Transformative and Subsistence Entrepreneurs: Origins and Impacts on Economic Growth

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Abstract

This paper explores the symbiotic relationship between transformative entrepreneurs and inventors, which is crucial for economic growth. We utilize microdata from Denmark to demonstrate that while the relationship between IQ and general entrepreneurship tends to be negative, it is strongly positive among transformative entrepreneurs. These individuals, often with higher IQ and education levels, significantly drive R&D and business growth, thereby providing substantial opportunities for inventors. In contrast, average entrepreneurs are more influenced by their family's entrepreneurship background. Our economic model links these dynamics to overall economic expansion, highlighting how higher education influences career paths in entrepreneurship and invention. We identify a talent misallocation caused by unequal education access, particularly affecting lower-income families. Our findings indicates the most effective policies strengthen the interplay between higher education, innovation, and entrepreneurship to foster transformative businesses and achieve long-term economic growth.

Keywords: Entrepreneurship, R&D Policy, Innovation, IQ, Endogenous Growth.
JEL Classification: O31, O38, O47, J24.

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1 Introduction

A symbiotic relationship between entrepreneurs and inventors is essential for technological progress, as each plays a distinct yet vital role in the innovation pipeline. Inventors develop new technologies and products. Entrepreneurs bring innovative ideas to the market, boosting their reach. Without inventors, entrepreneurs would lack the technological advancements that create economic value. Without entrepreneurs, inventors have no market for their innovations and no remuneration for their novelty. In this paper, we investigate how entrepreneurs and inventors jointly shape economic progress, by examining the following questions. Who chooses to become an entrepreneur, and how does that path differ from becoming an inventor? What factors contribute to an entrepreneur's success? How do policies shape economic performance by influencing the distribution of talent between these two roles?

In this paper, we address these questions, with novel microdata from Denmark on inventors, entrepreneurs, and firms. We build a set of facts using detailed information on individual education, parental background, IQ, and firm performance. We embed these facts in an endogenous growth model, where heterogeneous individuals can become production workers, inventors, or entrepreneurs. This process generates the demand and supply for innovative talent, shaping aggregate innovation and economic growth. The quantified model enables us to study innovation and education policies and the interaction with the talent allocation, firm growth, and economic growth.

One striking fact at the center of our analysis is the allocation of talent between entrepreneurs and inventors by IQ, illustrated in Figure 1.

Figure 1: R&D Worker and Entrepreneur by IQ

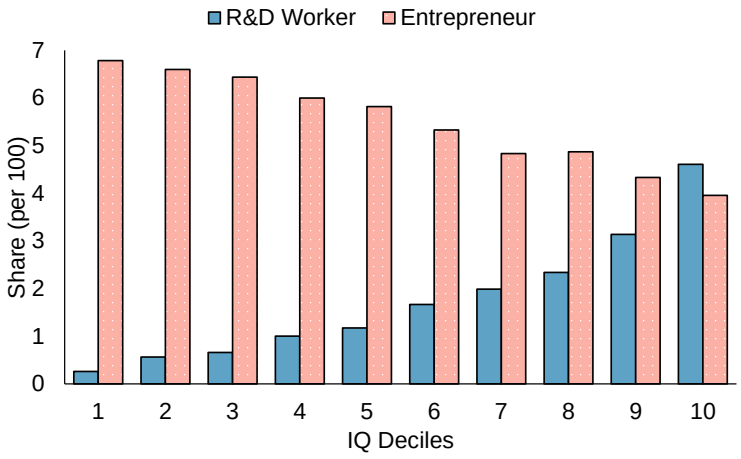


Figure 1 shows the probability that an individual is an R&D worker or an entrepreneur by deciles of the distribution of IQ test scores, which we interpret as a proxy for ability. The likelihood of being an R&D worker is increasing in IQ: the top decile is 20-times as likely as the bottom to become an R&D worker. On the contrary, the likelihood of being an entrepreneur declines with IQ, with the top decile a little over half as likely as the bottom to become an entrepreneur.

Next, we explore other important determinants that shape sorting into these professions, such as parental background and individual characteristics. We find that, while high IQ and higher education predict becoming an R&D worker, they decrease the likelihood of becoming an entrepreneur. Interestingly, we find that entrepreneurship is negatively related to IQ and family entrepreneurship experience has the strongest impact on the likelihood of becoming one. Our further analysis shows an important heterogeneity: While subsistence entrepreneurs dominate this result, transofrmative entrepreneurs, defined as the innovative ones, show a very strong correlation with IQ.

These results pave the way to explore heterogeneity in entrepreneurial types. Not all entrepreneurs seek to innovate and grow their business (Hurst and Pugsley, 2011). Only a handful of entrepreneurs are *transformative* and seek to bring new innovations to the market. In our data, we define *transformative* entrepreneurs as those who hire at least one R&D worker, as a signal of their intention to innovate. We find that the likelihood of being a transformative entrepreneur is increasing in IQ and higher education. Higher education, in turn, is correlated with higher parental income. Finally, transformative entrepreneurs' firms grow faster patent more, and exit less.

We collect our results into four main empirical facts on the determinants of initial career choice, entrepreneur type, and firm dynamics.

Fact 1 *As individual IQ increases, the likelihood of becoming an entrepreneur decreases.*

Fact 2 *Parental entrepreneurship is the strongest predictor of entrepreneurship.*

Fact 3 *IQ and education are the strongest predictors of becoming an R&D worker.*

Fact 4 *IQ and education are the strongest predictors of becoming an transformative entrepreneur, i.e., an entrepreneur who hires R&D workers.*

Fact 5 *Transformative entrepreneurs grow faster and create more jobs than subsistence entrepreneurs.*

To connect these findings to aggregate outcomes, we build an endogenous growth model that incorporates these facts into a theory of talent allocation and occupational sorting with Schumpeterian growth and firm dynamics. Individuals are born with heterogeneous ability and parental background that determines their initial educational choice, as we observe that both are important determinants of college attendance in the data. To become an R&D worker, one needs schooling (in line with Fact 1). Some individuals choose not to become R&D workers due to preference, whereas others cannot afford to pursue education due to low parental income. This friction in the access to education generates a misallocation that can propagate to the opportunity to become a transformative entrepreneur.

After choosing their initial career, both types of workers have the opportunity to become entrepreneurs throughout their lifetime. The arrival of an entrepreneurial opportunity is random, and the intensity of arrival depends on an individual's childhood exposure to entrepreneurship (Fact 2) and college education (Fact 4). Entrepreneurs hire production workers to produce goods and R&D workers to innovate, which allows the firm to expand into new product lines. Crucially, there are two types of entrepreneurs, transformative and subsistence, which are driven by talent and college attainment (Fact 4). Only transformative entrepreneurs can hire R&D workers. As a result, innovative entrepreneurs grow their firms (Fact 5) which contributes to overall innovation and growth.

This model presents novel forces that interact to link micro-level choices to macroeconomic outcomes. In particular, we highlight two effects of family background on career sorting and in particular on entrepreneurship. First, individuals with childhood exposure to entrepreneurial parents are more likely to become entrepreneurs. Second, individuals from lower income families cannot afford to pursue education and, as a result, are less likely to become transformative entrepreneurs.

The model contains two key stages that shape the innovative capacity of the economy and connect to aggregate growth. The first force is sorting into initial occupations. R&D workers represent the *supply* of innovative talent, and the drivers of their career selection are essential for overall innovation in the economy. The second force is the selection into entrepreneurship: without *demand* for R&D workers to grow firms, there is no way to transmit raw talent into overall innovation, firm dynamics and growth. Education thus serves as a bottleneck for both R&D and transformative entrepreneurship. When individuals cannot obtain education due to low parental income, they cannot become R&D workers, reducing the supply of innovative talent. Furthermore, individuals with education are more than 5-times more likely to become transforma-

tive entrepreneurs; inability to access higher education can thus reduce the demand for innovative talent. Due to the synergy between R&D workers and entrepreneurs, each misallocation channel can have important impact on innovation and growth.

After characterizing the solution of the model, we calibrate the underlying parameters by matching key feature of the microdata, with the technique of Simulated Method of Moments. The quantification focuses on the role of career sorting based on individuals characteristics and family background, driven by heterogeneous returns to R&D and production work and the life cycle of subsistence and transformative entrepreneurship.

Using the quantified model, we highlight four main results. First, higher education is a bottleneck in accessing innovative careers, due to the reliance in parental income for college education. To illustrate this point, we study a counterfactual exercise that removes financial barriers in access to education, allowing all individuals to pursue college if they wish to. Eliminating these frictions boosts economic growth by 11.1%, expands R&D worker share by 15%, and raises transformative entrepreneur share by 7.5%. The expansion of R&D workers and transformative entrepreneurs occurs mainly among individuals from the lower end of the income distribution and the upper end of the talent distribution. These results highlight that financial constraints on education create talent misallocation, preventing some high-ability individuals from becoming inventors or transformative entrepreneurs.

Second, the inability to access higher education generates talent misallocation in the economy at both the *supply* side (R&D workers) and the *demand* side (transformative entrepreneurs). To highlight the complementarity between the demand and the supply of innovative talent, we conduct a partial equilibrium counterfactual exercise with the alleviation of financial frictions, as above, but where we keep the number of entrepreneurs of each type and the firm size distribution fixed to the baseline. If the firm side of the model stays fixed, growth only picks up by 6.6%, compared to the 11.1% in the full general equilibrium described above. Thus, the demand side of innovative talent by accounts for 40% of the growth increase from alleviating financial frictions.

Third, we highlight the importance of education policy as a policy tool to foster transformative entrepreneurship and innovation. We study three policies for the same government budget equivalent to 0.05% of GDP, in the form of subsidies to either (i) education, (ii) R&D, or (iii) startup costs, which affect different margins of talent allocation and firm dynamics in the economy. Traditional industrial policy tools such as startup and R&D subsidies improve innovation by targeting, respectively, the supply and the demand side for innovative talent, with feedback effects between demand and supply. On the other hand, education subsidies can directly tackle frictions in

education access for individuals from lower income families and increase the value of education and R&D careers for all. Overall, with a 0.05% of GDP budget, education subsidies increase innovation by 15%, against 4% for startup subsidies to transformative entrepreneurs and 2% for R&D subsidies. The success of education subsidy is due to the alleviation of the education bottleneck, achieving a substantially larger increase in the shares of both transformative entrepreneurs and R&D worker compared to the other policies.

Finally, we explore the optimal mix of the three subsidies and we find that a pecking order of policies emerges. With a low budget, the entirety of the subsidy should be allocated to education, introducing innovative startup subsidies for mid-range of budgets (e.g., 0.4% of GDP), and finally including R&D subsidies only at higher budgets (e.g., 0.7% of GDP). This exercise demonstrates both the critical importance of addressing educational bottlenecks to improve innovation and the importance of mixing policies to build an ecosystem of transformative firms and R&D workers.

The rest of the paper is organized as follows. After reviewing the literature, Section 2 introduces the data and facts in the data. Section 3 introduces a model that incorporates the main facts, focusing on individual heterogeneity and the innovation production function. Section 4 reports the estimation and discusses the main quantitative mechanisms in the model. Section 5 focuses on the normative aspects of the quantified model, talent misallocation, and policy counterfactuals that address different margins. Section 6 concludes.

Literature Review. Empirically, there is a growing line of research that explores the origins of entrepreneurship and the drivers of entrepreneurial success. Much of this literature studies the forces that determine the decision to become an entrepreneur. Evans and Jovanovic (1989) and Blanchflower and Oswald (1998) find that family background is important for entrepreneurship, insofar as entrepreneurs access wealth or capital for startup. Levine and Rubinstein (2016) also argue that human capital and background characteristics play an important role in the choice to become an entrepreneur. Lindquist et al. (2015) use adoption data to show that both genetic and environmental forces determine the propensity for an individual to become an entrepreneur. We find, in line with Levine and Rubinstein (2016), that individuals are more likely to become entrepreneurs if they have parental entrepreneurs. We also extend these studies by studying who becomes an *transformative* entrepreneur with the potential to produce transformative technology.

We connect our facts in the microdata to questions of macroeconimic interest. Dat-

ing back to the early contribution of Schumpeter (1911), economists have long highlighted the connection between entrepreneurship and aggregate growth. Lucas (1978), Baumol (1990), Murphy et al. (1991), Gennaioli et al. (2013) highlight that the human capital of entrepreneurs is important in determining the productivity of firms and, in turn, the growth rate of entire economies. Decker et al. (2014) document extensively the importance of entrepreneurship in job creation. Hurst and Pugsley (2011) show that only a handful of entrepreneurs have the potential to grow and be transformative, which we incorporate in this paper. The ability of transformative entrepreneurs to scale is a key ingredient in aggregate growth (Akcigit et al., 2021). This finding connects to conceptual insights that returns to R&D workers will be low if there are not entrepreneurs who can demand their services (Michelacci, 2003). We complement this work with an extensive empirical analysis of the determinants of entrepreneurial choice and success, which leverages unique micro-level administrative data on individuals from Denmark.

Entrepreneurs must be team players. They need to focus on the vision and connect investors and employees to their core goal. This connects to word more broadly on entrepreneurial skill and how entrepreneurs must be balanced (Lazear, 2004) in their skills, which incorporates communication and networking ability (Kaplan et al., 2012). Further, an entrepreneur's network matter for their financing (Hochberg et al., 2007, 2010). As we show in this paper, schooling plays an important role for the *type* of entrepreneur. Entrepreneurs who go to school receive technical training and the chance to connect with R&D workers; this increases the likelihood of becoming a transformative entrepreneur (Hurst and Pugsley, 2011). Further, there is evidence entrepreneurial skill is persistent (Gompers et al., 2010), which is an essential ingredient to understand given how central entrepreneurs are to economic output.

