Board of Governors of the Federal Reserve System

International Finance Discussion Papers

ISSN 1073-2500 (Print)
ISSN 2767-4509 (Online)

Number 1410

June 2025

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Please cite this paper as:
Akcigit, Ufuk, Harun Alp, Jeremy Pearce and Marta Prato (2025). "Transformative and Subsistence Entrepreneurs: Origins and Impacts on Economic Growth," International Finance Discussion Papers 1410. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2025.1410.

Transformative and Subsistence Entrepreneurs: Origins and Impacts on Economic Growth

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June 26, 2025

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. Transformative entrepreneurs, 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 progress, highlighting how higher education influences career paths in entrepreneurship and invention. We identify talent misallocation caused by unequal education access, particularly affecting lower-income families. Our findings indicate the most effective policies strengthen the interplay between higher education, innovation, and entrepreneurship to foster transformative businesses and achieve long-run economic growth.

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

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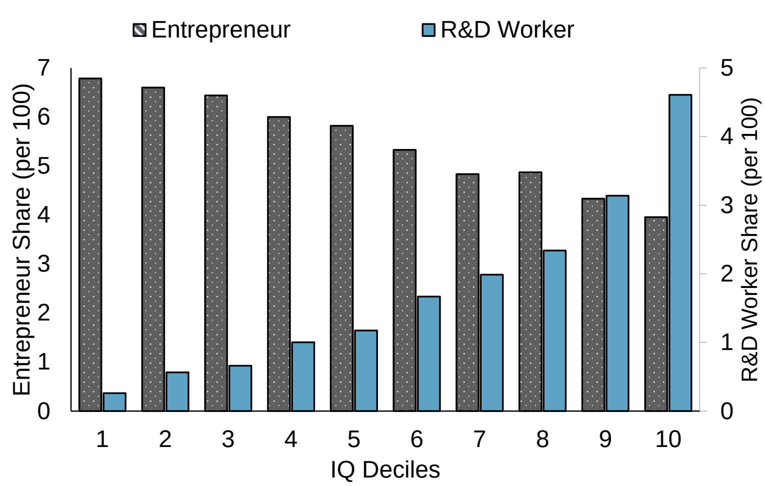
1 Introduction

A symbiotic relationship between entrepreneurs and inventors is essential for technological progress. Yet, this symbiotic relationship depends on the nature of entrepreneurs; unlike *subsistence* entrepreneurs who focus on day-to-day survival, *transformative* entrepreneurs push boundaries by turning groundbreaking ideas into real-world applications. Without the visionary drive of transformative entrepreneurs, inventors would lack the commercial pathways needed to bring their innovations to market. Conversely, without inventors, transformative entrepreneurs would not have access to the new technologies that underpin significant market disruptions. In this paper, we explore the career choices of different types of entrepreneurs and inventors and study the dynamic interplay among them. Specifically, we ask: Who becomes a transformative entrepreneur, and how does that path differ from becoming an inventor or subsistence entrepreneur? Is there talent misallocation in the economy? How do policies shape the distribution of talent among these occupations?

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 their interaction with talent allocation, firm growth, and economic growth.

Figure 1: R&D Worker and Entrepreneur by IQ



One striking fact at the center of our analysis is the allocation of talent between entrepreneurs and inventors by IQ, illustrated in Figure 1. It shows the share of individuals who choose to become either R&D workers—inventors that are employed in innovation-related occupations—or entrepreneurs 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. This surprising finding challenges the common portrayal of entrepreneurs as individuals who drive creativity and growth, a narrative often seen in both academic literature and popular media. A central aim of this paper is to unravel this intriguing puzzle. This exploration not only sheds light on the heterogeneity among entrepreneurs but also investigates the career choices of different talents in society.

Next, using multivariate regression analysis, we explore other important determinants that shape the 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. While there is no direct effect of parental income on becoming an R&D worker, there is an indirect effect through schooling, which is highly correlated with parental income even conditioning on IQ and parental education. Interestingly, we find that family entrepreneurship experience has the strongest impact on the likelihood of becoming an entrepreneur.

These results pave the way for exploring 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 aim to bring new innovations to the market. In our data, we define transformative entrepreneurs as those who hire at least one R&D worker, signaling an intention to innovate. Importantly, we do not define them based on ex-post outcomes such as firm growth, as this would risk excluding entrepreneurs who aimed to grow but ultimately failed. Instead, we focus on their ex-ante incentives by examining their business strategy — specifically, the types of workers they bring into the firm who are likely to drive future growth. According to this definition, only a handful of entrepreneurs are transformative and hire technical personnel for innovation. The likelihood of being a transformative entrepreneur increases with IQ and higher education, and these transformative entrepreneurs lead firms that grow faster, patent more, and have lower exit rates.

