguese data to study the effect of human capital, as measured by years of schooling, on firm outcomes. While his notion of human capital is restricted to formal education, we show that entrepreneurial human capital accumulated on the job is at least as important in explaining business success. Hincapié (2020) explicitly takes into account the life cycle dimension of entrepreneurship and estimates a rich structural model. He finds that information frictions, entry costs and risk aversion are the key factors holding back young entrepreneurs. We contribute to this literature using a new administrative panel data set on Danish entrepreneurs which links individual with firm-level information. Observing individual characteristics before and after the transition into entrepreneurship for a wide range of private business owners we can document new stylized facts on the entry dynamics of entrepreneurship over the life-cycle.

Finally, our paper relates to recent studies that try to investigate which economic factors explain business creation and success. For example, Sohail (2020) explores the importance that founding teams have for future business performance and show that most high performing businesses were created by teams. Karmakar et al. (2021) argue that serial entrepreneurs, en-

trepreneurs owning multiple businesses over time, are on average performing better, but that the premium in performance is already present when considering their first business. This suggests that entrepreneurial talent is likely in part innate or accumulated on the job rather than through repeated attempts of business creation and failure.
We now turn to the next section in which we describe our dataset and the empirical evidence.

2 Empirical Evidence

2.1 Overview of the data

We combine multiple administrative data sources to construct a unique dataset, that maps all firm ownership in the Danish economy between 2000-2019. This includes direct and indirect ownership of both incorporated firms (ltd. corporations)[3], and of unincorporated firms (proprietorships, partnerships), the timing of ownership relations, and the allocation of ownership shares in cases with multiple owners.

Our primary interest lies in identifying individuals that transition into entrepreneurship for the first time, their main characteristics at the time of transition, and the subsequent performance of their firms. We characterize individual entrepreneurs using detailed records of labor market histories, education, wealth, income, age, gender and we measure firm performance using annualized data on employment, revenue and value-added. The next section describes the construction of the dataset in some detail, and provides relevant definitions and summary statistics.

2.2 Data sources

The main data source is the Danish Central Business Register (CVR), that contains historical and real-time information on all firms registered in Denmark, at least since 1980. The database contains detailed firm level information, such as the timing of establishment and liquidation, administrative region, legal form and industry code (nace 08). It also contains detailed ownership records of proprietorships, partnerships and corporations, providing the timing, identity

[3]There are three types of limited corporations in Denmark, relevant to the data period: A/S, ApS and IvS, that differ mainly in terms of capital requirements. As per 2020, A/S has a capital requirement of 250.000 dkk, ApS has a capital requirement of 40.000 dkk, and IvS has a capital requirement of 1 dkk. The capital requirement of ApS was reduced from 125.000 dkk to 80.000 dkk in 2010, and then reduced further to 50.000 dkk in 2014, and 40.000 in 2020. IvS was introduced in 2014 and discontinued in 2019.

and ownership shares of all direct owners.[4] As ownership records referring to corporations are limited to the period after 2014, we combine the CVR database with data from the commercially available KOB database, published by Experian Denmark, that contains hand-collected ownership information, that completes missing ownership in the early data years of the CVR database. The KOB database also contains detailed accounting records of corporations. All firms in the resulting dataset are identified by unique CVR-numbers, and all individuals are identified by unique PNR-numbers, that can be matched directly to other data sources.

The other main data source is Statistics Denmark's research database (DST), that publishes detailed information on firms and individuals in the Danish population. The data is provided regularly by relevant Danish authorities, including the Ministry of Taxation, the Ministry of Education and the Ministry of Employment. The database contains general data on individuals, such as gender, age, education, wealth and income composition. In addition, detailed employment registers provides the identities of all current and previous employment relationships (employer-employee), with corresponding salaries, hours worked, and occupational codes (isco 08), that are used to characterize individual labor market histories, as well as firm-level employment. The DST database also provides annual records of firms' sales, derived from VAT statements, and more detailed accounting records for the subset of firms with annual turnover above 300,000 DKK. All data on firms and individuals is tied to unique CVR- and PNR-numbers, that correspond directly to those available in the CVR and KOB databases.

2.3 Measuring firm ownership and performance

The main dataset is built around individual firms, and the mapping of their ultimate owners[5]. It should be noted that partnerships and corporations may be owned by multiple individuals, as well as other firms, and are often connected though networked ownership structures, that involve multiple levels of intermediate firms. Focusing on individual firm ownership, we therefore map all direct ownership links, that depart from individual owners, and we calculate the implied ownership shares within each chain. By nature of this iterative approach, we map the ultimate owners of each firm, in each year, disregarding any inter-firm relationships in the data.

[4]Reporting requirements on firm ownership vary across legal forms and within the data period, and hence does also data availability in the sample period of interest. Due to the feature of unlimited and collective liability, the CVR reports all owners of unincorporated firms (proprietorships, partnerships), covering 99% of firms in the data, and dating back as far as 1980. In the case of incorporated firms (ltd. corporations), however, the CVR only reports direct owners that control minimum 5% equity or voting rights, and it provides the identities of founders.

[5]We calibrate direct ownership shares, so that they always sum to 100%. In the case of corporations, we combine direct ownership reported in the CVR database with hand-collected data from the KOB database. We use founder information and/or earliest/latest quoted owners to proxy for ownership in remaining missing years.

A unique feature of this approach is that it enables the identification of individual owners that enter into the data for the first time during the data period of interest, between 2001–2019, and it allows for measuring entrepreneurial activity across all firms that are owned by a single individual.

While most firms in the data are owned by a single individual throughout the life-cycle, some entrepreneurs register multiple firms, either simultaneously or sequentially, and some register firms in collaboration with other entrepreneurs, or own multiple firms within a downstream ownership chain. Focusing on individual entrepreneurs, rather than individual firms, we construct aggregated measures of entrepreneurial performance, by aggregating all firm-level data across individual owners, in proportion to their ownership shares. For example, if an entrepreneur owns 20% of firm A with 5 employees, and 50% of firm B with 10 employees, that entrepreneur accounts for 6 employees in total. We calculate such aggregate measures of employment (emp), revenue (rev) and value-added (vad)[6]. In cases where an individual owns firms in multiple industries, we consider the industry accounting for the largest share of employment (or revenue, if tied) as the main industry. Following standard practice in the entrepreneurship literature, we exclude entrepreneurs in agricultural, financial, and real estate industries, and we exclude those with unreported industry.

Between 2001-2016, approximately 500,000 individuals became business owners for the first time. We distinguish between entrepreneurial and other self-employment activities, by constructing 4 classifications of entrepreneurship. E^0 denotes the least restrictive measure of entrepreneurship, referring to any firm ownership, regardless of economic activity. It simply refers to the number of new business registrations. E^1 denotes an individual that registered a firm which generates positive revenue, E^2 denotes a business owner whose firm generates value-added equivalent to 0.5 full-time equivalent salary in the industry and E^3 denotes a business owner whose firm generates real employment equivalent to 0.5 full-time equivalent in the industry. Table 1 summarizes the number of new entrants per year, according to these measures. By looking at the number of new entrants across the different definitions it is clear that being able to properly measure entrepreneurship is crucial for providing evidence on business formation and start-up dynamics. For example, on average only around 12% of all new businesses that are registered actually ever manage to hire anybody and only around 20% of registered businesses with positive revenues hire at least one employee.

[6]Since corporations and partnerships may pay salaries to their owners, we subtract these from the overall payroll to obtain a real measure of employment, that is unbiased by the number of owners.

Table 1: Number new entrepreneurs by year

Year	E^0	E^1	E^2	E^3
2001	30,733	26,961	12,988	5,135
2002	31,584	27,663	12,566	4,703
2003	29,143	25,184	12,324	4,786
2004	29,222	25,451	12,685	5,039
2005	29,975	26,111	13,288	4,943
2006	31,144	27,145	13,494	5,002
2007	31,287	26,846	12,634	4,653
2008	28,617	23,546	10,348	3,890
2009	23,827	19,183	7,745	2,986
2010	23,916	19,678	8,113	3,119
2011	25,496	20,759	8,379	3,264
2012	26,678	20,983	7,932	3,100
2013	27,265	20,479	7,713	2,920
2014	30,614	21,896	8,369	3,368
2015	33,974	21,649	8,112	3,191
2016	33,951	21,297	8,116	3,171

Note: The table shows the number of new first time entrepreneurs in the Danish economy, entering each year between 2001-2016, according to the classifications of entrepreneurial spells: E^0, E^1, E^2, E^3.