There is also a significant literature on the role of inventors in producing ideas that lead to economic growth dating back to (Romer, 1990). This literature varies in terms of its focus on who becomes an inventor (Aghion et al., 2017, Akcigit et al., 2024, Bell et al., 2018), teams (Wuchty et al., 2007; Pearce, 2020), learning (Akcigit et al., 2018), and the interaction with firms (Aghion et al., 2018). We connect the literature on entrepreneurs to the literature on inventors as we document novel empirical evidence on the matching patterns and team effort in generating innovation.

We formalize and quantify the macroeconomic importance of the interaction of entrepreneurs and inventors by providing a new theory of innovation-led growth, which puts at the center the allocation of human capital to entrepreneurship, innovation and production. Our theory incorporates a model of the allocation of talent between en-

trepreneurship and work, as in Lucas (1978), into a micro-founded model of Schumpeterian growth following Aghion and Howitt (1992) and Klette and Kortum (2004), which has been used as workhorse theory of firm dynamics (see, e.g., Akcigit and Kerr, 2018; Garcia-Macia et al., 2019; Lentz and Mortensen, 2008). The importance of occupational sorting for economic growth is also highlighted by Hsieh et al. (2019). Our model enriches the existing framework by explicitly modeling the role of family background for occupational choice, building on and expanding on the work of Akcigit et al. (2024). Additionally, our model provides a micro-foundation of the complementarity between highly-skilled entrepreneurs and R&D workers in the firm.

The framework builds on a literature that has stressed the importance of matching between firms and workers. The model most closely follows the theoretical work of Eeckhout and Kircher (2018). Empirically, we add to a literature on the importance of entrepreneurs and teams in firm growth. Kaplan et al. (2009) and Choi et al. (2019) provide evidence on the importance of the entrepreneur and the managerial team for the success of a firm. Bloom and Van Reenen (2007) note how the difference in management practices is highly predictive of success. We use new empirical evidence on patterns of matching between entrepreneurs and workers with a direct proxy for ability, given by IQ, to characterize this in further detail.

2 Motivating Empirical Evidence

We start our analysis by expanding on the determinants of occupational choice employing individual and firm-level data from Denmark. We start by discussing the data with a main focus on R&D workers, entrepreneurs, and firms. We then discuss the determinants of becoming an entrepreneur and in particular a *transformative* entrepreneur, and the nature of the firms of transformative entrepreneurs. For more data detail, see Appendix B.

2.1 Data Environment

The empirical and quantitative analysis in this project uses detailed micro-level data from the Denmark Statistical Office (DST) for the years 2001-2013. We rely on four datasets that (i) contain individual background and test information; (ii) contain matched employee-employer data with detail on wages and occupations; (iii) information on entrepreneur firms and firm-level outcomes; (iv) patent data to link innovative behavior

to individuals and firms.[1]

In the empirical analysis, we group individuals into three categories of workers. Our main sample consists of entrepreneurs, R&D workers (jobs that innovate), and production workers (all workers in our sample except for R&D workers and entrepreneurs). We categorize as "R&D workers" those individuals who work in occupations with high patenting rate. More precisely, we select all occupations where at least 1% of workers ever file a patent. We then classify all individuals in those occupations as R&D workers. Thus, not all individuals who are categorized as R&D workers have ever filed a patent. Overall, individuals in R&D occupations account for 56% of total patents, while making up approximately 3% of the working population.[2] We categorize as "production workers" those individuals who work but do not have an R&D occupation.

Finally, we categorize as "entrepreneurs" those individuals who are the primary owners of a business, according to the IVPS/IVPE database. For transformative entrepreneurs, we leverage the fact that entrepreneurs that aim to transform society often leverage insights from the frontier of science and technology. In terms of data measurement, this means they are much more likely to hire R&D workers and operate in high-technology sectors. We define subsistence and transformative entrepreneurs accordingly. A *subsistence* entrepreneur is defined as an entrepreneur that does not hire an R&D worker, while a transformative entrepreneur is defined as one that hires at least one R&D worker.

2.2 The Nature of Transformative Entrepreneurs

As noted in Figure 1, individuals with higher IQ are much more likely to become inventors or R&D workers. On the other hand, entrepreneurs are *negatively* selected in terms of IQ. In this section, we focus on the determinants of career choice with particular attention to the nature of entrepreneurs. Here, we build on the growing literature that notes the important distinction between subsistence and transformative entrepreneurs.

Entrepreneurs are heterogeneous in their contributions and goals (Baumol, 1990). Across types of entrepreneurship, there is rising awareness in two types of entrepreneurs: subsistence entrepreneurs and transformative entrepreneurs (noted in Hurst and Pugsley, 2011 and Akcigit et al., 2021, among others). Subsistence entrepreneurs focus on

[1] More detail is provided in Appendix B.

[2] Appendix B.3 lists the R&D occupations, which consists of occupations where greater than 1% of individuals innovate. Due to our restriction that working occupations must be R&D or production workers, we drop individuals with a higher degree who we do not classify as R&D workers.

maintaining their business and enjoying entrepreneurship instead of employment, but do not attempt to grow or innovate. The other types of entrepreneurs are transformative: they attempt to change the nature of production in society. In our data, we define transformative entrepreneurs or those who attempt to be transformative entrepreneurs as individuals who hire an R&D worker at some point during the lifecycle of the firm.

By focusing on a *transformative entrepreneur*, we thus split our occupational categories into four groups. There are production workers, R&D workers, subsistence entrepreneurs, and transformative entrepreneurs. We plot the three non-production worker groups as a share of the labor market by IQ decile below, where the residual group is individuals in production.

To understand the determinants of *transformative entrepreneurship*, we plot the IQ deciles and ask what share of individuals in each group become subsistence entrepreneurs (left-axis) and transformative entrepreneurs (right axis). Figure 2 plots the results.

Figure 2: IQ and Entrepreneurship

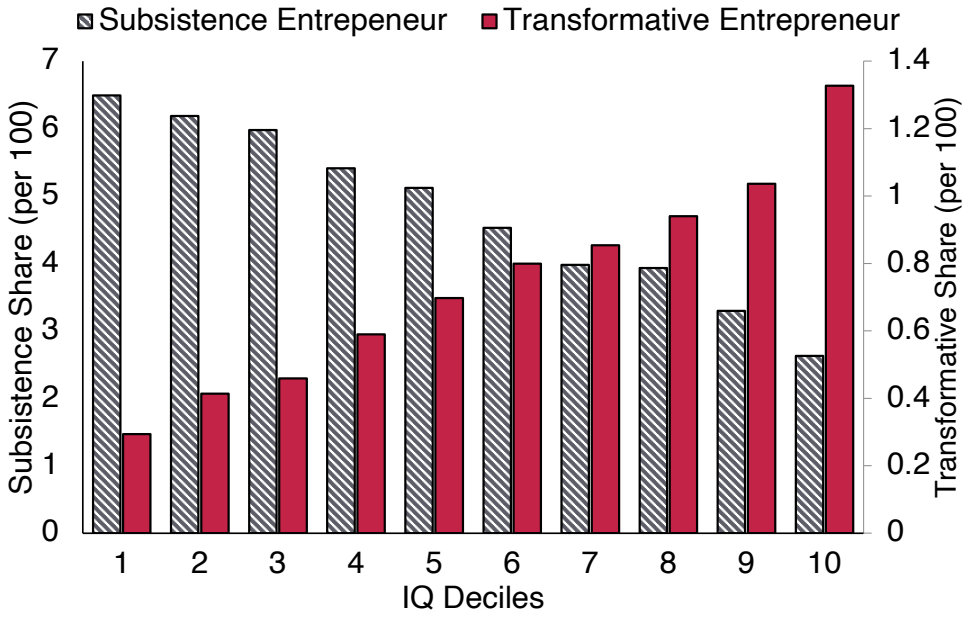


Figure 2 indicates a starkly different relationship between IQ and subsistence and transformative entrepreneurship. Rates of transformative entrepreneurship are significantly increasing by IQ, while subsistence entrepreneurs are steeply declining by IQ. For entrepreneurs in the bottom decile, 4% of them are transformative, whereas 33% of entrepreneurs in the top IQ decile are transformative. This sorting will be an important element in our framework. Next, we turn to specifications that control for various other components that drive sorting into occupations to understand the main overall

determinants.

We now report the results from two multinomial logits on the determinants of career choice for R&D workers, entrepreneurs, and entrepreneur type. We compare the determinants of entering an occupation k against becoming a production worker in Equation (1).

$$\begin{aligned}\log \frac{P_{i,k}}{P_{i,p}} =& \beta_1 college_i + \sum_{j=2}^{4} \omega_i \mathbb{I}\{IQ\ Quartile_i = j\} \\ &+ \beta_2 entrepreneur\ parents_i + \beta_3 R\&D\ worker\ parents_i \\ &+ \beta_4 production\ worker\ parents_i + \phi parent\ income_i + \epsilon_i \end{aligned} \tag{1}$$

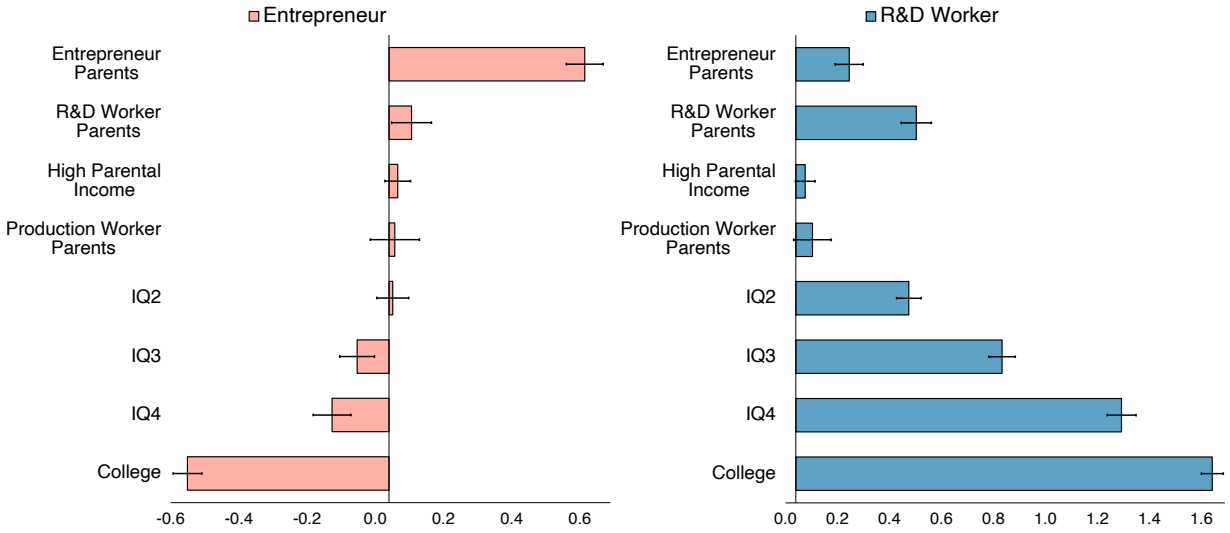
We plot the coefficients from two logistic regressions with the structure of Equation (1) in Figure 3. We focus on the likelihood of becoming an entrepreneur as opposed to a production worker in Figure 3a. We focus on the likelihood of becoming an R&D worker against production worker in Figure 3b and the likelihood of becoming a subsistence versus transformative entrepreneur in Figure 3c. We compare these to the baseline propensity to become a production worker.

As seen in Figure 3b, there is a strong connection between schooling and IQ and becoming an R&D worker. This is not so for entrepreneurs, where the strongest predictor of entrepreneurship is whether one had a parent who was an entrepreneur. In fact, those with more education and higher IQ are less likely to be an entrepreneur overall. One key factor omitted from this section is the role of parental income for college attendance. Even parental income does not affect the propensity to become an R&D worker conditional on education, it is a strong predictor for college education, conditional on IQ and parental education level. This creates a bottleneck for becoming an R&D worker through education.

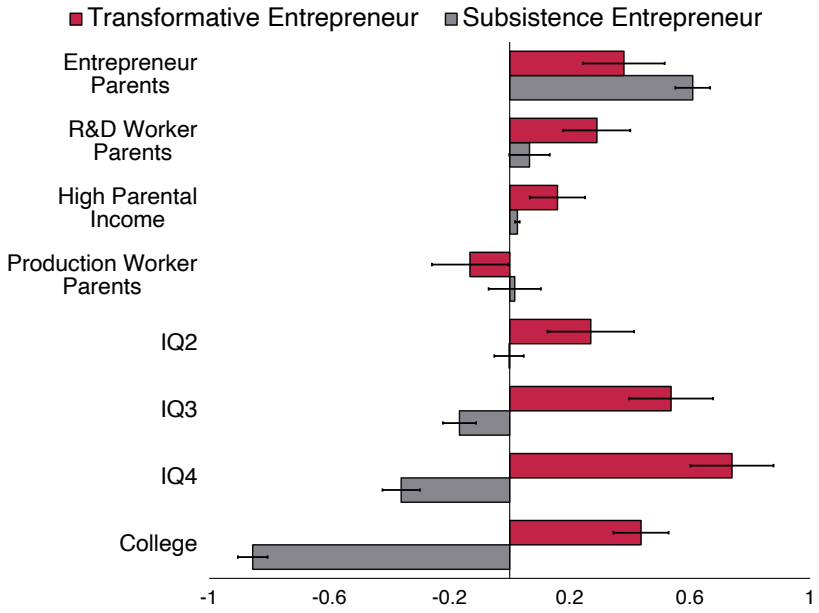
Figure 3a presents more detail on sorting into entrepreneurship types. While parental entrepreneurship is still important for transformative entrepreneurs, IQ and schooling also play essential roles, which is less important for general entrepreneurship. Subsistence entrepreneurs see the parental effect and no positive effect from IQ. Consistent with the model later discussed, there is a slight *negative selection* into subsistence entrepreneurship.