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

Fact 1 *IQ and education negatively predict becoming an entrepreneur.*

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 a 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 link these findings to aggregate economic 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 in the model are born with heterogeneous ability and parental income that determines their initial educational choice, as we observe that both are important determinants of college attendance in the data. Education is a necessary prerequisite to becoming an R&D worker (in line with Fact 3). While some individuals choose not to become R&D workers due to personal preferences, others cannot afford to pursue education due to low parental income. This friction in the access to education creates 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, with frequency influenced by childhood exposure to entrepreneurship (Fact 2) and educational attainment (Fact 4). IQ and education may not have a positive impact on selection into entrepreneurship (Fact 1). Importantly, the model distinguishes between transformative and subsistence entrepreneurs, differentiated by levels of talent and education (Fact 4). Transformative entrepreneurs innovate and enhance product quality by employing R&D workers, while subsistence entrepreneurs do not engage in such innovation-oriented activities. As a result, innovative entrepreneurs grow their firms (Fact 5), contributing to overall innovation and growth.

The model highlights two key mechanisms that determine an economy's capacity for innovation and its connection to aggregate growth. The first mechanism involves occupational sorting, specifically how individuals select their initial careers. Workers in R&D represent the *supply* of innovative talent, and the factors influencing their occupational choices significantly impact the overall level of innovation within the economy. The second mechanism centers on entrepreneurship: without sufficient *demand* for R&D talent by growing firms, their innovative potential cannot effectively translate into broader innovation, firm dynamics, and growth. Education serves as a critical channel influencing both the supply of R&D workers and transformative entrepreneurs. Individuals prevented from obtaining higher education due to low parental income are less likely to become R&D workers, thereby constraining the economy's supply of innovative talent. Moreover, educated individuals are over 5 times more likely to engage in transformative entrepreneurship. Consequently, limited access to higher education also diminishes the demand for innovative talent. Given the interdependence between R&D workers and transformative entrepreneurs, each form of educational misallocation can significantly impede innovation and aggregate economic growth.

After characterizing the solution of the model, we calibrate the underlying parameters by matching key features 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, distortions in educational choices caused by financial frictions create a bottleneck in access to innovative careers, due to the reliance on parental income for higher education, a dynamic that can have significant aggregate implications. 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 the 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 in education create talent misallocation, preventing some high-ability individuals from becoming inventors or transformative entrepreneurs.

Second, there is a symbiotic relationship between R&D workers and entrepreneurs that matters for the effectiveness of policies. To highlight this complementarity, 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, consistent with no effect on entrepreneurship, growth only picks up by 6.6%, compared to the 11.1% in the full general equilibrium described above. Thus, the demand side for innovative talent accounts for 40% of the growth increase from alleviating financial frictions.

Third, we highlight education subsidies as a superior policy tool to foster transformative entrepreneurship and innovation. We study four policies in the form of subsidies to either (i) all startups, (ii) R&D (incumbent) subsidy, (iii) innovative startups, and (iv) education, which affect different margins of talent allocation and firm dynamics in the economy. A uniform entrepreneurship subsidy proves largely ineffective as it primarily attracts subsistence entrepreneurs who don't drive innovation. An R&D subsidy for incumbents generates moderate growth by increasing demand for R&D workers but faces diminishing returns at the firm level. The innovative startup subsidy, targeting transformative entrepreneurs who hire R&D workers, more effectively boosts growth-oriented startups and innovation. However, education subsidies emerge as the most effective policy, addressing the foundational issue of human capital development by expanding both the pool of potential R&D workers and transformative entrepreneurs simultaneously, stimulating increases in both the supply of and demand for R&D talent. Overall, with a 0.05% of GDP budget, education subsidies increase innovation by 16%, against 4% for startup subsidies to transformative entrepreneurs and 2% for R&D subsidies, and 0.1% for general startup subsidies.