2.4 Stylized facts

Entrepreneurs in Denmark are relatively old when they found their first business. On average first time entrepreneurs are 37.8 years old at business founding, while ex-post successful entrepreneurs are even older, being on average 39.1 years old. Table 2 below provides an overview of summary statistics on first time entrepreneurs in our dataset. All variables refer to E^3 definition of entrepreneurship. On average entrepreneurs higher 3.5 employees and 70% of them are males. Their average education, expressed in years, is around 12.6.

We define an entrepreneur as successful if, conditional on survival, in year five from business

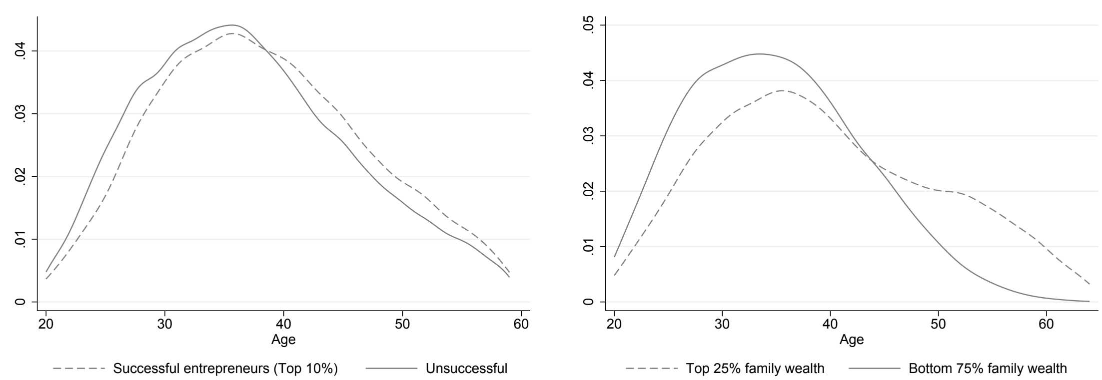
Table 2: Summary statistics

	E^3 **entrepreneurs**
Average employment	3.49
Average revenues	7,638
Share of males	0.69
Age at founding	37.8
Average education	12.6
Average annual gross salary	361
Average wealth	185

Note: The table provides summary statistics on the main demographic variables of interest of the entrepreneurs in our sample. Revenues, salaries and wealth are expressed in 1000 dkk. Salaries an wealth are measured the year prior to opening the business.

start his firm belongs to the top decile of the employment distribution. The graph below plots a kernel density estimation of the age distribution at founding for high-growth (successful) entrepreneurs versus the rest. We see that ex-post successful entrepreneurs are on average older when they found their first business. To understand whether this life-cycle pattern is completely explained by the need to accumulate more wealth to run a successful business, the plot on the right shows the age distribution at founding of entrepreneurs that belong to wealthy families versus the rest. We use family wealth as a proxy for the tightness of the individual borrowing constraint. Specifically, we rank entrepreneurs depending on their parents' wealth at business start. We define an entrepreneur as coming from a rich family if his parents belong to the top quintile of the wealth distribution. If financial frictions were the only cause holding back young business owners, and under the assumption that entrepreneurs who belong to wealthy families are less borrowing constraint, we would expect to observe a left shift in the age distribution at founding for rich entrepreneurs. However, in figure 1 below we show that this is not the case. If anything, we observe that rich entrepreneurs start their first business even slightly later. We interpret this first evidence as suggestive of the fact that financial frictions alone cannot explain the life-cycle patterns of entry into entrepreneurship.

Figure 1: Firm creation over the life-cycle



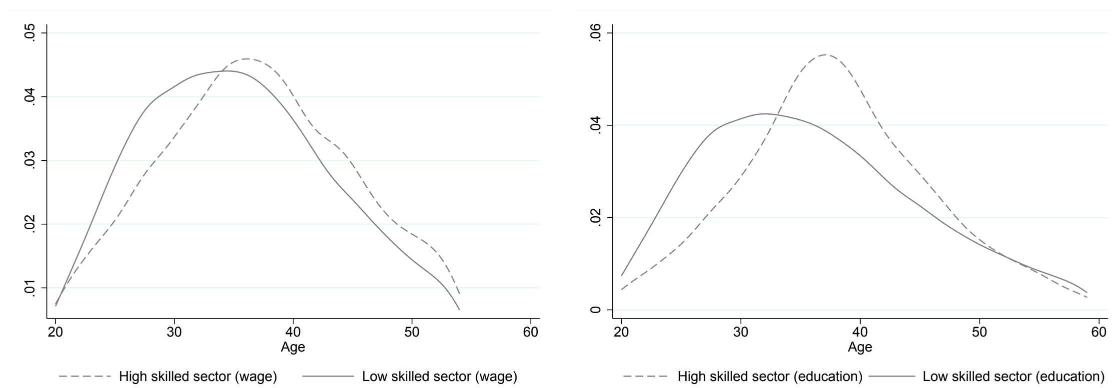
(a) Age distribution at founding

(b) Age distribution at founding by family wealth

Notes: In panel (a) we plot the age distribution at founding of first time entrepreneurs, for both successful and unsuccessful ones. Panel (b) show the same plot, conditional on the entrepreneur's parents wealth.

Next, we ask whether there is heterogeneity in age at founding depending on the skill-intensity of the sector in which the entrepreneur operates. We create two indexes for the skill intensity as follows. For each sector at the 2-digit industry level we compute the ratio between skilled and unskilled workers. In the first index we define a skilled worker as anybody earning a wage above the median wage in the economy. In the second skill index we define a skilled worker as anybody that has acquired more years of education than the average worker in the economy. We then compute the average of these ratios across sectors and define a sector as skill-intensive if it's above the average. The graph below plots the kernel density estimation of the age distribution at founding for skill-intensive sectors and the rest. We observe that in sectors that require

Figure 2: Age distribution at founding by sector



(a) Skill intensive sector based on wage definition

(b) Skill intensive sector based on education definition

Notes: In panel (a) we plot the age distribution at founding of first time entrepreneurs in skill-intensive sectors versus the rest, where the definition of skill intensity is constructed using the average wage in the industry. Panel (b) plots the same distribution using the skill intensity definition based on years of education.

more skills, entrepreneurs start their firm later and this is true independently from which definition of skill intensity we use. Together, these facts point towards a positive relationship between the life-cycle patterns of entrepreneurship and the need of accumulating the appropriate skills. In the next section we dig deeper into the role of human capital and financial capital on future business outcomes using different regression specifications.

2.5 Regression specification

We explore the relationship between human capital and wealth at business foundation on future firm outcomes to understand which of the two factors matters most. Specifically, we investigate the role of entrepreneurial human capital accumulated on the job and own wealth in explaining firm survival and firm productivity, conditional on surviving. We measure human capital with the entrepreneur's position in the wage distribution the year prior to opening the firm. Wealth is measured as the entrepreneur's position in the wealth distribution the year prior to starting the business. Wealth is the entrepreneur's net wealth holdings.

2.5.1 Firm survival

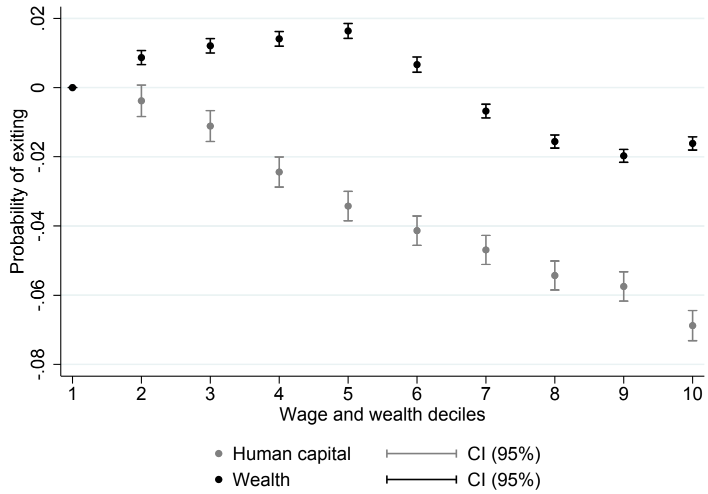
Most start-ups fail within the first years from their foundation. To understand the role that human capital has on start-up survival we regress a dummy indicator that takes value one whenever the entrepreneur exits within the first 5 years from business start and zero otherwise. We use the E^1 definition of entrepreneurship when studying firm survival[7]. We regress this outcome variable on our human capital and wealth measure and several controls, which include the entrepreneur's gender, education, age at founding and two digit industry-year dummies. The regression reads:

$$Pr[y_i = 1|x_i] = \beta_0 + \beta_1 h_i + \beta_2 w_i + \text{controls} + \epsilon_i \tag{1}$$

where x_i are all the explanatory variables, h_i stands for human capital, w_i for wealth, "controls" is a shortcut for all the control variables mentioned above and $\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2)$. Our finding, summarized in Figure 3, is twofold. First, the probability of failing within the first five years from business start is linearly decreasing in the entrepreneur's level of human capital at business start and both economically and statistically significant. Moving from the lowest to the highest level of human capital decreases the probability of failure by almost 8%. Second, the effect of wealth on exit is non-linear, slightly positive up to the median wealth and decreasing thereafter but much lower in magnitude. For example, moving form the lowest to the highest wealth decile reduces the probability of exiting by only 2%. On average, the effect of wealth at business start on firm survival is zero.