The role of education appears to create a bottleneck for both R&D workers and transformative entrepreneurs. Education increases the log odds of being an R&D worker against a production worker by more than 100%. Yet, it also increases the

Figure 3: Multinomial Logit for Career Choice



(a) Entrepreneur (b) R&D Worker

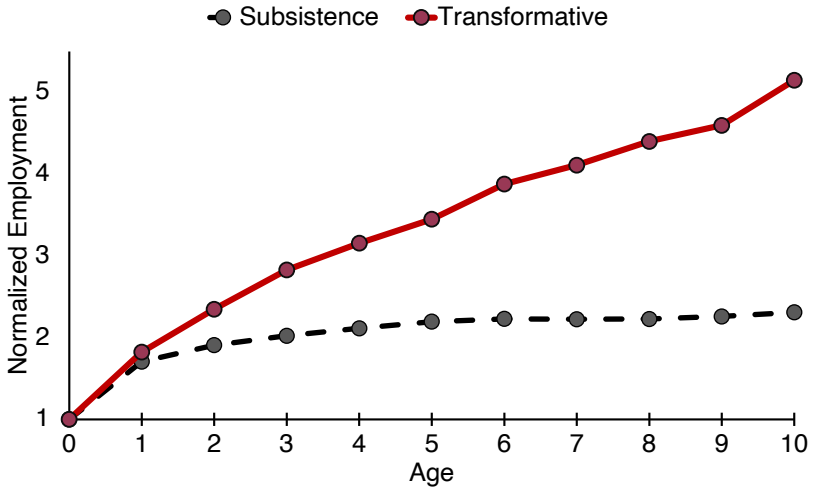


(c) Entrepreneur Type

log odds of being a transformative entrepreneur vis-a-vis a subsistence entrepreneur by more than 100%. This outsized effect of education is an important channel for opportunities into entrepreneurship. This result delivers Fact 4, that transformative entrepreneurs have higher IQs and obtain higher education.

Individuals who become a transformative entrepreneur must tie together relevant

Figure 4: Employment by Entrepreneur Type/Age



skills in both technical and entrepreneurial domains. This connection may have be important for policymakers to recognize if they want to increase entrepreneurship and growth. However, hiring R&D workers and entering innovative sectors may not lead to firm success. We next to to study the nature of firms owned by entrepreneurs and their lifecycles.

Firms. Are transformative entrepreneurs more likely to produce a successful firm? This section asks about the evolution of the employment within the firm. Figure 4 shows the log employment of firms held by transformative and subsistence entrepreneurs. We normalize their initial value to be one, even though transformative entrepreneurs start larger.

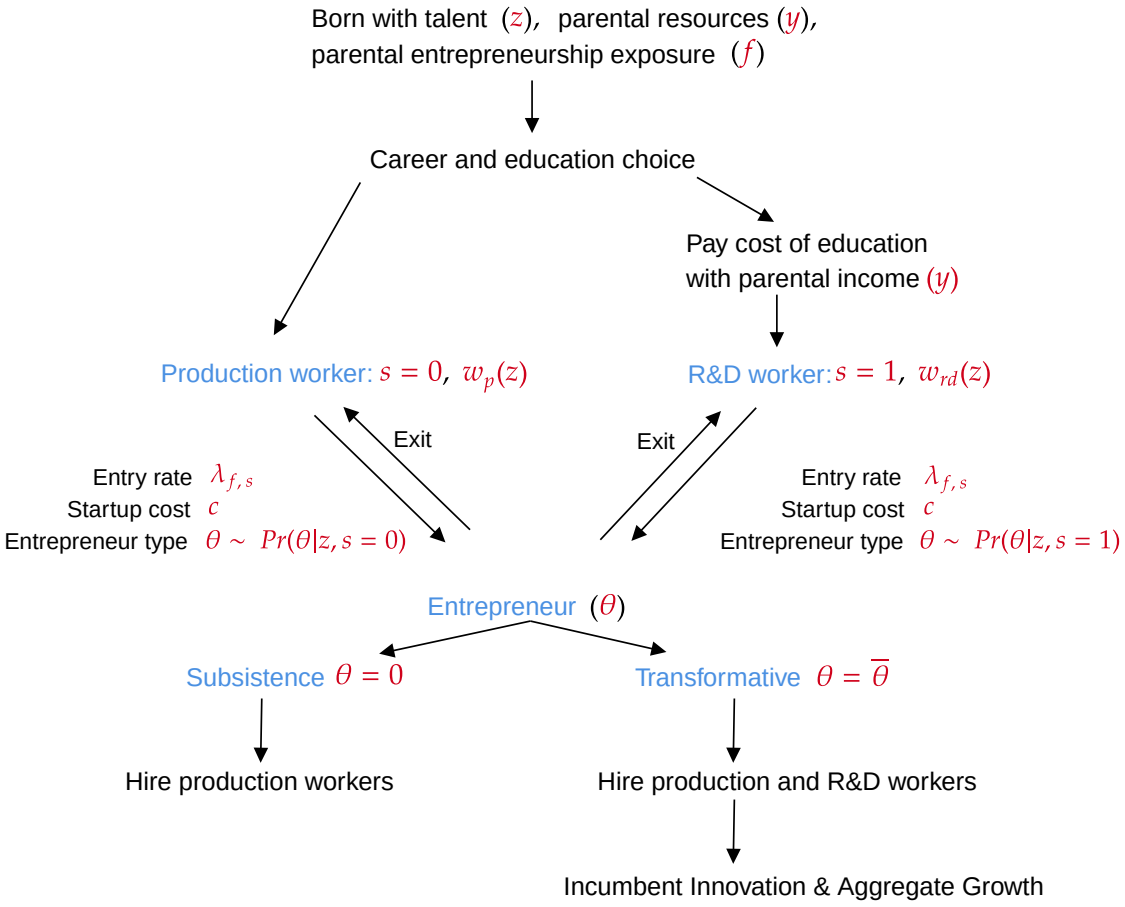
We find that transformative entrepreneurs start larger and grow faster. Transformative entrepreneurs start around twice as large as subsistence entrepreneurs and grow more than 9% faster per year. This leads to start differences in the firm size distribution of the two firm types.

3 Model

In this section, we develop a life-cycle model of career choice, entrepreneurship, and firm dynamics, built around the facts outlined in the previous section. In our model, individuals differ in ability, family background, and exposure to entrepreneurial activity. These differences affect educational decisions and ultimately shape occupational choices and the evolution of firms in the economy. The model is formulated in con-

tinuous time and designed to capture the interplay between talent allocation across occupation and firm growth along a Balanced Growth Path (BGP) equilibrium. Figure 5 illustrates the key elements of the model.

FIGURE 5: MODEL MAP



3.1 Economic Environment and Agent Heterogeneity

The economy is populated by agents that are heterogeneous in three dimensions: (i) worker ability (z), (ii) parental resources (y), and (iii) exposure to entrepreneurship through parents (f). In every period, a measure m of new agents enters the economy, with characteristics drawn from the joint distribution

$$(z, y, f) \sim \Omega(z, y, f).$$

Agents die at an arrival rate ψ and are immediately replaced by new agents with

the same characteristics such that the distribution of characteristics in the economy remains unchanged.

3.2 Education and Career Choice

When individuals are born, they first choose whether to become production worker or R&D worker. An R&D career requires acquiring costly education, where the cost of education is denoted by the parameter c_s. We interpret this cost broadly—not only as tuition fees but also as the opportunity cost of foregone income during higher education. Importantly, we assume that this cost must be paid in advance through parental resources, reflecting a form of financial friction. Therefore, individuals with $y < c_s$ cannot afford schooling and they become production worker. In addition, individuals have preferences over education characterized by (i) disutility from education, χ, and (ii) idiosyncratic preference shock ϵ_s following a type I extreme value distribution with mean zero and scale parameter ς. We denote the choice of schooling with the indicator variable $s \in \{0, 1\}$, which takes the value 1 for an individual who acquires education, which also corresponds to being an R&D worker in the model. Accordingly, we use the terms "being educated" and "being an R&D worker" interchangeably throughout the paper.

The education decision problem of an individual with state (z, y, f) who can afford education is expressed as:

$$\max \{V(z, f, 1) - c_s - \chi + \epsilon_1, V(z, f, 0) + \epsilon_0\}$$

Here, $V(z, f, s)$, $s \in \{0, 1\}$, which will be derived in the next subsection, denotes the lifetime values associated with a career as a production worker and an R&D worker, prior to accounting for education costs and preference shocks.[3] Given the distributional assumption on the preference shock, this decision problem implies that the probability of acquiring education and becoming an R&D worker is given by

$$\mathbf{P}(s = 1|z, y, f) = \mathbb{1}(c_s < y) \times \frac{1}{1 + \exp\left(\frac{V(z,f,0)}{\varsigma} - \frac{V(z,f,1)-c_s-\chi}{\varsigma}\right)}. \tag{2}$$

This equation highlights two key channels through which initial career selection operates: (i) the direct role of financial resources in restricting education access and (ii)

[3] As will become clear later, family resources influence only the education decision and play no role in other aspects of the model. Thus, worker values do not depend on y.

the economic trade-offs between present schooling costs and future career returns. The first component, $\mathbb{1}(c_s < y)$, is an indicator function that equals 1 if parental resources exceed the cost of education, and 0 otherwise. This represents the financial constraint that individuals face—education is only possible when family resources can cover its costs. This formulation directly captures the credit market imperfections that prevent talented individuals from low-resource backgrounds from obtaining education rather than due to lack of aptitude or preference. The second component, a standard logit function derived from the extreme value distribution of preference shocks, reflects the trade-off between the lifetime values of being a production worker $V(z, f, 0)$ and an R&D worker $V(z, f, 1)$, adjusted for schooling costs c_s and disutility χ. A higher ς increases the role of idiosyncratic preferences, making the decision more dispersed and less deterministic.

3.3 Workers Value and Entrepreneurial Startup Decision

After making the initial career choice, agents enter the competitive labor market where they start earning wage income $\omega(z, s)$ based on their ability z and educational attainment s. We allow for heterogeneity in productivity across occupations by assuming that a worker with talent z supplies z^{α_s} efficiency units in the labor market, where α_s governs the rate at which productivity increases with ability for a given occupation $s \in \{0, 1\}$. Consequently, the wage income per period is given by

$$\omega(z, s) \equiv w_s \, z^{\alpha_s},$$

where w_s denotes the wage per efficiency unit for a worker with education level s.

In addition to wage income, agents receive random opportunities to become entrepreneurs over the course of their life cycle. This opportunity arrives at rate $\lambda_{f,s}$ which depends on whether the agent has an entrepreneur family, $f \in \{0, 1\}$, and her education s. When the entrepreneurship opportunity arises, the agent draws an entrepreneur type θ coming from a distribution $\Pi(\theta|z, s)$, where $\theta \in \{0, \bar{\theta}\}$. The types $\bar{\theta}$ are *transformative entrepreneurs*: they hire both production workers as R&D workers, and the latter enables them to innovate in an attempt to expand their firms. The types $\theta = 0$ only engage in production and do not innovate, but they may still grow exogenously.

The worker's decision to transition from being an worker to an entrepreneur involves comparing the expected benefits of starting a firm—net of a stochastic entry cost

c_e—with the continuing value of remaining a worker.[4] If she decides to become an entrepeneur, she leaves the labor force and starts a firm. Thus, an agent can occupy one of three roles at any given time: (i) production worker, (ii) R&D worker, and (iii) entrepreneur.

Given this setting, lifetime value of the workers solves the following equation:

$$\begin{aligned} rV(z,f,s) = \omega(z,s) & \\ &+ \lambda_{f,s}\left[\mathbb{E}_{c_e,\theta}\left(\max\left\{V_e(\theta) - c_e, V(z,f,s)\right\}\right) - V(z,f,s)\right] \\ &+ \psi\left[0 - V(z,f,s)\right]. \end{aligned} \tag{3}$$

The left-hand side, $rV(z,f,s)$, represents the required return on the worker's lifetime value at the discount rate r. On the right-hand side, the first term, $\omega(z,s)$, captures per period wage income earned by the worker based on their ability and education. The subsequent term, scaled by the arrival rate of entrepreneurial opportunities $\lambda_{f,s}$, reflects the net benefit of the option to transition into entrepreneurship: the worker compares the expected payoff from entering entrepreneurship—which is given by the maximum of the firm value $V_e(\theta)$ net of the entry cost c_e and the continuation value $V(z,f,s)$—to simply remaining a worker. This expectation is taken over the distributions of the entry cost and entrepreneurial type θ. Finally, the last accounts for the possibility of death at rate ψ, which effectively reduces the worker's value to zero upon exit from the economy.

We next turn to describe what entrepreneurs do and the resulting firm dynamics.