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 budgets (e.g., 0.4% of GDP), and finally including R&D subsidies only at higher budgets (e.g., 0.7% of GDP). Once the budget is high enough (e.g., greater than 0.7% of GDP), the optimal strategy is to mix the three policies. This exercise demonstrates both the critical importance of addressing bottlenecks in access to education to boost 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. Dating back to the contribution of Schumpeter (1911), economists have long highlighted the connection between entrepreneurship and aggregate growth. Schumpeter (1911) further noted a core difference between an inventor and an entrepreneur:

> *As long as they are not carried into practice, inventions are economically irrelevant. And to carry any improvement into effect is a task entirely different from the inventing of it, and a task, moreover, requiring entirely different kinds of aptitudes. Although entrepreneurs may be inventors..., but not by nature of their function but by coincidence and vice versa.*

While economists have understood this connection, data and theoretical tools to unpack this question have been limited. This paper develops this insight on the dual roles of inventors and transformative entrepreneurs, connecting strands of the literature on entrepreneurs and inventors. 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 central to our paper 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 a comprehensive empirical and quantitative analysis of the factors shaping entrepreneurial choice and success, integrating inventors into the analysis to explore their symbiotic relationship with entrepreneurs. This is made possible by leveraging rich micro-level administrative data from Denmark.

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. Levine and Rubinstein (2016) also argue that human capital and background characteristics play an important role in the choice to become an entrepreneur. We find, in line with Levine and Rubinstein (2016) and Hvide and Oyer (2018), that individuals are more likely to become entrepreneurs if they have parental entrepreneurs. 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. Bhandari et al. (2024) find that the non-pecuniary benefits of entrepreneurship are small and their income growth is higher, which is consistent with our framework. This connects to the distinction between subsistence and transformative entrepreneurship — building on Schoar (2010) and Hurst and Pugsley (2011) — and examine how these different entrepreneurial types generate demand for inventors within a general equilibrium framework.

Entrepreneurs must be team players, and our paper focuses on how they must hire R&D workers to realize their vision of firm growth. This observation connects to work more broadly on entrepreneurial ability and how entrepreneurs must be balanced in their skills (Lazear, 2004), which incorporates communication and networking ability (Kaplan et al., 2012). Our paper is also related to work focusing on inventor teams (Wuchty et al., 2007; Pearce, 2020), which we extend to entrepreneurs and the inventors they hire, and to the literature showing the importance of entrepreneurial networks (Hochberg et al., 2007, 2010). In this paper, we show that schooling plays an important role for the type of entrepreneur because individuals with college education receive technical training, increasing the likelihood of becoming a transformative entrepreneur. This result is consistent with evidence that entrepreneurial skill is persistent (Gompers et al., 2010) because it is shaped by both the education and career decisions of individuals (Lerner and Malmendier, 2013; Morazzoni, 2021; Queiró, 2022). In our framework, as in Queiró (2022), entrepreneurial human capital affects firm dynamics, but we further introduce an interaction with the supply of innovative talent through the demand for inventors and life cycle opportunities.

One of the main messages of this paper is about connecting the dynamics of firms and entrepreneurs to the canonical literature of inventors 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., 2025, Bell et al., 2018), learning (Akcigit et al., 2018), and the interaction with firms (Aghion et al., 2018). In this literature, we advance on two fronts. First, we provide novel empirical evidence on the careers of entrepreneurs and inventors jointly; second, we connect the entrepreneurial career to a macroeconomic environment, a component that has received less attention in the literature.

Connecting inventors and entrepreneurs to the macroeconomy requires a new theory of innovation-led growth, which connects the development of human capital to entrepreneurship, innovation, and production. Our theory incorporates a model of the allocation of talent between entrepreneurship and work, as in Lucas (1978), into a microfounded 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 and talent allocation for economic growth is also highlighted by Hsieh et al. (2019) and Prato (2024). We also contribute to a strand of the literature that uses these frameworks to study the aggregate impact of innovation policies (Atkeson and Burstein, 2019) by studying a rich set of policy tools for innovation. Our model enriches the existing framework by explicitly modeling the role of family background for occupational choice, building on the work of Akcigit et al. (2025), who focus only on inventors, and expanding it to examine the contribution of entrepreneurs and R&D workers to the growth of the firm.

2 Motivating Empirical Evidence

We motivate the core features of our model of career choice and firm dynamics by 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, particularly a transformative one, and the firms of transformative and subsistence entrepreneurs.