[7]We know that by doing so we will include some individuals that are simply self-employed and have no intention to grow. However, we preferred to do so rather than using the E^3 definition of entrepreneurship because we would otherwise have excluded all those individuals that started a business, wanted to hire somebody and grow, but failed before even hiring anybody.

Figure 3: Human vs financial capital on firm survival



Notes: This figure plots the probability of closing the business within the first five years from business start as a function of the entrepreneur's human capital and wealth measured the year prior to opening the business.

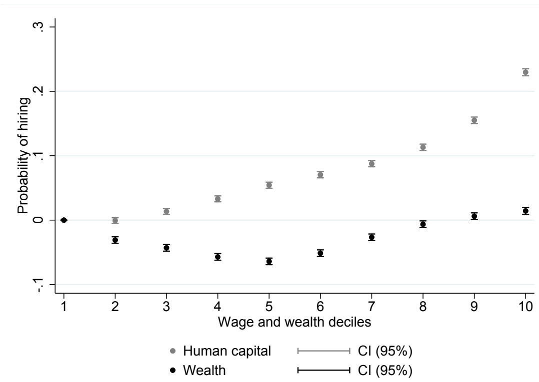
2.5.2 Firm productivity and success

Next, we turn to some measures of success and firm productivity, conditional on surviving at least five years. Our first measure of success is a dummy taking value one if the entrepreneur hires somebody within the first 5 years. This outcome variable can be viewed both as success and survival measure as most firms that do not hire anybody within this time horizon tend to exit the market. For the same reasons as for firm survival in this case we use the $E1$ definition of entrepreneurship.

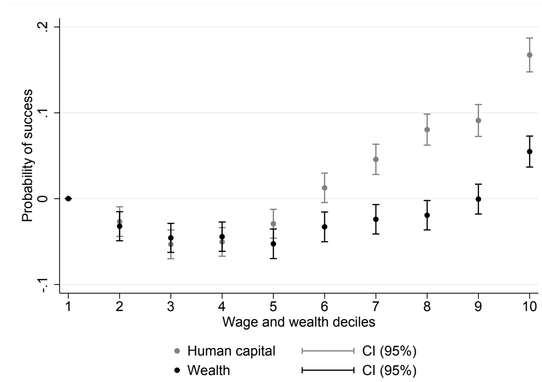
Our second measure of success is a variable taking value one if the entrepreneur's firm belongs to the top decile of the employment distribution within its sector of activity after 5 years from business start. Third, we regress 5 year horizon log productivity, as measured by real value added per worker, on human and financial capital. In these two cases we condition on the entrepreneur being able to hire at least one employee. In all our regressions we control for gender, education, age at founding of the entrepreneur and two digit industry-year dummies. The figure below plots the effect of human capital and wealth on success.

A clear pattern emerges also for our success measures. From panel (a) we see that the probability of hiring somebody is linearly increasing in human capital. Moving from the lowest to the highest wage decile increases the probability of hiring somebody by more than 20%. Wealth,

Figure 4: Effect of human vs financial capital on success



(a) Probability of hiring somebody



(b) Probability of success

Notes: In panel (a) we plot the effect of human and financial capital on the probability of hiring at least one worker within the first 5 years from business start. Panel (b) plots the probability of belonging to the top decile of the employment distribution in year 5. The observed difference in the standard errors is due to the fact the panel (a) uses many more observations as it includes all individuals that register a business and make positive revenues. Panel (b) restricts to those that have at least one employee.

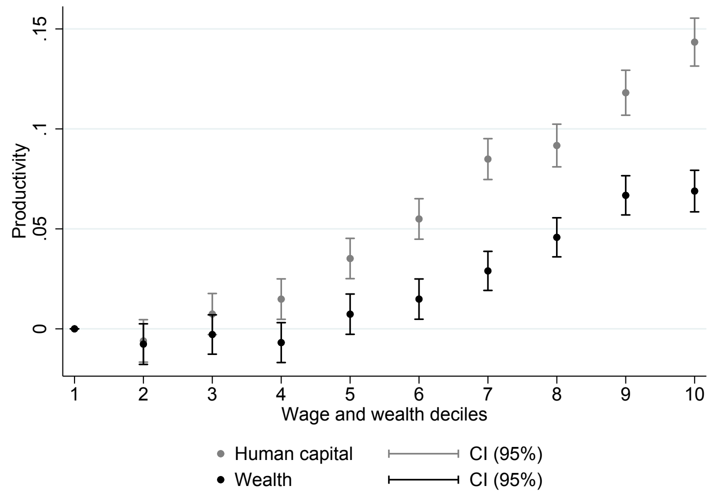
on the other hand, has a non-linear pattern and almost no effect in predicting whether the entrepreneur will ever hire somebody. This outcome variable mixes notions of survival with success. In fact, we observe a positive correlation between hiring at least one employee and firm survival. This is why in panel (b) we use a more stringent measure of success. First we restrict our sample to entrepreneurs that have at least one employee. We define a dummy variable success that takes value one if the entrepreneur's firm belongs to the top decile of the employment distribution in year 5 from business start. Also in this case, human capital has a positive and significant effect on the probability of success. However, these effects become statistically significant only from the median decile. Moving from the bottom to the tenth decile increases the probability of being in the top decile of the employment distribution by almost 15%. Wealth matters only at the very top of the distribution but the estimated coefficient is about one-third of the effect of human capital.

Finally, we change the outcome variable to understand how robust our results are to the definition of success. Specifically, we run the above regression again, where the outcome variable now is the log of firms' productivity during the first five years of business activity. Firm productivity is defined as real value added per worker. The regression equation reads:

$$\log(y_i) = \beta_0 + \beta_1 h_i + \beta_2 w_i + \text{controls} + \epsilon_i \tag{2}$$

where $\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2)$ and y_i is the real value added per worker. All other explanatory variables are the same as above. Figure 5 below shows the results. The results change quantitatively but

Figure 5: Human vs financial capital on firm productivity



Notes: This figure plots the effect of human and financial capital on the log of firm productivity as measured by real value added per worker.

not qualitatively. Our measure of human capital explains a big fraction in the variation of firms' productivity at early ages. Interestingly, owner's wealth now does explain some of the variation in firm productivity but all estimated coefficients are less in magnitude compared to the ones of human capital.

To sum up we find that:

- *Fact 1:* Entrepreneurs are on average 38 years old when starting their first business and ex-post successful ones are older.
- *Fact 2:* Fact 1 holds when controlling for family wealth, meaning that not all life-cycle patterns are explained by the need of accumulating wealth to start a business.
- *Fact 3:* Entrepreneurs with higher human capital at business start have higher probability of surviving.
- *Fact 4:* Conditional on survival, entrepreneurs with higher human capital run more productive and successful firms.
- *Fact 5:* Owner's wealth at founding matters very little in explaining firm survival and only modestly in explaining business success and productivity.

Given this evidence, in the next section we outline our model economy in which entrepreneurs can endogenously accumulate human capital and financial wealth and use our model to shed more light on the role of entrepreneurial human capital for business formation.