3.4 Entrepreneurship and Firm Dynamics

The firm side of the model draws on the framework by Klette and Kortum (2004) to capture the dynamics of innovation and firm growth. In our setting, each firm is owned and operated by entrepreneurs, and conceptualized as a portfolio of product lines that generate static profits, while the firm's overall value is determined by its capacity to invest in innovation. Firms engage in R&D activities with the goal of enhancing product quality and adding new product lines, thereby expanding their market presence. However, this growth is counterbalanced by competition—innovative efforts by competing firms leading to the loss of product lines. As a result, a firm's value evolves dynamically

[4]Here, the cost of starting a new firm is orthogonal to family background, which is consistent with our empirical evidence as well as current evidence from the literature (Robb and Robinson, 2012).

in response to both successful innovations, which boost its competitiveness and growth potential, and adverse events that reduce its portfolio. Firms enter the market with a single product line, reflecting the minimal initial scope of an entrepreneurial venture. Exit arises through two distinct channels. On the one hand, creative destruction drives the exit of product lines as innovations by competitors render existing technologies obsolete, reducing a firm's portfolio. On the other hand, an exogenous death rate, ψ, forces the firm's value to drop to zero upon the entrepreneur's exit from the economy. Together, these entry and exit processes generate a dynamic equilibrium in which the composition and size of firms continuously evolve, thereby driving aggregate growth and the reallocation of resources across the economy.

In this section, we introduce the intertemporal decision problem for a firm, which optimizes innovation effort to attempt to grow. Innovation is undirected across product lines and allows firms to develop a new product and thus add one product line to its portfolio at arrival rate X. The innovation technology to produce arrival rate X for a firm with type θ and n product lines is the following:

$$X(n,\theta) = \theta L_{rd}^{\sigma} n^{\eta} \tag{4}$$

where L_{rd} is the quantity of R&D workers efficiency units that the firm hires from the market and $\sigma + \eta \leq 1$, so that we allow for decreasing returns to scale, motivated by the evidence provided by Akcigit and Kerr (2018). R&D workers are paid a wage w_{rd} per efficiency units. This implies the following cost function for R&D:

$$C(x,n,\theta) = w_{rd} n x^{\frac{1}{\sigma}} \theta^{-\frac{1}{\sigma}} \tag{5}$$

where $x \equiv X/n$ is the "innovation intensity" (innovation effort per product). Notice that the entrepreneur type θ enters into the innovation function: only the type $\theta = \bar{\theta}$ can produce a positive innovation arrival rate, while the type $\theta = 0$ produces no innovation and thus will choose not to hire any R&D workers.

When innovation is successful, the firm with the improved technology in product line j takes over the product line at the expense of the previous incumbent. As a result, all firms are subject to the risk of losing one of their product lines due to innovation by competitors at an endogenous rate τ, which we term the *creative destruction* rate. Additionally, the entrepreneur dies rate $\psi > 0$, which causes the firm to exit and shut down all its product lines.

Given the above innovation production function, we introduce the value of a firm,

V_f, which satisfies the following equation :

$$\begin{aligned}
\rho V_f(n,\theta) &= \pi n && (6)\\
&+ \tau n \left[V_f(n-1,\theta) - V_f(n,\theta)\right] && (7)\\
&+ \max_x \left\{xn \left[V_f(n+1,\theta) - V_f(n,\theta)\right] - C(x,n,\theta)\right\}\\
&+ \psi \left[0 - V_f(n,\theta)\right]\\
&+ \upsilon n \left[V_f(n+1,\theta) - V_f(n,\theta)\right],
\end{aligned}$$

subject to Equation (4) and Equation (5). The first term on the right-hand side, πn, captures the aggregate flow profits generated by the n product lines. The subsequent term, $\tau n \left[V_e(n-1,\theta) - V_e(n,\theta)\right]$, reflects the loss in value due to creative destruction, where each product line faces the risk of being displaced, reducing the firm's overall value. The maximization component, $\max_x \left\{xn \left[V_e(n+1,\theta) - V_e(n,\theta)\right] - C(x,n,\theta)\right\}$, represents the firm's decision on how much to invest in innovation; by choosing an optimal innovation effort x, the firm aims to expand its portfolio (increasing the number of product lines from n to $n+1$) at an associated cost $C(x,n,\theta)$. The term $\psi \left[0 - V_e(n,\theta)\right]$ accounts for the risk of exit due to the death of the entrepreneur, which immediately nullifies the firm's value. Finally, the additional term $\upsilon n \left[V_e(n+1,\theta) - V_e(n,\theta)\right]$ captures exogenous factors that contribute to growth by effectively augmenting the firm's product lines.

The terms in Equation (6) can be interpreted as follows. The first term to the right of the equal sign indicates the static flow profits earned by a firm with n product lines. The second term indicates that each product line of the firm is subject to creative destruction at rate τ due to innovation activities by other incumbents and new entrepreneurs, in the event of which the firm will lose one product. The third term represents the innovation problem of the firm, which optimizes the number of R&D workers to hire in order to obtain innovation rate x. The fourth term indicates the event of the death of the entrepreneur, at rate ψ, in which case the value of the firm goes to 0. The last term indicates the exogenous arrival of a vacant product line assigned to the entrepreneur, at rate υ. We note that the exogenous arrival of vacant product lines is not associated with a productivity increase in the production process, because it is not the result of an innovation. The rate υ is exogenous to the firm but determined endogenously in equilibrium so that all the inactive product lines are distributed randomly across firms in proportion to their size. As a result, the exogenous arrival rate of vacant product

lines is a source of exogenous growth for those subsistence firms with $\theta = 0$.

The endogenous creative destruction rate τ captures the total amount of innovation by new entrants and incumbent firms and is given by:

$$\tau = \sum_{\theta} e_{\theta} + \sum_{n} x(\theta) n \Psi(n, \theta), \tag{8}$$

where e_θ denotes the innovation due to entrants of type θ, while the second term indicates the innovation due to incumbents with n product lines, which have innovation rate per product line $x(\theta)$ and $\Psi(n, \theta)$ denotes the mass of type-θ firms with number of product lines n.

3.5 Market Clearing and Growth Conditions

In our model, equilibrium requires that labor markets clear and that the process of creative destruction is consistent with aggregate growth. In what follows, we detail the market clearing conditions for production and R&D workers, and then describe how the overall rate of creative destruction feeds into the growth rate of the economy.

The production worker market clearing condition ensures that the aggregate supply of labor in production matches the labor demand across all product lines. In our framework, each production worker supplies labor according to their ability, represented as z^{α_p}, where α_p governs the returns to talent in production. The market clearing condition for production workers is thus given by

$$\begin{aligned}
\int_{\mathcal{N}} l_j &= \sum_{f} \int_{z,y} \phi(z, y, f, 0)\, z^{\alpha_p} \frac{1}{\omega_P \gamma} \sum_{s} \sum_{f} \sum_{\theta} \sum_{n} n \int_{z} \Psi(n, \theta, z, f, s) \\
&= \sum_{f} \int_{z,y} \phi(z, y, f, 0)\, z^{\alpha_p} \frac{1}{\omega_P \gamma} \sum_{\theta} \sum_{n} n \Psi(n, \theta) \\
&= \sum_{f} \int_{z,y} \phi(z, y, f, 0)\, z^{\alpha_p}.
\end{aligned}$$

Here, $\phi(z, y, f, 0)$ denotes the density of production workers with characteristics (z, y, f), while $\Psi(n, \theta, z, f, s)$ characterizes the distribution of firms by the number of product lines n, entrepreneurial type θ, and worker state. It is important to note that, although we normalize the total mass of product lines to one, the term $\sum_n n\, \Psi(n, \theta, \cdot)$ does not sum to one because of the presence of an exogenous death rate ψ, which reduces the effective mass of product lines.

The R&D labor market clearing condition equates the aggregate supply of R&D

labor with its corresponding demand in the innovation sector. In our model, a worker's contribution to R&D is adjusted by a factor that depends on the innovation intensity and the type-specific parameter θ. This condition is formalized as

$$\sum_s \sum_f \sum_\theta \sum_n \left(\frac{1}{\theta}\right)^{\frac{1}{\sigma}} x(\theta)^{\frac{1}{\sigma}} n \int_z \Psi(n,\theta,z,f,s) = \sum_f \int_z \phi(z,f,1)\, z^{\alpha_{RD}},$$

or equivalently,

$$\sum_\theta \sum_n \left(\frac{1}{\theta}\right)^{\frac{1}{\sigma}} x(\theta)^{\frac{1}{\sigma}} n\, \Psi(n,\theta) = \sum_f \int_z \phi(z,f,1)\, z^{\alpha_{RD}}.$$

In this expression, $\phi(z,f,1)$ represents the density of R&D workers and $z^{\alpha_{RD}}$ captures the productivity of R&D labor. Note that numerical integration is necessary in this condition due to the dependence of the probability distribution of θ on z, which introduces additional heterogeneity into the R&D labor supply.

The process of creative destruction is central to the dynamics of our model. It is driven by both new entrants and the innovation activities of incumbent firms. The overall rate of creative destruction, denoted by τ, is given by

$$\tau = \sum e_\theta + \sum_n \left[x(\theta) + \nu_n\right] n\, \Psi(n,\theta).$$

Here, $\sum e_\theta$ captures the contribution of entrants to creative destruction, while the term $\sum_n \left[x(\theta) + \nu_n\right] n\, \Psi(n,\theta)$ reflects the impact of incumbent firms' innovation efforts and the associated risk of losing product lines. The parameter ν_n represents additional exogenous factors that affect the innovation rate at the product line level.

The growth rate of the economy, g, is intimately linked to the process of creative destruction. In our model, growth is determined by the quality improvements achieved through successful innovation. Specifically, the growth rate is expressed as

$$g = \ln(\gamma)\, \tau_g,$$

where $\gamma > 1$ is the quality step achieved through innovation, and τ_g is the effective rate of innovative entry contributing to growth. The effective innovation rate is defined as

$$\tau_g = \sum s_\theta^I e_\theta + \sum_n x(\theta) n\, \Psi(n,\theta),$$

with s_θ^I representing the share of innovative entry by θ-type firms that leads to a quality improvement. This parameter is calibrated using empirical evidence to reflect the relative impact of transformative innovations on the overall growth of the economy.

Model Takeaways

One of the main messages of this paper is the connection between talent allocation and firm dynamics. We incorporate this into the theory by developing a model that connects career choice with firm dynamics. The model of firm dynamics is standard but incorporates realistic components to connect it to career choice and to the data. The number of R&D workers and transformative entrepreneurs is scarce; entrepreneurs hire production workers to innovate and face diminishing returns to size due to span of control; finally, overall growth emerges as an outcome of the amount of R&D workers, entrepreneurs, and their sorting. Much of the model is simply an extension of a standard firm dynamics model to incorporate both the supply and demand of innovative talent.

As we move to the quantitative analysis, we focus on the talent allocation and the mechanics of firms through their hiring and growth. As in the model, the quantitative section marries the decisions that determine career choice with firm-level outcomes in order to speak to policy counterfactuals. We turn to this next.

4 Estimation

In this section, we connect the empirical facts to the model framework in order to uncover fundamental parameters driving education choice, occupational choice, and firm dynamics from entrepreneurs. We start by calibrating the model parameters to the data and then provide a set of counterfactual analyses to quantify talent misallocation in the economy and the effectiveness of various policies to alleviate this misallocation.

4.1 Functional Forms and Identification

We assume that z and y follow a bi-variate lognormal distribution with mean parameters μ_z and μ_y, standard deviation σ_z and σ_y, and correlation $\rho_{z,y}$, and probability of being exposed to entrepreneurship through parents is given by p_f. Motivated by our empirical evidence, the probability of drawing a type $\bar{\theta}$ and becoming a transformative

entrepreneur depends both on talent z and investment in schooling s, according to the following equation:

$$Pr(\theta = \theta | \bar{z}, s) = \frac{\epsilon + \iota \times s}{1 + \exp\left(-\kappa\left(z - \zeta\right)\right)},$$

where ϵ, κ, ζ, and ι are parameters. Lastly, entry cost for entrepreneurship c is drawn from a Pareto distribution with shape parameter φ and scale parameter 1.[5].

We start by describing our estimation procedure. Our model has 21 parameters, 5 of which are calibrated externally. We set the discount rate ρ to 3 percent. Following the microeconometric literature on innovation, we set the curvature of innovation production function $\sigma = 0.5$, indicating a quadratic cost function.[6] The death rate ψ is set to 0.025, implying 40 years of expected working life. Finally, we calibrate μ and ϑ_y to match the correlation between individuals' IQ and their family income and dispersion in family income, respectively.

The remaining 16 parameters are calibrated jointly by matching 37 moments from the data to model-generated moments, which are presented in Table 1. We use several moments that reflect the talent allocation in the economy to identify our model parameters. These moments center on occupation shares by several cuts of the data, the performance of transformative entrepreneurs and aggregate growth rate, selected in each case because of their economic importance for the mechanisms of the model. For example, we target R&D workers and entrepreneurs share by IQ deciles to discipline the parameters the determines the returns to each occupation occupation, such as α_s, γ and c_s. We target the share of transformative entrepreneurs by IQ deciles as well as by schooling to pin down the parameters determining the probability distribution of types (κ_0, κ_1, ζ and ι). Moments on entrepreneurship rates by parental entrepreneurship background are useful to pin down λ_0 and λ_1.

We combine individual level moments with firm-level moments to connect these two core features of our framework. We use the average firm size growth of transformative entrepreneurs relative to the growth of subsistence entrepreneurs to identify $\bar{\theta}$. A core component of our framework is the innovation production function, which delivers firm growth of $x(n, \theta) = \theta L_{rd}^{\sigma} n^{\eta - 1}$. Thus, . To identify the curvature of the innovation production function with respect to the size of the firm, we run the following regression at the firm level:

[5]In our formulation, the arrival rate of entrepreneurship opportunity, λ, and scale parameter of the entry cost cannot be identified separately, therefore we normalize the latter to 1

[6]See Akcigit and Kerr (2018) and Acemoglu et al. (2018), who discuss this evidence in more detail.

$$\log(R\&D\ Worker_f) = \beta_0 + \beta_1 \log(Total\ Worker_f) \tag{9}$$

This leverages the following equation with the innovation intensity x given by the firm-level incentives,

$$\log L_{rd} = \frac{\log x - \log \theta + (1-\eta)\log n}{\sigma}.$$

This relationship between how firm innovation intensity scales with growth is going to identify the span of control of entrepreneurs given σ. How entrepreneurs can scale R&D workers matches their optimal innovation intensity. This element creates decreasing returns to entrepreneurship, as R&D workers do not scale one-to-one with firm size. This is consistent with the economy's need to have a robust pool of entrepreneurs pool to absorb R&D workers without hitting diminishing returns. We now turn to the estimation results to connect the moments to the underlying parameters.

4.2 Estimation Results

We present the target moments in the model and the data in Table 1 and Figure 1 and the estimated parameters in Table 2. Overall, the calibrated model closely aligns with the target moments in the data. The quantification connects central elements of the theoretical and empirical framework, which we discuss below.

Table 1: Moments

Description	Model	Data
R&D workers share by IQ	In Figures	
Entrepreneurs share by IQ	In Figures	
Transformative entrepreneur share by IQ	In Figures	
R&D workers share in highest family income decile	0.027	0.028
Entrepreneur share by entrepreneur parent	0.100	0.100
Entrepreneur share by non-entrepreneur parent	0.060	0.060
Entrepreneur family share	0.080	0.080
Average firm size at age 10 - Subsistence entrepreneur	2.297	2.270
Average firm size at age 10 - Transformative entrepreneur	4.963	5.080
Share of transformative entrepreneurs within uneducated entrepreneurs	0.006	0.007
Share of transformative entrepreneurs within educated entrepreneurs	0.049	0.050
R&D workers log wage premium - highest to lowest IQ decile difference	0.089	0.090
Share of financially constrained agents	0.300	0.300
Regression coefficient in Equation (9)	0.378	0.380
Aggregate growth rate(%)	1.000	1.000

Notes: Average firm size moments are relative to entry size.

The estimation matches the specific moments and the occupational distribution quite well. We turn to the parameters that generate these moments in Table 2.

Some of the moments are directly linked in the model and data, such as the income distribution, talent distribution, and the correlation of income and talent. The education cost, innovation step size, labor share in the innovation function, and discount rate come from the literature. The death rate comes from an expected working life of 40 years.

When it comes to internal calibration, we perform a joint estimation as discussed. We focus on some key moments here that capture the main intuition of the model. Some central moments to the model are the life cycle of firms, where we look at the different life cycle of subsistence versus entrepreneurial firms. These life cycles plus the selection into entrepreneurship are well matched through the calibration of the draw from the entrepreneurial distribution as well as the

Our estimation delivers that the relative arrival rate of entrepreneurial ideas is higher for individuals with entrepreneurial parents ($\lambda_1 > \lambda_0$), consistent with their

Table 2: Parameter Values

Parameter	Description	Value
	— Panel A. External Calibration —	
r	Discount rate	0.050
ψ	Death rate rate	0.025
σ	Labor share in innovation function	0.500
σ_z	SD of talent distribution	0.224
σ_y	SD of family income distribution	0.619
$\rho_{z,y}$	Correl of talent and family income	0.144
p_f	Probability of parental entrepreneurship exposure	0.080
c_s	Education cost	0.275
γ	Innovation step size	1.250
	— Panel B. Internal Calibration —	
λ_1	Entrepreneurship arrival rate w/ entrepreneur parent	0.0005
λ_0	Entrepreneurship arrival rate w/o entrepreneur parent	0.0002
λ_e	Contribution of education to entrepreneurship arrival rate	0.001
$\bar{\theta}$	Scale for innovation function	0.235
κ	Entrepreneurial type draw function	1.413
ι	Entrepreneurial type draw function	3.358
ζ	Entrepreneurial type draw function	3.519
ϵ	Entrepreneurial type draw function	0.354
α_{rd}	Wage function - R&D workers	0.545
α_p	Wage function - Production workers	0.495
m	Entrant cohort mass	0.181
μ	Mean of family income distribution	0.461
η	Product line share in innovation function	0.338
χ	Disutility from education	3.153
ς	Education preference shock scale	0.389
ν	Exogenous arrival rate of products	0.125

Notes: All parameters are estimated jointly.

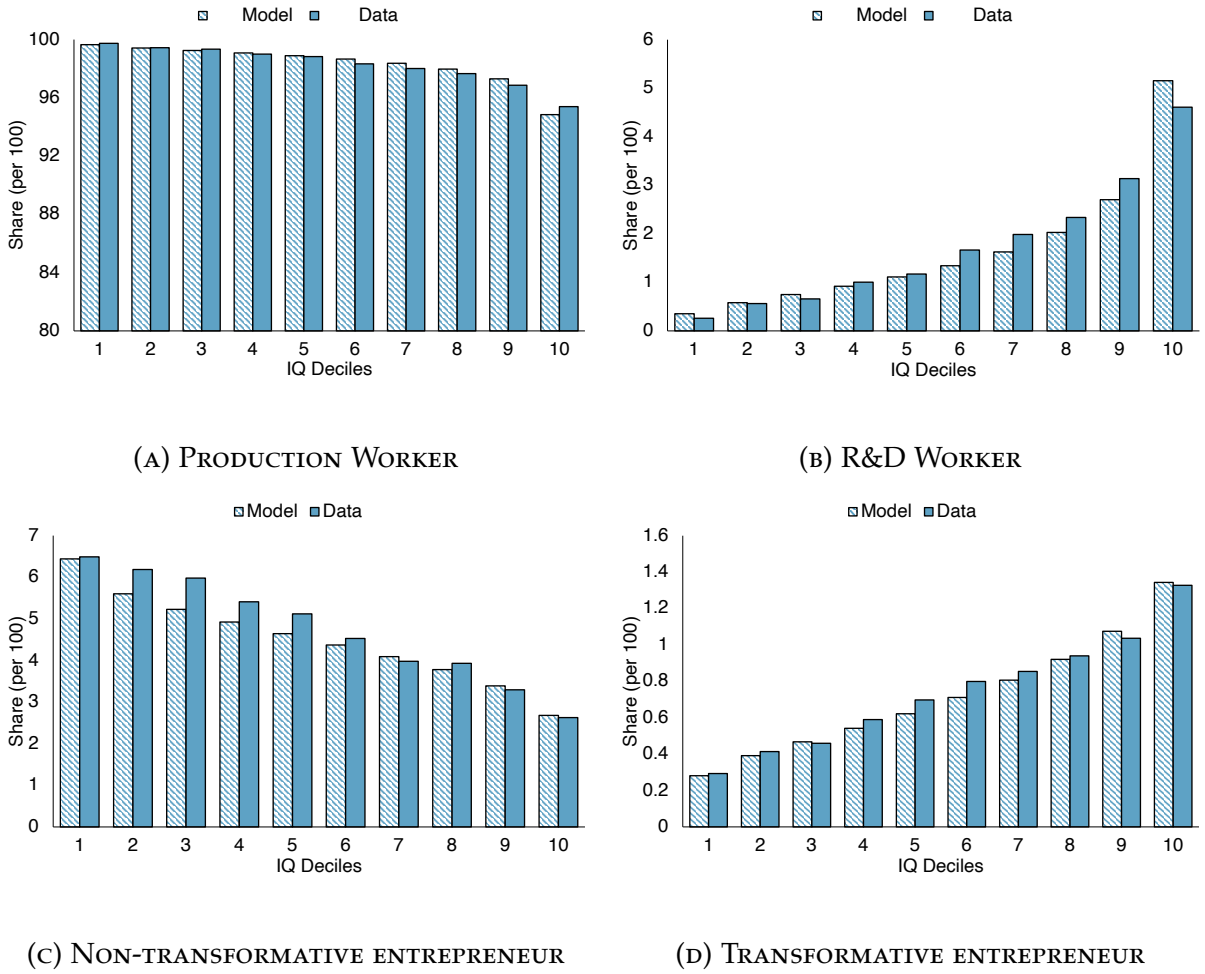
higher entrepreneurship rates in the data. Individuals with family exposure to entrepreneurship are about 67% more likely to become entrepreneurs than individuals without exposure, both in the model and in the data, as illustrated in Table 1. We view this effect as a feature that can hardly be improved by policy, given that it captures exposure effects such as information about entrepreneurial careers conveyed by parents or networks of contacts that can be useful to start a firm.

The reliance on parental resources to cover the cost of education implies that there

are individuals of high ability who would like to invest in education but cannot afford it, leading to talent misallocation in the economy. In particular, our model predicts that an individual in the top talent decile who chooses to get educated is about twice as likely to become a transformative entrepreneur than an individual in the same talent decile who would like to invest in education but cannot afford it.

On the career choice side, we see in Figure 7 the share of individuals by occupation and IQ decile, as calibrated in the model and in the data. Overall, the model provides a close match for the talent allocation pattern across occupations in the data.

Figure 6: Talent Allocation across Types



(a) Production Worker

(b) R&D Worker

(c) Non-transformative entrepreneur

(d) Transformative entrepreneur

We highlight several important results on talent allocation. To begin with, there is a positive selection of R&D workers by talent in the model and the data. Both production workers and R&D workers wage is increasing in their ability. The former one being positive identifies the decline in entrepreneur by IQ. The second one is identified both

from the premium increasing in IQ... In the model, positive selection to become an R&D worker is driven by two reasons. First, individuals with higher IQ have a steeper wage profile as R&D workers, because in our estimation $\alpha_{rd} = 0.545$ is larger than $\alpha_p = 0.495$, implying that the wage premium increases in ability. Thus, individuals with higher ability have more incentive to obtain education and become an R&D worker to earn a higher wage.

Second, the positive selection of R&D workers is also explained by the option value of becoming an R&D worker. In particular, talented individuals are more likely to draw a transformative entrepreneurial idea, because of our estimation of a positive $\kappa = 1.413$. In addition, college attainment boosts the arrival rate of entrepreneurial ideas by the factor $\lambda_e = 0.001$. This boost is particularly valuable for highly talented individuals, who are more likely to draw a high type idea, conditional on idea arrival.

Next, we further evaluate selection into entrepreneurship, which we split into *subsistence* and *transformative* entrepreneurs. The share of subsistence entrepreneurs is monotonically declining across the IQ distribution. The transformative entrepreneur share, on the other hand, increases across the distribution. This selection is explained by the positive effect of higher IQ on the probability of drawing a high-type entrepreneurial idea, due to our estimation of a positive parameter κ, as explained above. Overall, higher-IQ individuals and those with more schooling are more likely to become transformative entrepreneurs. The effect of college on transformative entrepreneurs is captured by two parameters: $\iota =$, which increases the probability of drawing a high type idea, and the higher arrival rate λ_e. These two parameters allow us to match the empirical result that the rate of transformative entrepreneurship is higher among college-educated individuals.

Overall, the positive sorting of highly talented individuals into transformative entrepreneurship comes from higher returns to higher-skill types in school and the effect of education on the arrival rate of transformative entrepreneurial types. However, individuals' family background may distort the career sorting and talent allocation in the economy due to two effects: (i) parental exposure to entrepreneurship (affecting λ) and (ii) parental resources to cover the education cost (affectingf .

The career choice of individuals also impacts firm growth. We identify the relative growth of subsistence and transformative entrepreneurs, and find substantial differences in their growth rates. By age 10, transformative entrepreneurs are more than twice as large, relative to their initial size, as subsistence entrepreneurs. This effect is even larger in levels. We also see, as expected, transformative entrepreneurs with higher patenting rates and more likely to be in high-tech industries.

4.3 Untargeted Moments

In the calibration, we connected career choice and firm dynamics. However, there are a rich set of interactions between background, career choice, and firm dynamics that we did not directly target in the calibration. In this section, we compare our quantified model against untargeted features of the data with respect to occupational sorting and firm dynamics.

First, we examine the transition probability from being a worker to being a transformative entrepreneur split by worker type. This was something not directly targeted in the data. Panel A of Table 4 shows that, in the data, 76% of the entrepreneurs with a background as R&D workers are transformative, while the remaining 24% are subsistence entrepreneurs. On the contrary, production workers who become entrepreneurs are much more likely to be subsistence types, while only 11% of them are transformative entrepreneurs. The table indicates that the quantified model aligns closely with the data in terms of the higher propensity of entrepreneurs with R&D background to be transformative compared to those with a production worker background.