3 The model economy

We consider an occupational choice model featuring a realistic life-cycle structure. Every period agents decide whether to become entrepreneurs or workers given their wealth, exogenous abilities and entrepreneurial human capital. Human capital can be accumulated both while being a worker and while being an entrepreneur with a learning by doing technology (LBD). Both workers and entrepreneurs supply labor exogenously and the latter also use capital and external labor in production. The human capital accumulation technology differs across workers and entrepreneurs. In the first case, the efficiency in accumulating human capital depends on the learning ability of the worker and his productivity. In the latter case, the ability of effectively acquiring entrepreneurial skills also depends on the firm size. This reflects the fact that entrepreneurs learn how to better manage their firm through learning spillovers which increase in firm size.The accumulated stock of human capital affects the entry decision into entrepreneurship over the life-cycle. Higher levels of human capital make entrepreneurs more productive and enables them to obtain higher profits. However, weighting too much before starting a firm reduces the present value of future cash flows. Entrepreneurs face collateral constraints and every period have to decide how much capital and labor to hire. Markets are assumed to be incomplete so agents save to self-insure against idiosyncratic risk. In addition, individuals save to overcome the collateral constraint and be able to operate their business at a profitable scale. Agents retire at an exogenous age J_r and obtain exogenous pension benefits b.

Demographic structure

Time is discrete and agents can live up to a maximal age J, facing a probability s_j of surviving up to age j, conditional on having survived until age $j-1$. Agents retire at age J_r with social security benefit b, which is independent of their labor market history.

Endowments

Every agent is endowed with two types of abilities, one as a worker and the other as entrepreneur, and a learning capacity. Workers' ability follows a deterministic and stochastic component over the life-cycle. Let z be the stochastic component of workers' ability, we can then define a mapping $e(z,j)$ which for every possible combination of age and realized productivity shock z maps into the ability level. The stochastic component z follows an AR(1) process, while the deterministic part is given by a second order polynomial in age. Workers' ability has two effects. On one side it determines total labor income, on the other it affects the individual ability in accumulating human capital. Workers which on the work are more productive, also accumulate human capital faster.

Entrepreneurs' ability θ is assumed to be fully stochastic and affects their efficiency in accumulating human capital. It follows a first order autoregressive Markov process where the innovations are drawn from a Pareto distribution. Finally, the learning capacity is a worker's fixed personal trait that is constant throughout his life-cycle and is drawn at age $j = 1$ from a log-normal distribution.

Technology

Workers have access to the following human capital accumulation technology:

$$h_{j+1} = (1-\delta)h_j + \xi_i e(z,j)h_j^{\phi_1}$$

where ξ_i stands for the worker's learning capacity and is time-constant. This functional form implies that high skilled workers with good learning abilities accumulate entrepreneurial skills more efficiently and in turn are likelier to become entrepreneurs.

Entrepreneurs can accumulate human capital according to:

$$h_{j+1} = (1-\delta)h_j + \theta_j h_j^{\phi_1}(k_j)^{\psi}$$

With this modeling device we want to capture two facts. First, idiosyncratic shocks hit the productivity of the business by affecting the entrepreneur's human capital, rather than directly affecting the scale of production. Second, the human capital accumulation technology depends on the firm size to capture the idea that the bigger the firm, the more efficiently an entrepreneur accumulates human capital because of increased interaction among peers and learning spillovers.

Entrepreneurs decide how much capital k and external labor units n to hire, while being endowed with the following production technology:

$$y = h_j \left(k_j^{\gamma} (n_j)^{1-\gamma}\right)^{v},\ v \in [0,1)$$

The parameter $v < 1$ implies that entrepreneurs face decreasing returns to scale. The term γ determines the share of income accruing to the variable factors of production, namely capital and labor.

Preferences

All agents have identical preferences and choose consumption to maximize the following objective function:

$$\mathbb{E}\left[\sum_{j=1}^{J} \beta^{j-1} \left(\prod_{t=1}^{j} s_t\right) u(c_j)\right] \tag{3}$$

where the period utility function $u(c)$ is assumed to be of the CRRA class.

Market arrangements

Markets are incomplete in the sense that agents cannot fully insure themselves against idiosyncratic sources of risk by trading state-contingent assets.

Workers are not allowed to borrow, but can save in a risk-free asset. Entrepreneurs can borrow capital within a period to invest in their firm. However, a fraction π of them faces collateral constraints, meaning they can only borrow up to a fraction λ of their wealth: $k \leq \lambda a$. The fraction π is calibrated internally as described in the next section. The collateral constraint faced by entrepreneurs is motivated by the fact that financial markets are assumed to work imperfectly, due to non perfectly enforceable contracts. On the other hand, the fact that some entrepreneurs are not borrowing constrained reflects the fact that in the data individuals coming from wealthy families have no difficulty in accessing credit.

3.1 The household problem

At the beginning of every period each household has to decide whether to become an entrepreneur or a worker [8]. Individuals know their learning capacity ξ, as well as their abilities as workers z and as entrepreneurs (θ) and form expectations about future ability levels. Workers accumulate entrepreneurial human capital through a LBD technology. In every period they decide how much to consume and save. Entrepreneurs choose how much capital and external

[8] We use the word individual and household interchangeably as they coincide in our economy.

labor to hire to maximize profits. They can also build up entrepreneurial human capital with a LBD technology. In addition, they make a standard consumption-savings choice. Each individual at beginning of life is endowed with some positive level of entrepreneurial human capital stock.

We write the household problem in recursive form. Let $\mathbf{x}_j = (a, z, \theta, h, \xi, f)$ be the individual state vector at age j, where a stands for asset holdings, z is the labor income shock, θ is the exogenous entrepreneurial ability level, h is the stock of entrepreneurial human capital, ξ represents the learning ability and f is a flag for whether the individual belongs to a wealthy family and faces no borrowing constraints as future entrepreneur or not. The value function of a household at age j is $V_j(\mathbf{x}_j) = \max \left\{V_j^w(\mathbf{x}_j), V_j^e(\mathbf{x}_j)\right\}$ where $V_j^w(\mathbf{x}_j)$ and $V_j^e(\mathbf{x}_j)$ represent the value of being a worker and an entrepreneur at age j respectively. The occupational choice takes place before the consumption-savings decision but after the ability levels have realized.

Consider a household of age $j < J_r$. If $V_j^e(\mathbf{x}_j) \geq V_j^w(\mathbf{x}_j)$ he decides to become an entrepreneur and solves the following dynamic problem:

$$V_j^e(\mathbf{x}_j) = \max_{c_j, a_{j+1}, k_j, n_j} \{u(c_j) + s_{j+1}\beta\mathbb{E}\left[V_{j+1}(\mathbf{x}_{j+1})\right]\} \tag{4}$$

s.t

$$c_j + a_{j+1} = \pi(h_j, k_j, n_j) + (1+r)a_j \tag{5}$$

$$k_j \leq \lambda a_j \tag{6}$$

$$a_{j+1} \geq 0 \tag{7}$$

$$n_j \geq 0 \tag{8}$$

$$h_{j+1} = (1-\delta)h_j + \theta_j(h_j)^{\phi_1}(k_j)^{\psi} \tag{9}$$

where $\pi(h_j, k_j, n_j)$ stands for entrepreneurial profits. Business profits depend on the entrepreneur's human capital stock, his investment into physical capital k_j and the amount of external labor inputs hired n_j. The value of the collateral constraint λ depends on the flag f. If the individual comes from a wealthy family it is $\lambda = \infty$, otherwise it is set to λ_L, which is calibrated internally.

The entrepreneur chooses capital and external labor to maximize profits:

$$\pi = \max_{k_j, n_j} \left\{ h_j \left(k_j^{\gamma} (n_j)^{1-\gamma} \right)^{v} - (r+\delta) k_j - w n_j - F \right\} \tag{10}$$

s.t

$$k_j \leq \lambda a_j \tag{11}$$

$$n_j \geq 0 \tag{12}$$

where F are fixed costs of production. If $V_j^w(\mathbf{x}_j) > V_j^e(\mathbf{x}_j)$ the agent becomes a worker and his dynamic problem reads:

$$V_j^w(\mathbf{x}_j) = \max_{c_j, a_{j+1}} \{ u(c_j) + s_{j+1} \beta \mathbb{E} \left[V_{j+1}(\mathbf{x}_{j+1}) \right] \} \tag{13}$$

s.t

$$c_j + a_{j+1} = we(z,j) + (1+r) a_j \tag{14}$$

$$a_{j+1} \geq 0 \tag{15}$$

$$h_{j+1} = (1-\delta) h_j + \xi_i e(z,j) h_j^{\phi_1} \tag{16}$$

The human capital accumulation technology changes over the life-cycle and with the idiosyncratic productivity of the worker through the term $e(z,j)$. The worker's problem is relatively standard, with the difference that human capital is occupation specific and does not contribute to the workers' productivity. At age J^r agents retire and they all solve the same problem:

$$W_j(\mathbf{x}_j) = \max_{c_j, a_{j+1}} \{ u(c_j) + s_{j+1} \beta \mathbb{E} \left[W_{j+1}(\mathbf{x}_{j+1}) \right] \} \tag{17}$$

s.t

$$c_j + a_{j+1} = b_j + (1+r) a_j \tag{18}$$

$$a_{j+1} \geq 0 \tag{19}$$

The transfer b_j is independent of the individual labor income history.