Table 3: Untargeted Moments

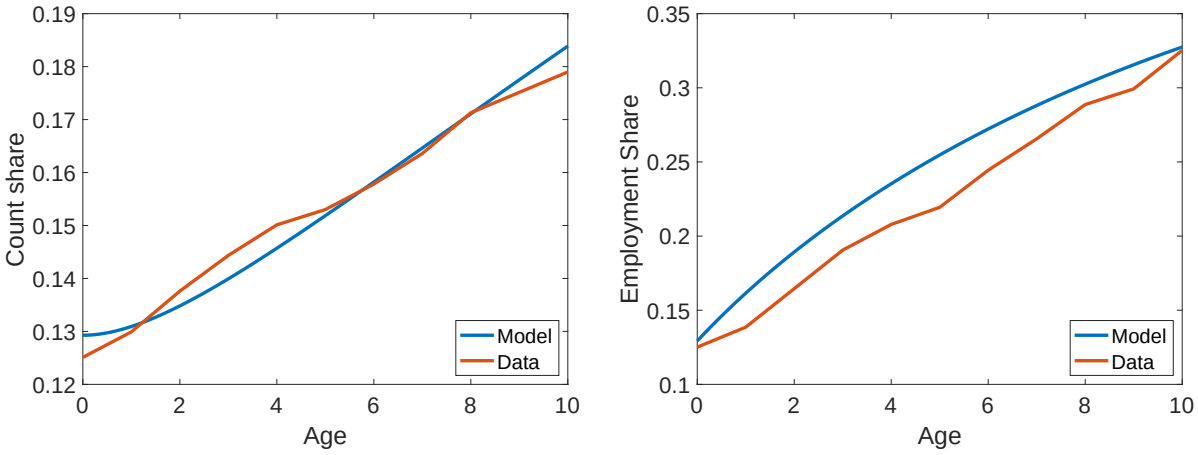
	— Career Choice —		*— Firm Dynamics —*			
	Transformative Share		**Firm Age 5 size**		**Firm Age 10 size**	
	Data	*Model*	*Data*	*Model*	*Data*	*Model*
R&D Worker	0.76	0.91	3.16	2.99	4.35	4.72
Production Worker	0.11	0.12	2.62	1.81	3.04	2.61

Next, we examine the dynamic evolution of a firm's size depending on the entrepreneur's talent and occupation background. Panel B of Table 4 reports the average firm employment at ages five and ten relative to age 0. The table indicates that, in the data, firms with entrepreneurs who have R&D worker background grow by a factor of 3.16 after five years and 4.25 after ten years. Firms run by entrepreneurs with a production worker background tend to be grow less instead, by a factor of 2.62 after five years and 3.04 after ten. The quantified model closely matches the data along these dimensions. In addition, the table shows that firm run by high-IQ entrepreneurs, measured as those with IQ above the median, tend to be larger than those run by low-IQ entrepreneurs. The model replicates the larger size for firms run by IQ entrepreneurs, although it somewhat misses on the level of employment reached after ten years.

Finally, we examine the dynamics of firm size by entrepreneurial type. Figure 7 shows the share of firms, in Panel (A), and the share of total employment, in Panel (B),

accounted for by transformative entrepreneurs by firm age.[7]

Figure 7: Untargeted Moments: Share of Transformative Entrepreneurs



(a) Share of Transformative Entrepreneurs (b) Employment Share of Transformative Entrepreneurs

The pattern is monotonically increasing, as transformative inventors account for a share of firms that increases from about 13% at age zero to 18% at age ten, and a share of total employment that increases from about 13% at age 0 to more than 30% at age ten. Both the model and the data are quite aligned, indicating the rising role of transformative entrepreneurs over the firm life cycle. The role of these transformative entrepreneurs will also be central to misallocation and policy counterfactuals.

4.4 Education and Entrepreneurship

Before turning to the counterfactual analysis, we direct our focus to the importance of education for entrepreneurship and firm dynamics. The quantified model suggests education is not just important for the creation of R&D workers, but also for the role of entrepreneurs. To highlight the role of education, we run a counterfactual exercise where we shut down the effect of college on the arrival rate of a transformative entrepreneurial idea. Specifically, we set the parameters $\lambda_e = 0$ and $\iota = 0$, neutralizing the college advantage on the frequency of idea arrival and on the probability of drawing a high-type idea. We then solve for the counterfactual BGP equilibrium under these

[7] We normalize the initial count of firms to adjust for the share of all individuals in the economy (whereas our career choice identification is based on IQ, we leverage the entire sample for our firm life-cycle components).

assumptions.

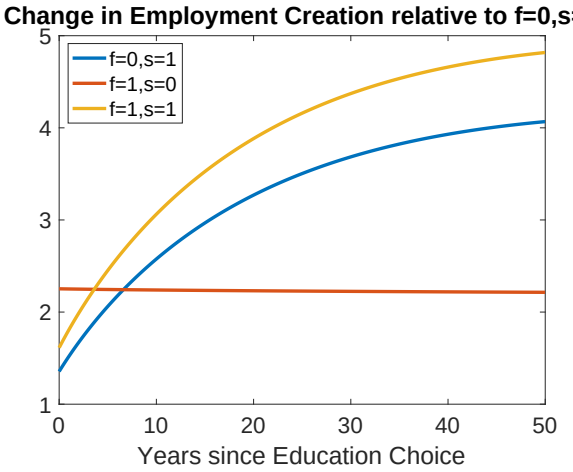
Table 4: Importance of Education for Entrepreneurship

	Baseline	No Educational Impact on Entrepreneurship	Change(%)
Growth (%)	1.00	0.92	-7.95
	Occupations Shares (% Change wrt Baseline)		
Production Workers	96.33	96.47	0.15
R&D Workers	1.58	1.44	-8.55
Subsistence Entrepreneurs	1.59	1.63	2.57
Transformative entrepreneurs	0.50	0.45	-9.20
	Wages (% Change wrt Baseline)		
Production worker wage	0.050	0.050	-0.24
R&D wage	0.132	0.132	0.14

Table 4 presents the results of this counterfactual analysis, illustrating the impact of removing the effect of college education on transformative entrepreneurship. The findings indicate that shutting down this effect leads to a 7.95% reduction in the overall growth rate. This decline can be attributed to several factors. First, the share of transformative entrepreneurs decreases by 9.20%, while the proportion of subsistence entrepreneurs rises by 2.57%. Second, the share of R&D workers decreases by 8.55%. The occupational decision of R&D worker changes because part of the motivation to obtain education and choose an R&D occupation is the expectation that this path increases the likelihood of becoming a transformative entrepreneur. Eliminating the link between college education and transformative entrepreneurship reduces the perceived benefits of higher education, thereby discouraging individuals from choosing careers in R&D. Overall, these changes result in a lower demand for R&D workers by transformative entrepreneurs, coupled with a decreased supply of R&D workers. The latter effect dominates, leading to a 0.14% increase in the R&D wage.

Figure 8 shows the firm lifecycle by individuals college attainment and parental exposure to entrepreneurship. The lines represent three group of indviduals: (i) those with parental exposure to entrepreneurship and no college (f=1, s=0, red line); (ii) those with college attainment but no parent entrepreneurs (f=0, s=1, blue line); (iii) those with college education and with parental entrepreneurship exposure (f=1, s=1, yellow line). Each line represents the average employment creation for a group of entrepreneurs relative to the group with no college and no parent entrepreneurs. The

Figure 8: Firm Life Cycle by Schooling and Parental Entrepreneurship



average employment creation is unconditional on starting a firm: thus, the figure captures both the probability of starting a firm and the average size of the firm for each group. First, we observe that, for entrepreneurs without college, parental exposure leads to over twice as much job creation throughout the lifecycle. This effect is due to the higher propensity of becoming entrepreneurs for individuals with a parent entrepreneur. Second, we observe that individuals with college education have a steeper job creation profile. The college education makes these individuals more likely to draw a transformative idea, conditional on idea arrival. Thus, in the first few years since their education choice, the are more likely to delay the decision to start a firm if they draw a low-type idea relative to the individuals with parent entrepreneurs and no college, as they expect a high probability to draw a transformative idea in the future. As a result, compared to individuals with parent entrepreneurs and no college, individuals with college education have lower job creation for the first few years, but higher job creation in the central and final part of their careers. Finally, we observe that individuals with both college education and parental exposure to entrepreneurship have the steepest employment creation profile.

5 Misallocation and Policy Counterfactuals

Given the allocation of labor and the spillovers and frictions, we now turn to talent misallocation and policy counterfactuals. Our interest in both of these channels relates to how individual career choice and firm dynamics intersect. We start by focusing on the interaction of misallocation, career choice, and firm dynamics. We then turn to policies that can boost growth through career choice and the promotion of startups

and the growth of firms.

In the next exercises, we quantify the magnitude of talent misallocation, study the role of financial frictions for both career choice and firm dynamics, and how different policies can improve talent allocation in the economy.

5.1 Talent Misallocation

The presence of financial frictions in the access to education produces talent misallocation in the economy: some highly talented individuals who would like to invest in education and pursue an R&D career might be unable to do so if they are born from lower-income families and cannot afford the cost of education. This observation opens up the following question: are there missing entrepreneurs and missing R&D workers in the economy due to the inability to pursue education and R&D careers because of their family background? To answer this question, we solve for a counterfactual BGP equilibrium focusing on the alleviation of the financial frictions in schooling, by enabling all individuals in the economy to access education if they wish to. The results of this exercise are illustrated in Table 5, where we report the share of R&D workers and entrepreneurs in the population, the share of transformative entrepreneurs among all entrepreneurs, and the growth rate for our baseline economy and the counterfactual where all individuals can afford education.

Table 5: Alleviating Financial Frictions in Education Access

	Baseline	**No Financial Frictions**	**Change (%)**
Growth (%)	1.00	1.11	11.08
	Occupations Shares (% Change wrt Baseline)		
Production Workers	96.33	96.11	-0.23
R&D Workers	1.58	1.82	15.24
Subsistence Entrepreneurs	1.59	1.53	-3.60
Transformative entrepreneurs	0.50	0.54	7.49
	Wages (% Change wrt Baseline)		
Production worker wage	0.050	0.050	0.35
R&D wage	0.132	0.129	-2.01

The results indicate that alleviating the frictions in access to education would increase the R&D workers population share by 15.24%, the share of entrepreneurs who are innovative by 7.49%, and the growth rate by 11.08% relative to the baseline.

This exercise shows that education is a bottleneck in accessing R&D careers due to individuals' reliance on family income to cover the cost of education. Education access has a sizable effect on talent allocation to entrepreneurship and innovation and alleviating financial frictions sorts talented individuals from lower-income families to become R&D workers and transformative entrepreneurs.

In our framework, the education bottleneck operates on both the demand of R&D talent by transformative entrepreneurs, and the supply of R&D talent through the career choice of R&D workers. Alleviating financial frictions increases both the demand and the supply for talent, but the latter channel quantitatively dominates, as the R&D wage decreases by 2.01%.

To highlight the complementarity between the demand and the supply of innovative talent, we conduct a partial equilibrium counterfactual exercise with the alleviation of financial frictions, as above, but where we keep the number of entrepreneurs of each type and the firm size distribution fixed to the baseline. Table 6 reports the results from this exercise. If we focus on the supply side effect of financial frictions, allowing for an increase in the share of R&D workers, but keep the demand side fixed to the steady state, the growth rate only increases by 6.6 p.p., which amounts to 60% of the total general equilibrium effect when both demand and supply adjust. These results underscore the complementarity of R&D workers and transformative entrepreneurs in the innovation pipeline.

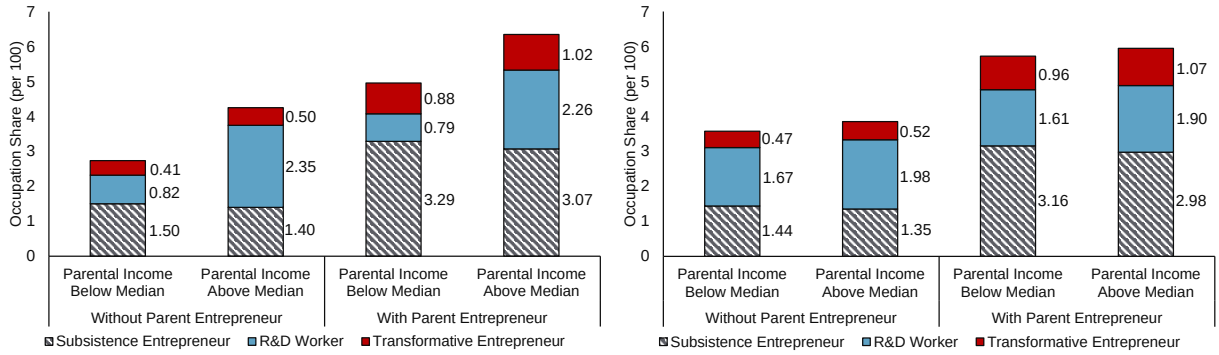
Table 6: Synergy between R&D Workers and Entrepreneurs

	Baseline	**No Change in Entrepreneurship**	**Full GE**
Growth (%)	1.000	1.066	1.111

Next, we return to the full genereal equilibrium counterfactual exercise of removing financial frictions and we examine the role of family background in producing talent misallocation in the economy.

Figure 9 shows the share of individuals who choose an occupation as subsistence entrepreneur, R&D worker of transformative entrepreneur depending on their parental background. We group individuals into four parental background categories, which are the combinations of two dimensions of parental background: (i) having a parent entrepreneur, and (ii) having parental income above or below the median. The figure compares the occupational shares in the baseline in Panel (A) and in the counterfactual

Figure 9: Alleviating Financial Frictions : Occupational Shares by Family Background



(a) Baseline (b) No Financial Frictions

with no financial frictions in Panel (B). The figure illustrates that alleviating financial frictions increases the share of individuals with low parental income who become R&D workers and transformative entrepreneurs, reducing the gap in access to careers in innovation by family income. A small gap remains due to the underlying differences in talent distribution for individuals with different parental backgrounds, driven by the intergenerational talent correlation. In addition, we note that, conditional on parental income, individuals with parental exposure to entrepreneurship are more likely to undertake a career innovation, and they are about twice as likely to be transformative entrepreneurs. These results underscore the importance of family background in determining career choice in the innovation sector and as a source of talent misallocation.