4 Mapping the Model into Data

We bring the model to the data with a two-step calibration procedure. In the first stage we estimate, or calibrate using external evidence, those parameters that can be cleanly identified outside of the model. In the second step we calibrate the remaining parameters by minimizing the squared distance between a number of targeted empirical moments and their simulated counterpart. In the rest of this section we outline these two stages in more detail and provide evidence that the moments chosen as targets are informative about the underlying parameters we aim to calibrate. We conclude the section by showing that our calibrated model performs well along other dimension of the data. This validation step brings us to the final section of the paper in which we use our model to disentangle the role of human capital versus financial capital accumulation for business creation, age composition of new entrepreneurs, firm productivity, and aggregate output through different counterfactual experiments.

4.1 First stage

In the first stage we select some parameter values following the literature and estimate others directly from the data.

4.1.1 Externally calibrated parameters

Preferences

The utility function is assumed to be of the CRRA type, i.e.

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

where we set $\sigma = 1.5$ and the discount factor β to 0.96, following Bruggemann (2021).

Demographics

We allow agents to live up to a maximum of $J = 71$ periods (real age 96) and assume that they retire at age $J_r = 45$ (real age 65). Every agent enters the economy at age $j = 1$ (real age 20). The survival probabilities are taken from the life tables of Bell and Miller (2005).

Financial Frictions

We set π, the fraction of individuals who are not collateral constrained, to 10%. This reflects the assumption that individuals with parents in the top decile of the wealth distribution can easily access credit directly through their family or being indirectly financially supported by them. In the appendix, we check the sensitivity of our results to this assumption. The severity of the collateral constraint, λ_L, is set to match the median personal debt to asset ratio of entrepreneurs in their first year of business activity [9] . This leads to a value of $\lambda = 2.1$, which means that individuals can borrow up to 110% of their wealth.

4.1.2 Estimated parameters

We estimate from the data both the deterministic and stochastic part of the labor income process.

Income process

We specify the income process as a deterministic component that follows a second order polynomial in age and a stochastic part which we assume to follow an AR(1) process. The labor productivity process reads:

$$
\begin{aligned}
e(z,j) &= \exp(z_{ij})\left(\lambda_0 + \lambda_1 j + \lambda_2 j^2\right) \\
z_{ij} &= \rho z_{ij-1} + \epsilon_{ij}
\end{aligned}
$$

where $\epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2)$. To estimate the labor income process we follow a standard approach in the literature and first regress the log of men wages on observable factors:

$$
\log(w_{it}) = \lambda_0 + \lambda_1 age + \lambda_2 age^2 + \beta X_{it} + \gamma_i + \delta_t + z_{it} \tag{20}
$$

where the set of controls X_{it} contains the education level and a dummy for the type of occupation, while γ_i and δ_t capture individual and time fixed effects respectively. The idiosyncratic component is then assumed to follow:

$$
z_{it} = \rho z_{it-1} + \epsilon_{it} \tag{21}
$$

where $\epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2)$. The coefficients of the polynomial in age are $\lambda_0 = 1.98$, $\lambda_1 = 0.089$ and $\lambda_2 = -0.00069$. The persistence parameter is $\rho = 0.88$ and the standard deviation of the innovations is $\sigma_\epsilon = 0.41$. The AR(1) process is discretized in a 4 state discrete Markov chain using Tauchen's method.

The table below provides an overview of the parameters chosen so far.

[9] Note that we do this algebraically, before calibrating the remaining parameters internally.

Description	Parameter	Value	Source
Coefficient of risk aversion	σ	1.5	Bruggemann (2021)
Discount factor	β	0.96	Bruggemann (2021)
Factor income shares	γ	0.36	Cagetti and De Nardi (2006)
Collateral constraint	λ	2.1	Derived
Persistence parameter	ρ	0.88	Estimated
Std of innovations	σ_ϵ	0.41	Estimated
Polynomial coefficient	λ_0	1.98	Estimated
Polynomial coefficient	λ_1	0.089	Estimated
Polynomial coefficient	λ_2	-0.00069	Estimated

Table 3: Externally calibrated/estimated parameters

4.2 Second stage

In the second step we take the first stage parameter values as given and calibrate internally the remaining parameters. There are ten parameters to calibrate internally and we do this by targeting ten different empirical moments. The parameters we need to calibrate are those governing the human capital accumulation equations and the fixed operating costs. The human capital accumulation technologies for workers and entrepreneurs read as follows:

$$h_{j+1} = (1-\delta)h_j + \xi_i e(z,j)h_j^{\phi_1}$$

$$h_{j+1} = (1-\delta)h_j + \theta_j (h_j)^{\phi_1}(k_j)^{\psi}$$

where θ_j captures the entrepreneur's efficiency in accumulating entrepreneurial human capital. θ_j follows an AR(1) process of the type:

$$\theta_{it} = \zeta\theta_{it-1} + v_{it} \tag{22}$$

where the innovations are drawn from a Pareto distribution with location parameter a and scale b, $v_{it} \sim \mathcal{P}(a,b)$. The learning ability ξ is drawn from a log-normal distribution $\xi \sim \mathcal{LN}(\mu_\xi, \sigma_\xi)$. The parameters to calibrate are: $[\zeta\ a\ b\ \delta\ \phi_1\ \psi\ F\ v\ \mu_\xi\ \sigma_\xi]$.

We target the following data moments: average, standard deviation, median, second and eighth decile of the age distribution at founding of entrepreneurs with rich parents. Additionally, we target the aggregate share of entrepreneurs in the economy, the exit rate, the share of entrepreneurs of age 50, the ratio between the median entrepreneur's to worker's wealth at age 40 and 50.

We define the parents of an entrepreneur as rich in the data if they belong to the top decile of the wealth distribution, while we define an entrepreneur rich in the model if he is not collateral constrained at age $j = 1$.

The calibration procedure follows a standard simulated method of moments approach. For a set of candidate parameter values we solve the household problem and simulate a panel of $N = 100,000$ households. We compute the moments from the simulated and empirical data and we minimize their squared distance. The solution to the minimization problem is a vector $\hat{X}$ of parameter values such that the following objective function is minimized:

$$L(X) = \min_{X} (\hat{\Omega} - \Omega(X))' W (\hat{\Omega} - \Omega(X))$$

where $\Omega(X)$ are the moments computed from the simulated data, $\hat{\Omega}$ are the empirical moments and $W = I$. The minimization is performed using a version of the Tik-Tak algorithm. We first generate a Sobol sequence inside the parameter space and evaluate the objective function at each of these points. We then choose the 10 lowest values of the objective function and the associated parameter combinations and use those values as starting points in a local optimization algorithm using Nelder-Mead. The minimum among these gives us the solution to the calibration exercise.

4.3 Identification

Given the complexity and non-linearity of the model, all moments are jointly affected by all parameters in equilibrium. However, some moments are more informative than others for certain parameters. In this section we provide intuitive arguments regarding identification. In the appendix we use the structure of the calibration algorithm and elasticity tables to provide quantitative evidence on the identification mechanisms.

The main parameters to calibrate are those governing the accumulation equations of human capital as a worker and as an entrepreneur. To calibrate μ_ξ and σ_ξ, the mean and standard deviation of the learning ability respectively, we target the two central moments of the age distribution at founding of individuals belonging to rich families. The assumption is that since these individuals are likely not to be financially constraint, the decision to start a business is largely motivated by the need to acquire the right amount of entrepreneurial skills. A higher mean μ_ξ decreases the average age at founding and similarly a higher dispersion in learning ability σ_ξ generates more variation in the age at business start. We also target the median age to match the depreciation rate of human capital δ. Everything else equal, a higher depreciation rate shifts the median age to the right. Similarly, the curvature on human capital, ϕ_1, is calibrated by targeting the second decile of the age distribution at founding of rich individuals. A higher value of ϕ_1 makes it easier to acquire human capital in short time periods and allows earlier entry into entrepreneurship .

To calibrate the persistence of the shock process θ we target the exit rate. The higher the persistence parameter, the lower the exit rate from entrepreneurship. The scale and location parameter a and b of the Pareto distribution are calibrated by targeting the share of entrepreneurs of age 50 and the eighth decile of the age distribution at founding of rich entrepreneurs.

The aggregate share of entrepreneurs in the economy helps pinning down the fixed costs of production. If fixed costs are too high, nobody is willing to become an entrepreneur. The concavity parameter of the production function v is pinned down by the ratio between entrepreneurs' and workers' median wealth at age 40. A higher value of v makes entrepreneurs more wealth-rich by generating higher profits for the same inputs.

Finally, ψ is calibrated by targeting the ratio between median entrepreneurial to worker wealth at age 50. A larger value of ψ enables entrepreneurs to accumulate human capital faster and boosts their productivity increasing their wealth compared to the one of the median worker.

4.4 Model fit

Targeted moments

Table 2 reports the model fit in terms of targeted moments. The model performs well along most dimensions of the data, overestimating a bit the ratio of median entrepreneurial to worker wealth at age 40 and generating a bit too few exit compared to the data. This happens because in our model part of the speed at which entrepreneurial human capital is accumulated as an entrepreneur depends on the size of the firm, k, which reduces the impact of the stochastic shock θ on the exit dynamics. The rest of the moments are matched well.

Moment	Data	Model
Average age at founding of entrepreneur belonging to rich family	37.5	37.8
Standard deviation age at founding of entrepreneur belonging to rich family	7.9	7.1
Second decile age at founding of entrepreneur belonging to rich family	31	31
Median age at founding of entrepreneur belonging to rich family	37	37
Eighth decile age at founding of entrepreneur belonging to rich family	44	44
Share of entrepreneurs	3.3%	3.3%
Exit rate	4.0%	2.8%
Share of entrepreneurs of age 50	4.8%	6.4%
Median E/W wealth age 40	4.9	7.1
Median E/W wealth age 50	3.8	3.7

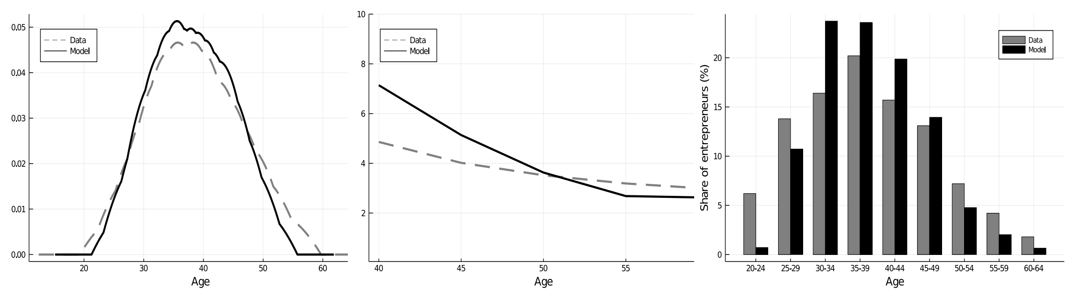
Table 4: Targeted moments

Untargeted data profiles

As external validity we show how the model performs along untargeted moments of the data. Panel (a) of Figure 5 plots the model implied and empirical age distribution at founding of first time entrepreneurs. Our model is able to replicate both qualitatively and quantitatively the age composition of new entrepreneurs remarkably well, considering that we do not explicitly target any moment of the overall age distribution at founding in the calibration exercise. The model also replicates the qualitative evolution of the ratio between median entrepreneurial to worker wealth at different ages as evident from panel (b). Quantitatively, we slightly overestimate the fraction of wealth held by entrepreneurs compared to workers at early ages.

In panel (c) we plot the share of entrepreneurs by founding age groups. The model is able to match the qualitative hump-shaped pattern of the distribution in the data but is quantitatively generating too many old entrepreneurs and loo little young ones compared to the data. The reasons for this result is that our model features no initial heterogeneity in human capital. As a consequence, every individual in the model needs a bit of time to acquire at least some entrepreneurial human capital to start a successful business, which implies that we have very few extremely young entrepreneurs in the model. We are currently working on a new calibration strategy in which we calibrate the initial distribution of human capital at age $j = 1$ to come closer in matching the fraction of young entrepreneurs in the data.

Figure 6: Untargeted data profiles



(a) Age distribution at founding (b) E/W median wealth (c) Share of entrepreneurs

Notes: In panel (a) we plot the age distribution at founding of first time entrepreneurs. Panel (b) plots the ratio of median entrepreneurial to worker wealth at different ages. Panel (c) plots the share of entrepreneurs by age groups.

5 Counterfactuals

In this section we use our model economy as a laboratory to decompose the role that financial frictions and human capital play in affecting individuals' decisions to start a business and its aggregate implications. We start by comparing our baseline economy to one in which no individual is collateral constraint, i.e. we set $\lambda = \infty$ for everybody. Next, we turn to the role of endogenous human capital accumulation. We show how agents, and the aggregate economy, react differently to a policy reform that subsidizes credit in a economy in which business productivity is assumed to be completely exogenous, like in Cagetti and De Nardi (2006), compared to our framework. We additionally provide empirical evidence on the elasticity of new business formation to changes in financial frictions by exploiting the 2014 Danish policy reform which lowered the initial capital requirements for incorporated businesses. We conclude by showing how in our model these policies are much less effective in spurring economic growth and business activity than traditionally found, but much more in line with the effect found in the data.

5.1 Eliminating financial frictions

We ask how the presence of collateral constraints affects individual decisions to start a business, the age composition of new entrepreneurs, as well as its aggregate implications on the economy.

We eliminate financial frictions by setting the parameter $\lambda = \infty$ for everybody. Table 3 below summarizes the main aggregate results. With no financial frictions, the share of entrepreneurs in the economy increase. This happens because without collateral constraints a higher fraction of potential entrepreneurs can immediately reach their target firm size and increase their potential profits. In turn, this increases the value of entrepreneurship. Without financial frictions, those individuals which in the baseline scenario had the right amount of skills but not enough financial capital find it now optimal to transit into entrepreneurship. This explains the higher share of entrepreneurs.

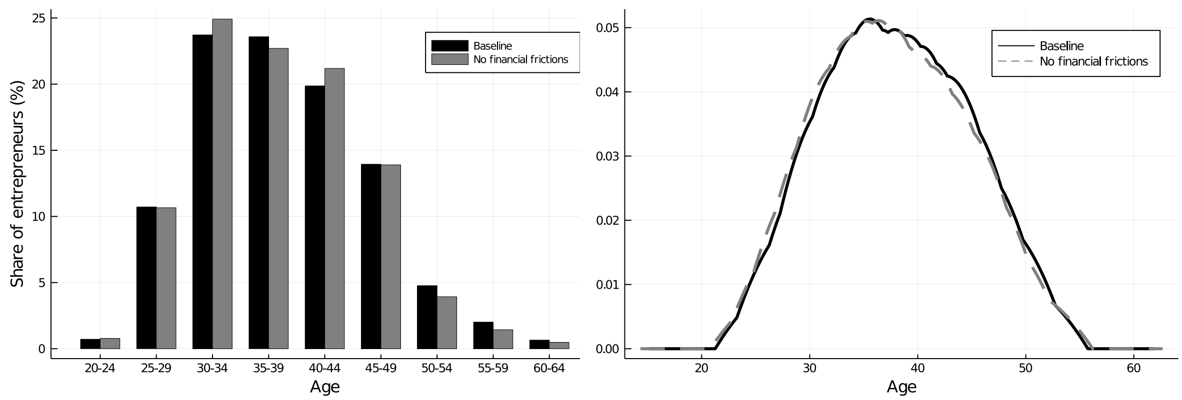
	Baseline	**No financial frictions**	**Difference**
Share of entrepreneurs	3.3%	3.7%	+0.4%

Table 5: Aggregate outcomes

In Figure 7 below we plot the share of entrepreneurs by age and the age distribution at founding. Remarkably, eliminating financial frictions only has a modest impact on the age composition of new entrepreneurs, suggesting that the life-cycle dynamics are mainly explained by the human capital accumulation process. The share of young entrepreneurs, age groups between 20-29, substantially does not change in the two scenarios. The individuals that mostly benefit from the removal of collateral constraints are individuals in their thirties with the appropriate skills but too little wealth to start a business at the right size.