Finally, we investigate the change in occupational shares along the talent distribution. Figure 10 shows the change in the share of individuals in each occupation between the baseline and the counterfactual with no financial frictions.

Alleviating financial frictions leads to an increase in the share of R&D workers and transformative entrepreneurs in the economy across all talent quartiles, but the increase is more pronounced for highly talented individuals. In particular, alleviating financial frictions increases the shares of R&D workers and transformative entrepreneurs by 0.26p.p. and by 0.06p.p. respectively for individuals in the top IQ quartile, but only by 0.18p.p. and 0.02p.p. in the bottom quartile. On the contrary, the share of subsistence entrepreneurs declines along all segments of the talent distribution.

Figure 10: Alleviating Financial Frictions by IQ



Firm Dynamics and Financial Frictions. Financial frictions matter not only for talent allocation but also for firm dynamics. The latter effect emerges because entrepreneurs' background and education decisions affect their firms' performance. Figure 11 explores how talent misallocation affects the dynamics of firms and innovation. We present the counterfactual BGP without financial frictions presented in the previous section (red lines) against the baseline case (blue). Panel (A) shows how the average employment of transformative entrepreneurs relative to subsistence changes with firm age relative to the baseline. We see higher employment. In panel b, we evaluate the share of transformative entrepreneurs. In panel c, we should the employment share in the economy.

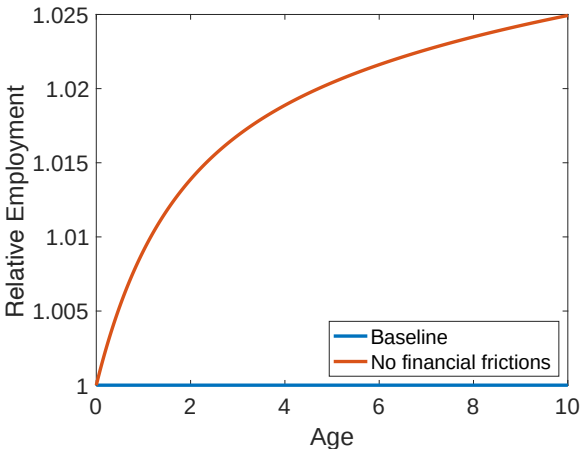
We see here how alleviating financial frictions not only changes the R&D worker pool, but also the amount and growth of transformative entrepreneurs. Given the importance of frictions in access to education as a bottleneck to innovative careers, we next investigate how different policies can improve the allocation of talent and the innovative capacity of the economy.

5.2 Policies

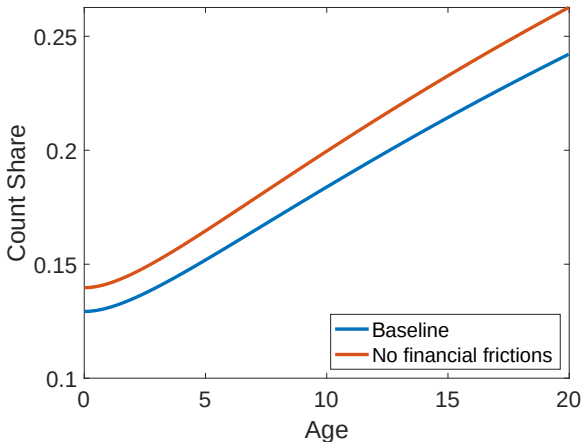
In this section, we study how different policies affect various margins of the career sorting process, the allocation of talent in the economy, and the overall innovation capacity and productivity growth. With this same amount of budget, a government could subsidize R&D, transformative entrepreneurship, or access to education.

We assume that the government levies a lump sum tax to finance the policies by balancing the budget in every period. We consider four different policies: (i) a subsidy

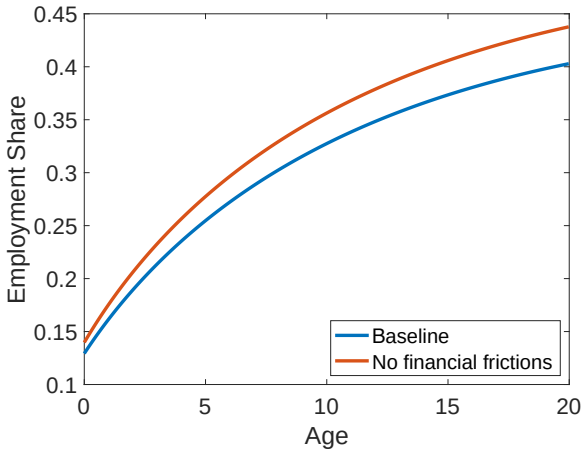
Figure 11: Firm Outcomes w/ Alleviating Financial Frictions



(a) Average Employment of Transformative Entrp.



(b) Share of Transformative Entrp.



(c) Employment Share of Transformative Entrp.

to the wages of R&D workers, (ii) a subsidy to the entry cost for transformative entrepreneurs, (iii) an education loan, which provides access to education to those who cannot afford it, although they will have to eventually pay the education cost back (i.e., the cost of education still enters their value function and education decision), and (iv) a subsidy to the cost of education, which provides access to education to those who cannot afford it but also lowers the cost of education to everyone. We compare alternative BGP equilibria with policies that use the same total government budget. Table 7 reports the results for a government budget equivalent to 0.05% of GDP. Figure 12 below illustrates how results change for larger budgets.

Table 7: Policy Outcomes for Equivalent Budget

	R&D Subsidy	Uniform Entry	Innovative Entry	Education Subsidy
Growth (% Change wrt Baseline)	2.31	0.11	4.38	16.14
	Occupations Shares (% Change wrt Baseline)			
Production Workers	-0.04	-0.01	-0.08	-0.33
R&D Workers	2.86	-0.02	4.04	22.26
Subsistence Entrepreneurs	-0.74	0.76	-1.45	-5.27
Transformative entrepreneurs	1.49	0.50	6.69	10.84
	Wages (% Change wrt Baseline)			
Production worker wage	0.07	0.04	0.13	0.52
R&D wage	0.36	0.01	0.43	-2.87

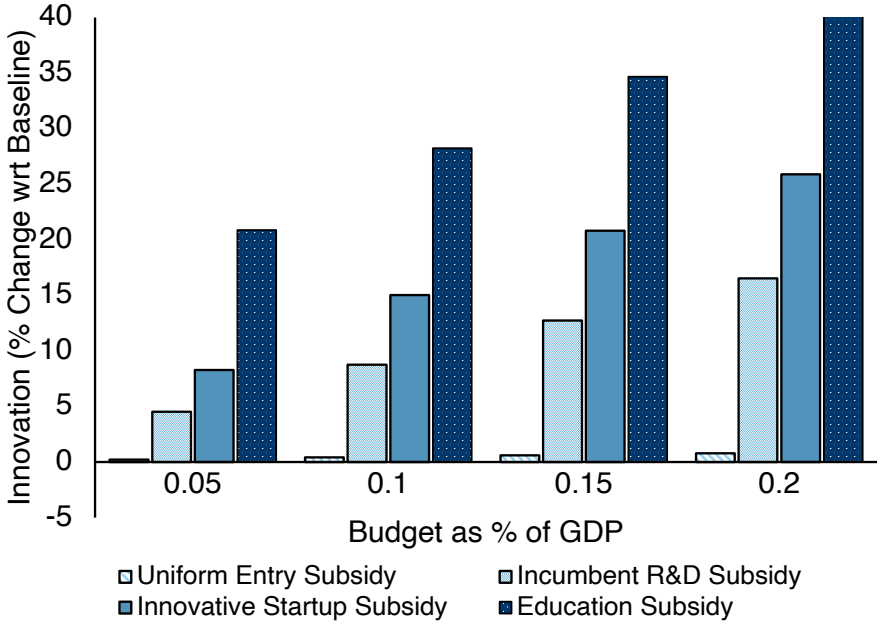
We stress a few takeaways from Table 7. First, education policy is the most effective in increasing innovation and growth. To understand why, we analyze each of the different policies.

A subsidy to the entry cost for innovative firms increases the share of transformative entrepreneurs by 5.24%. The increase innovative firms, in turn, raises the demand for R&D workers, whose wage increases by 0.04% and population share expands by 1.25%. This result illustrates an important synergy between entrepreneurs and R&D workers in our model: the subsidy to transformative entrepreneurs trickles down to R&D workers, further stimulating innovation and growth, which increases by 2.86% relative to the baseline.

An R&D subsidy increase the value of choosing an R&D career and it increases the population share of R&D workers by 4.80% and transformative entrepreneurs by 0.67%. As a result, the growth rate in the economy increases by 3% relative to the baseline. However, the effectiveness of both the R&D subsidy and the innovative entry subsidy is limited because they cannot alleviate the friction in access to education for those who cannot afford it.

An education loan policy, on the other hand, can alleviate the friction in access to education, enabling individuals who wish to pursue an R&D career to do so. Yet, unlike the R&D subsidy, this policy will not raise the value of an R&D career. Nonetheless, the education policy increases the share of R&D workers by 8.79%, the share of transformative entrepreneurs by 1.32%, and the growth rate by 5.57%, resulting more effective in stimulating growth than the R&D and entry subsidy at this budget level.

Figure 12: Policy Outcomes at Different Budget Levels

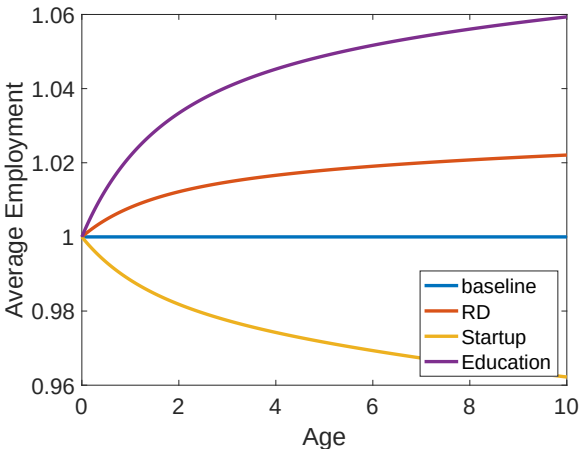


However, the education loan subsidy has limited scope in scaling up with larger government budgets: once all individuals who wish to get educated can afford to do so, the policy reaches its maximum effectiveness. As illustrated in Figure 12, the maximum effectiveness is reached at a budget of about 0.15% of GDP, which increases the growth rate of 12.45% relative to baseline; after that, this policy cannot increase the growth rate any further.

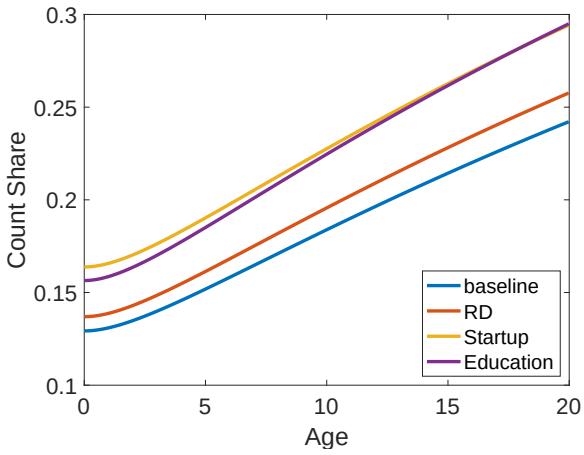
Finally, a subsidy to the cost of education can both increase the value of an R&D career and alleviate the friction in access to education, resulting as the most effective policy to address the education bottleneck for R&D careers. At a budget of 0.05% of GDP, this policy increases both the R&D worker share by 16.34% and the transformative entrepreneur share by 2.34%, in line with the alleviation of the financial frictions, raising th growth rate by 10.12%. In addition, given that this policy raises the value of an R&D carrer, its effectiveness keeps increasing at larger budgets, as illustrated in Table 8.

Overall, education policy is the most effective tool to boost growth at low budget levels, as it relives educational financial frictions and boosts both R&D supply and entrepreneurs. Note that the education and R&D policies induce entry into schooling across the distribution of IQ. This extensive margin is silent on the role of congestion in schooling. As a result, some policies may have some differences from previous literature (as in Akcigit et al., 2024).

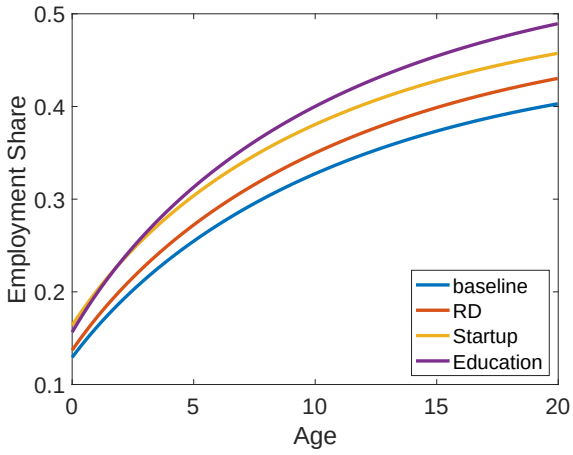
Figure 13: Firm Outcomes under Policies



(a) Average Employment of Transformative Entrp.