Financial frictions hold back some potential entrepreneurs and eliminating them increases the overall share of entrepreneurs in the economy. We next ask who these new entrepreneurs are in terms of human capital and productivity. Figure 8 plots the average productivity distribution at business foundation by age bins of all those individuals that started a firm when financial frictions were removed but did not start it under the baseline case. We compare their productivity to the average productivity of entrepreneurs in the same age groups under the baseline scenario. Interestingly, we find that removing financial frictions brings an inflow in the economy of low productive new entrepreneurs at all ages. In this sense, the elimination of financial constraints helps those young individuals with a relatively bad outside option and low human capital to start a business. Thus, while removing collateral constraints increases the aggregate number of new businesses it lowers average productivity. We cannot say anything on whether a policy that subsidizes credit would be desirable in our setting, but we do want to highlight the tradeoff. Subsidized credit must be financed and whether such a policy is desirable will eventually also depend on whether the extensive margin effect of increasing the overall number of entrepreneurs in the economy outweighs the decrease in average productivity such that the net effect on aggregate output is positive.

Figure 7: Baseline vs No financial frictions economy

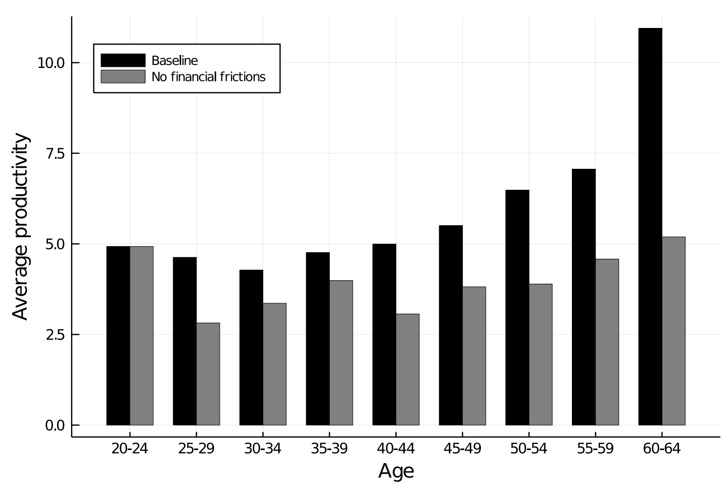


(a) Share of entrepreneurs by age

(b) Age distribution at founding

Notes: In panel (a) we plot the share of entrepreneurs by age under the baseline calibration and in the case in which financial frictions are removed. Panel (b) plots the age distribution at founding under the two scenarios.

Figure 8: Productivity distribution by age groups



Notes: This figure plots the average productivity at business start of those individuals that created a business when financial frictions were removed compared to the average productivity of those in the same age group under the baseline economy. Productivity is computed as revenues per worker.

6 The role of endogenous human capital accumulation

To quantify how human capital accumulation matters in explaining the life-cycle dynamics of entrepreneurship as well as how it interacts with collateral constraints in shaping the response of new business formation to changes in financial frictions we compare a policy that subsidizes credit in two economies. The baseline economy is our framework with endogenous human capital. The second one is the traditional model of Cagetti and De Nardi (2006), in which firm productivity is completely exogenous, augmented by a realistic life-cycle structure. To make the two economies comparable we calibrate the traditional model to match the following aggregate moments: share of entrepreneurs in the economy, exit rate, average and median age at founding, entrepreneurial to worker median wealth at age 40. We then implement the same policy measure consisting in subsidizing credit in the two economies and evaluate the differential impact on the total number of new businesses created as well as the age composition of new entrepreneurs. Finally, we exploit the 2014 Danish policy reform on incorporated businesses to asses which model predictions come closer to the effects observed in the data.

6.0.1 Traditional model

The main difference between the traditional model and ours is the absence of endogenous human capital accumulation. Specifically, we will assume that the production technology of entrepreneurs in the traditional model reads as follows:

$$y_j = \theta_j \left(k_j^{\gamma}(n_j)^{1-\gamma}\right)^{v} \tag{23}$$

where the productivity of the business θ_j follows a completely exogenous stochastic process of the type:

$$\theta_{ij} = \rho_2 \theta_{ij-1} + \mu_{ij} \tag{24}$$

where the innovations are drawn from a Pareto distribution with location parameter c and scale d, $\mu_{ij} \sim \mathcal{P}(c, d)$.

The rest of the economic environment, in terms of demographic assumptions, market arrangements, initial conditions is the same. We need to calibrate the following parameters: $[\rho_2, c, d, F, v]$. We do so by targeting the following moments: share of entrepreneurs in the economy, exit rate, average and median age at founding, entrepreneurial to worker median wealth at age 40. Given that we want to compare the two economies we target the moments computed on the simulated data, since they slightly differ from the empirical ones. Table 5 shows the fit of the traditional model in terms of aggregate moments.

Moment	**Human capital model**	**Traditional Model**
Share of entrepreneurs	3.3%	3.8%
Exit rate	2.8%	3.0%
Average age at founding	38.9	41.7
Median age at founding	38.0	42.0
Median E/W wealth age 40	4.9	5.4

Table 6: Targeted moments

We are roughly able to replicate the same aggregate moments with the traditional model, although we somehow overestimate the share of entrepreneurs in the economy and their age at founding. Given that we match these aggregate moments fairly well with our simplified model, we are ready to turn to the policy experiment.

6.1 Subsidizing credit

We consider two measures that subsidize credit and make access to credit easier. The first consists in simply removing the collateral constraint for everybody in the economy, i.e. $\lambda_L = \infty$. The second case, which we report in the appendix, consists in a reduction of the collateral constraint from $\lambda = 2.1$ to $\lambda = 2.9$, which corresponds to a percentage change of 37.5%. We consider these two different interventions to bound the effects of the policy reform that actually happened in Denmark, as outlined in the next section.

We want to understand how reducing the tightness of the borrowing constraint helps the creation of new businesses and whether the owners of the new businesses are young or old individuals.

We here consider the case in which we completely remove financial frictions and compare the outcomes across the two economies. Table 6 summarizes the main aggregate findings. Subsidizing credit in the traditional model spurs business creation as the fraction of entrepreneurs in the economy rises from 3.8% to 14.1%. The same policy has much more modest aggregate effects on the economy when human capital accumulation is endogenous. The reason for this result is exactly the interaction between entrepreneurial skills and financial wealth. In the traditional model, the only friction preventing agents from starting a business is the lack of credit as business productivity can change exogenously and jump from low to high levels between short time periods. In our framework the accumulation of human capital is much more sluggish and needs time. Even if accessing credit is easier, only few agents will be able to benefit from it, namely those individuals with relatively bad outside options but high enough human capital that makes it optimal for them to start a business.

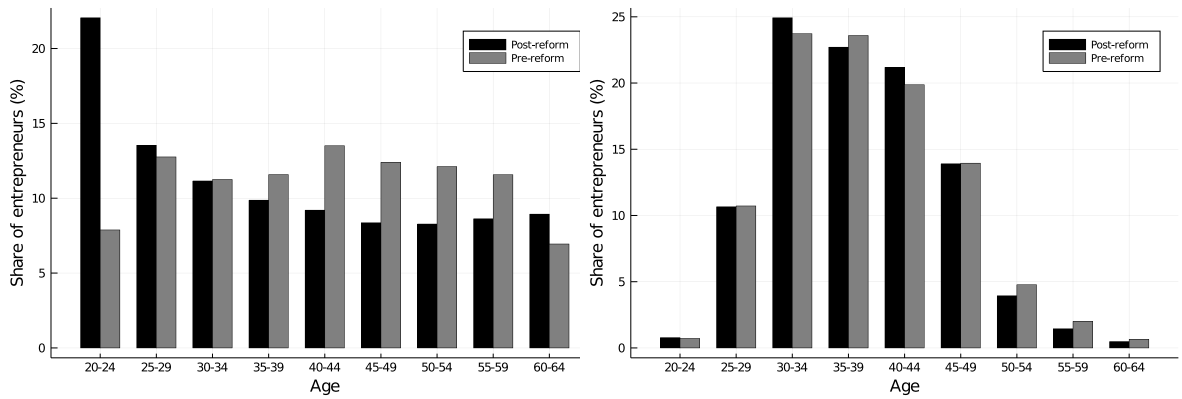
	Traditional model			Human capital model		
	Baseline	Subsidizing credit	Difference	Baseline	Subsidizing credit	Difference
Share of entrepreneurs	3.8%	14.1%	+10.3%	3.3%	3.7%	+0.4%

Table 7: Aggregate outcomes

Figure 9 below shows the effects of subsidizing credit on the share of entrepreneurs by age in the two different models. A clear pattern emerges. Making access to finance easier does not increase the share of young entrepreneurs in the human capital model as agents start with very little entrepreneurial skills and need some time to accumulate them. At older ages, the share of entrepreneurs does increase as some agents had the right amount of entrepreneurial skills later on in life but did not have sufficient financial wealth to operate at a profitable scale.

In the traditional model, subsidizing credit has a much stronger effect on increasing entrepreneurship, already at younger ages. This happens because firm's productivity is completely exogenous and does not follow an individual's life-cycle. In this environment the policy is much more effective at spurring business creation already at the beginning of the individual's life-cycle. However, the traditional model is unable to match, even qualitatively, the life-cycle dynamics of transition into entrepreneurship observed in the data.

Figure 9: Share of entrepreneurs by age under policy reform



(a) Traditional model (b) Human capital model

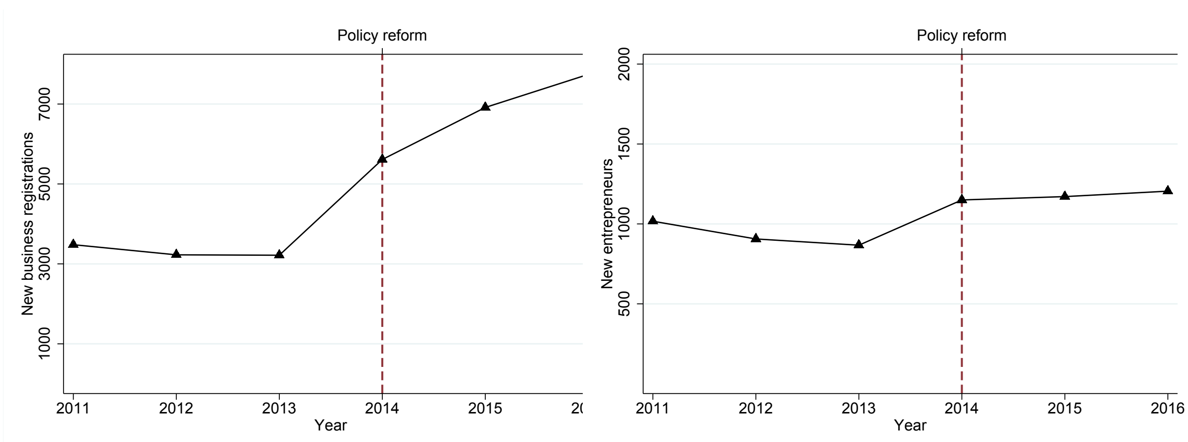
Notes: In panel (a) we plot the share of entrepreneurs by age in the traditional model without human capital under the baseline and under the policy reform scenario . In panel (b) we produce the same plot for our model with endogenous human capital accumulation.

6.2 Policy reform

In this section we compare the two different model predictions with the data. We exploit the fact that in 2014 the Danish government introduced a policy reform that lowered the initial capital requirements for incorporated firms, bringing them from 80DK to 50DK. At the same time, the government also introduced a new legal form of incorporated business to be opened with just 1DK. For this reason we considered two different policy interventions before, one which removes financial frictions completely and the other that reduces them by 37.5%, which corresponds to the drop in initial capital requirement from 80DK to 50DK. The purpose of the policy reform was to spur business activity by making it less costly to start a firm and indirectly loosening the borrowing constraint. The data suggests that indeed the policy reform was effective at increasing the number of new incorporated business registrations, but not at creating many more new entrepreneurs. In fact, most businesses that were registered after the reform actually never managed to hire anybody. This can be clearly seen from Figure 10. Panel (a) plots the total number of new incorporated business registrations three years before and after the policy reform. Indeed we see that the number increased in 2014 and remained high thereafter. Panel (b) of figure 10 plots the total number of new incorporated entrepreneurs over the same time period. We here use the E3 definition of entrepreneur, namely we require that the individual is a new owner of an incorporated business that hires at least 0.5 full time equivalent employees within the first three years from business registration. When restricting the definition, the effect of the policy is much more modest. The number of new incorporated entrepreneurs increased by 32.2% from 2013 to 2014. However, one has to consider that part of these new incorporated entrepreneurs might have opened a business in any case, but with a different legal form. To check whether this is actually true we computed the total number of new entrepreneurs across all legal types three years before and after the policy reform. We use the E3 definition of entrepreneurship, which requires to have positive revenues and at least 0.5 full time equivalent employees. The numbers of new entrepreneurs are in Table 1 of section 2. The overall increase in entrepreneurship in this case was only of 4.8%, meaning that a big fraction of the observed increase in the number of new incorporated entrepreneurs are just flows from one to another legal form.

We now compare these numbers with our model predictions. Table 6 below provides an

Figure 10: Business formation after the policy reform



(a) Total number new business registrations

(b) Total number new entrepreneurs

Notes: In panel (a) we plot the total number of new incorporated business registrations before and after the policy reform. In panel (b) we plot the total number of new entrepreneurs pre and post reform.

overview of the increase in the number of new entrepreneurs after the policy reforms in the two models. In the traditional model, the increase in the number of people who ever become entrepreneurs under the policy reform that eliminates completely financial frictions is of 163%. The same increase in the human capital model is of 13.1%. This is, however, an upper bound as the Danish policy reform did not eliminate financial frictions but just partly loosened the borrowing constraints for aspiring entrepreneurs. When computing the increase in the number of people who ever become entrepreneurs under the partial policy reform, which increased $\lambda = 2.1$ to $\lambda = 2.9$, the increase is of 23.6% in the traditional model and of 4.05% in the human capital model. The model with endogenous human capital accumulation comes much closer in matching the empirical response of new business formation to changes in financial frictions compared to traditional models, which predict much higher elasticities.

Table 8: New business formation

	Traditional model		Human capital model	
	Full reform	Partial reform	Full reform	Partial reform
Increase in entrepreneurship	163%	23.6%	13.1%	4.1%

Notes: This table computes the increase in the number of entrepreneurs after the policy reforms across the two models. The full reform consists in completely removing financial frictions, while the partial reforms consists in loosening the collateral constraint by 37.5%.

7 Conclusions

In this paper we provide new evidence on entrepreneurship dynamics over the life-cycle using a novel dataset that covers the universe of Danish businesses founded between 2000-2019. Contrary to anecdotical wisdom, we document that entrepreneurs are relatively old when they start their first business and that ex-post successful entrepreneurs are even older. We show that these life-cycle patterns of transition into entrepreneurship are mainly explained by the need of accumulating entrepreneurial human capital, rather than financial wealth. All our results show that human capital at entry is a much stronger predictor for firm survival, success and productivity dynamics compared to the owner's wealth at business start. Our empirical findings motivate the construction of a new framework to analyze entrepreneurship dynamics in which future business productivity depends on the entrepreneur's human capital. Through a number of counterfactual experiments we show that collateral constraints matter little in explaining the life-cycle patterns of entrepreneurship and that human capital plays a prominent role. Moreover, we find that the sluggish accumulation dynamics of human capital dampens the effects of any reform that tries to spur business creation by making access to credit easier. We compare the empirical increase in business formation to changes in financial frictions with the ones implied by our model and earlier models without human capital. We find that earlier models were overestimating the response of new business formation to changes in financial conditions. A model with endogenous human capital comes instead much closer in matching the data.

Our research question has direct policy implications. Entrepreneurs and start-ups significantly contribute to job creation. In order to spur business activity, and ultimately economic growth, it is crucial to know which economic factors hinder people from opening a business and what determines the success of their firm. Financial frictions are regularly cited as detrimental to business creation and several government policies are aimed to help potential entrepreneurs raise funds to overcome borrowing constraints. We stress the fact that these policies might be much less effective than believed, in light of the importance that human capital has for firm entry and the type of businesses that are started.

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