(b) Share of Transformative Entrp.



(c) Employment Share of Transformative Entrp.

6 Conclusion

New technologies emerge in firms primarily from entrepreneurs assembling teams that produce ideas. This paper presents new facts within a framework of the entrepreneur and inventors at the center of innovation-led growth. To incorporate this, we focus on the sorting of individuals into occupations, entrepreneurial activity and innovation-driven firm growth.

We proceed by linking detailed microdata from Denmark on individual entrepreneurs, inventors, and firms to a novel quantitative endogenous growth model with occupa-

Table 8: Optimal Policy Mix at Different Budget Levels

	Budget Share, %			
Budget (% of GDP)	*Incumbent R&D*	*Innovative Startup*	*Education Subsidy*	*Change in Innovation, %*
0.05	0.0	11.6	88.4	20.0
0.10	0.0	52.0	48.0	27.5
0.20	0.0	73.9	26.1	39.4
0.30	0.0	81.5	18.5	48.9
0.40	0.0	85.5	14.5	56.7
0.50	0.0	87.9	12.1	63.4
0.60	5.0	84.5	10.5	69.4
0.70	13.9	76.8	9.3	74.9

tional sorting. Empirically, we find that while parental exposure is a key determinant of entrepreneurship, sorting into inventing occupations is primarily determined by education and IQ. Entrepreneurs with higher ability, as proxied for by IQ, and college attainment are more likely to become *transformative entrepreneurs*, who hire R&D workers.

We build these facts into a quantitative framework that incorporates our main facts and has entrepreneurs and inventors jointly driving economic growth. We find that education sorting affects both the share of R&D workers and entrepreneurs in the economy. Further, parental exposure interacts with this important role. "Missing entrepreneurs" may be those with entrepreneurial, low-income, parents but significant potential. The missing entrepreneurs can have an important growth impact. Alleviating frictions to education boosts both R&D workers (by 20%), and transformative entrepreneurs as a share of total entrepreneurs (by 6%). These forces interact to boost growth in the economy by 12%.

We find that education and R&D policies both interact with the propensity for entrepreneurs to become innovative. When education is subsidized, this creates, in addition to a direct effect of an increase in R&D workers, a downstream effect of more entrepreneurs with the potential to be innovative. These alleviated frictions build opportunities for individuals who otherwise might be missing entrepreneurs. R&D subsidies also indirectly subsidize transformative entrepreneurship, but do not directly alleviate financial frictions for talented but poor youth. Both R&D and education policies can drive growth through different mechanisms.

A key message of this paper is the joint role of the supply and demand of innovative talent. To build a society with the ability to innovate and grow, one needs talented

individuals to fulfill both entrepreneurial and inventive roles. Ignoring the role of the demand or supply may miss significantly on policy counterfactuals. Furthermore, to become a transformative entrepreneur one needs a rich combination of talents. This has been known amongst economists for generations, but this paper can serve as a foundation for developing an understanding of how these entrepreneurial potential interacts with the environment and economic policy.

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Appendix

A Model Appendix

A.1 Final Good and Static Profits

A representative firm produces the final good, Y_t with a Cobb-Douglas production function that aggregates intermediate goods $y_{j,t}$:

$$\ln Y_t = \int_{j \in \mathcal{N}} \ln y_{j,t} dj.$$

There is a measure of 1 product lines available, some of which might be inactive[8], so $\mathcal{N}$ is the set of active product lines. The price of the final good is normalized to 1. It follows that the final good producer will spend the same amount Y_t on each variety j. An intermediate firm is defined as a collection of product lines. Each intermediate good is produced with a linear technology:

$$y_{j,t} = q_{j,t} l_{j,p,t}$$

where $l_{j,p,t}$ indicates the amount of production workers in terms of efficiency units and $q_{j,t}$ is the quality of the intermediate good at time t. This implies that the marginal cost of production is $w_{P,t}/q_{j,t}$, where $w_{P,t}$ is the wage per efficiency unit of production workers in the economy.

A firm can innovate on a good in order to add a new product line to its portfolio. When innovation is successful, the quality of intermediate j increases by a factor $\gamma > 1$, i.e. from q_j to γq_j. We assume that the new innovator and the latest incumbent engage in Bertrand competition, so the new innovator will capture the entire market for the good and will charge a price equal to the cost of the previous incumbent:

$$p_{j,t} = \frac{\gamma w_{P,t}}{q_{j,t}}.$$

As a result, the profits for intermediate line j are:

$$\pi_{j,t} = p_{j,t} y_{j,t} - w_{P,t} l_{j,p,t} = \frac{\gamma - 1}{\gamma} Y_t \tag{10}$$

[8]This happens due to the death of entrepreneurs.

and the labor demand for intermediate j is:

$$l_{j,p,t} = \frac{1}{\omega_{P,t}\gamma}$$

where $\omega_{P,t} := \frac{w_{P,t}}{Y,t}$. The static problem is the same for all firms and all product lines that a firm owns. Let n be the number of product lines held by a firm f. The total static profits are equal to $\pi_t n$. There is no type heterogeneity in firm profits; instead, we focus on type heterogeneity in innovation.

A.2 Firm and Worker Distributions in Equilibrium

This section describes the mass of firms and workers across different states. The stationary equilibrium of the model ensures that the distributions of firms and workers remain stable over time.

A.2.1 Firm Size Distribution

The equilibrium mass of firms is denoted by $\Psi(n, \theta, z, f, y, s)$, where firms are indexed by size $n \in \{1, 2, 3, ...\}$, technology $\theta \in \Theta$ and owner characteristics (z, y, f, s). The firm dynamics follow a process in which firms grow, shrink, or exit the market based on innovation, competition, and exogenous shocks.

In stationary equilibrium, In stationary equilibrium, the firm mass satisfies a set of conditions that regulate entry, transition, and exit:

$$\begin{aligned}
\tau\Psi(1,\theta,z,y,f,s) + \psi\sum_{n=1}^{\infty}\Psi(n,\theta,z,y,f,s) &= e_{\theta,z,y,f,s} \\
(\tau + x_{\theta,n} + v + \psi)\Psi(1,\theta,z,y,f,s) &= \tau 2\Psi(2,\theta,z,y,f,s) + e_{\theta,z,y,f,s} \\
\left[\tau n + (x_{\theta,n} + v)\, n + \psi\right]\Psi(n,\theta,z,y,f,s) &= (x_{\theta,n} + v)\,(n-1)\Psi(n-1,\theta,z,y,f,s) \\
&\quad + \tau(n+1)\Psi(n+1,\theta,z,y,f,s), \quad n \geq 2
\end{aligned}$$

where $e_{\theta,z,y,f,s}$ denotes the mass of firm entry, given by:

$$e_{\theta,z,y,f,s} = \lambda_f \Pr(\theta; z, s) \times \mathbb{P}\left(v(\theta) - c > V(z,y,f,s)\right)\phi(z,y,f,s)$$

The first equation describes the entry of firms, ensuring that the inflow of new firms

balances the outflow due to creative destruction and mortality of the entrepreneur. The right-hand side represents the entry flow $e_{\theta,z,y,f,s}$, which depends on the supply of entrepreneurs and their decision to start a firm. The second equation determines the equilibrium mass of firms of size one. The left-hand side represents the outflow of firms with size one, which can occur either due to firm exit or because they grow into larger firms through innovation. The right-hand side captures the **inflow into size one**, consisting of new firms entering the market and firms that shrink from larger sizes due to competition or innovation by others. Next equation describes the evolution of mass of firms with size $n \geq 2$ where firms experience stochastic growth due to innovation and shrinkage due to competitive forces driven by creative destruction. The outflow from firms of size n consists of those transitioning to larger sizes, shrinking to smaller sizes, or exiting due to mortality.

Firm entry $e_{\theta,z,y,f,s}$ depends on the probability of an agent choosing entrepreneurship. This probability is influenced by technological opportunities and the expected profitability of entering the market, relative to alternative career options.

A.2.2 Worker Distribution and Occupational Flows

The distribution of workers is represented by $\phi(z, y, f, s)$, the unnormalized probability density function of worker characteristics. In equilibrium, worker outflows (due to transitions to entrepreneurship and mortality) must be equal to inflows (occupation choice of new born and transitions out of entrepreneurship). The unnormalized density of workers satisfies:

$$\left(\lambda_f \times \sum_{\theta} \Pr(\theta; z, s) \times \mathbb{P}\left(v(\theta) - c > V(z, y, f, s)\right) + \psi\right) \phi(z, y, f, s) = f(z, y, f, s)M + \sum_{\theta} \left(\tau\Psi(1, \theta, z, y, f \right. \tag{11}$$

or, using equations (11), we derive:

$$\psi \left[\phi(z, y, f, s) + \sum_{\theta} \sum_{n=1} \Psi(n, \theta, z, y, f, s)\right] = f(z, y, f, s)M \tag{12}$$

Equation (12) ensures that total worker outflows due to mortality equal the inflow of new entrants, maintaining a stationary worker distribution. This balance ensures that firm and worker flows remain stable over time.

B Data Appendix

In the main text, we discussed how to construct data on inventors and entrepreneurs. This section provides further details on the data construction and occupation definition.

B.1 Dataset Construction and Information

For data on individuals, we use the Integrated Database for Labor Market Research (IDA); for employer-employee matched data, we use the Firm-linked IDA (FIDA); for information on business ownership, we rely on the Danish Entrepreneurship Database (IVPS/IVPE); for data on patents, we rely on the database of the European Patent Office (EPO). We connect these to IQ data, which is facilitated by military test, Borge Prien's Prove, which is required for males in Denmark at age 18. We merge these datasets together which enable tracking individuals across their lifetime across firms and occupations.

As discussed in the main text, we connect IQ data to individuals, their careers, and their firms. The IQ data is provided by the Danish military test, Borge Prien's Prove, which is required for males in Denmark at age 18. This test provides IQ data on most males entering the workforce or college after 1995. As a result, we observe IQ information for about 30% of males in our data.

The IDA assigns a unique identifier to each individual in Denmark. We thus observe a panel dataset on individuals on an annual basis. The variables used from this dataset include annual income, employment status, occupation, and highest completed education level. We also observe background family characteristics, including income and occupation of parents. This dataset additionally includes information on IQ for a subset of individuals.

The firm-linked (FIDA) dataset connects individuals to their primary place of employment (a unique employer identifier) for each year. Individuals have an occupational code and their primary firm. On the firm side, we observe industry code, number of employees, sales, profits, and firm age. Thus, we can connect individuals to their firms and occupation over time. We also connect individuals and firms to their patents to speak to innovation at the individual and firm-level. The EPO database provides information on patents assigned to Danish firms or individuals. The patent database is linked to individuals and firms in the DST data with a disambiguation algorithm developed by DST. We use patents as our primary measure of innovation.

The link between individual and firm is especially valuable for connecting the indi-

viduals behind the firm and their employees. This is primarily through the IVPS/IVPE entrepreneurship database. The IVPS/IVPE databases provide information on the primary founder of all privately owned firms in Denmark. IVPS contains individuals behind companies, while IVPE contains individuals behind proprietorships. We include both as entrepreneurs. Thus, we can observe the progression of individual firms and the individuals behind them. The dataset covers a wide array of firms and individuals. In total, we observe 305,052 unique firms matched to 3.92 million unique individuals over the years 2001-2013.[9] We identify the primary business owners of 28% of the total registered firms.

B.2 Dataset Details

In this section, we expand on the datasets we combine, the occupational and entrepreneurial definitions, and additional statistics on the main variables of interest. Our work in thei project combines:

- Detailed information on family background (e.g., parental occupation/income)
- Individual level income, IQ, occupation, and education data
- Patent data from European Patent Office (EPO)
- Firm-level data (matched employer-employee, revenue, innovation)
- 305,092 unique firms and 3.9 million unique individuals (450,000+ w/ IQ data)
- **R&D Workers:** Individuals in occupations with greater than 1% of individuals obtaining a patent for majority of career
- **Entrepreneurs:** Individuals founding companies (IVPE and IVPS ownership database) who hire at least one worker

B.3 Occupations

We focus on three different occupations in the main text. We expand on how we measure each occupation here.

[9] We define a firm as an entity with a firm identifier and at least one non-firm head employee.

R&D Workers. For classifying individuals, we discussed the occupations that we assign to R&D versus production. Table B1 lists the occupations of R&D workers in the economy.

Table B1: R&D Worker Occupations in Denmark Data

Occupation Code (ISCO)	Description
211	Physical and Earth Science Professionals
212	Mathematicians, Actuaries and Statisticians
213	Life Science Professionals
214	Engineering Professionals
215	Electrotechnology Engineers
231	University and Higher Ed. Teacher
251	Software Developer
311	Physical and Engineer Science Technicians
754	Craft and Related Workers
821	Assemblers

Table B2: R&D Occupations

ID	Description	Inventor Rate	Inventor Employment Share
211	Physics and Earth Science Professionals	0.135	0.011
215	Electrotechnology Professionals	0.048	0.007
214	Engineers	0.048	0.188
213	Life Science Professionals	0.041	0.021
231	Professors	0.029	0.083
311	Physics and Engineering Technicians	0.012	0.222
214	Engineers	0.048	0.188
222	Pharmacy and Health	0.011	0.116
200	General Scientist	0.023	0.104
123	Manager (R&D, info, supply)	0.018	0.085