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 contain (i) individual background and test information; (ii) matched employer-employee 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. Our main sample consists of R&D workers, production workers, and entrepreneurs. We categorize as “R&D workers" those individuals who work in occupations with high patenting rates. More precisely, we select all occupations where at least 1% of workers ever file a patent and classify all individuals in those occupations as R&D workers. By identifying R&D workers based on their occupational classifications, we capture a broader

[1] More details on data construction and variable definitions are provided in Appendix B.

set of contributors to innovation—recognizing that not all R&D workers hold patents, yet still play a vital role in technological development. With this definition, individuals in R&D occupations account for approximately 3% of the working population in our data.[2] We categorize production workers as individuals who work but do not have an R&D occupation.

Finally, we define entrepreneurs as individuals identified in the IVPS/IVPE database as primary founders of a firm with at least one employee. To distinguish transformative entrepreneurs, we avoid relying solely on ex-post measures of firm growth; instead, we aim to capture entrepreneurs' ex-ante intention to innovate and expand their businesses through their hiring choices. Specifically, an entrepreneur who intends to grow her business is more likely to hire R&D workers—a behavior we can directly observe in our data. Thus, we categorize an entrepreneur as transformative if they hire at least one R&D worker, whereas a subsistence entrepreneur is one who does not hire any R&D workers.

2.2 Transformative and Subsistence 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. At the center of this analysis are the heterogeneous goals and impacts of entrepreneurs (Baumol, 1990).

In the literature, there is a bifurcation across two types of entrepreneurship: subsistence and transformative entrepreneurs (e.g., Schoar, 2010, Hurst and Pugsley, 2011, and Akcigit et al., 2021). Subsistence entrepreneurs focus on maintaining their business and often prefer entrepreneurship to wage employment but do not attempt to grow or innovate. The other types of entrepreneurs are transformative: they attempt to grow and contribute to technological progress. In our data, we define transformative entrepreneurs as entrepreneurs who hire an R&D worker at some point during the life cycle of the firm, consistent with an *intention* to grow rather than an outcome.

To examine entrepreneur types, we split our occupational categories into four groups: production workers, R&D workers, subsistence entrepreneurs, and transformative entrepreneurs. First, we note that only a handful of entrepreneurs are transformative, accounting for about 17% of firms in our data. Next, to understand the determinants

[2] Appendix B.3 lists the top R&D occupations, which consists of occupations where more than 1% of individuals have a patent.

of transformative entrepreneurship, in Figure 2, we plot the share of individuals in each IQ decile who become subsistence entrepreneurs (left axis) and transformative entrepreneurs (right axis).

Figure 2: IQ and Entrepreneurship

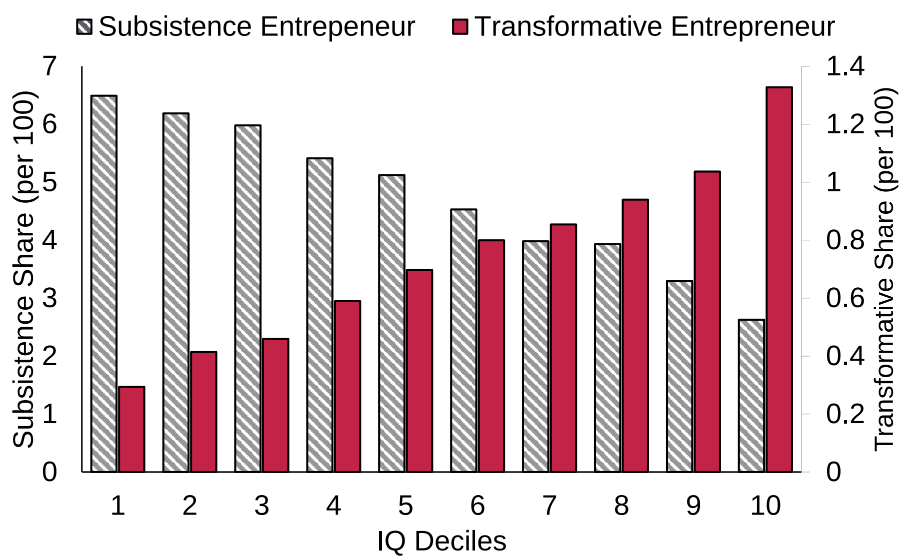


Figure 2 shows a starkly different IQ sorting for subsistence and transformative entrepreneurship. The prevalence of transformative entrepreneurship rises significantly with IQ, while the share of subsistence entrepreneurs declines sharply. Among entrepreneurs in the bottom IQ decile, only 4% are transformative, compared to 33% in the top decile. This sorting mechanism is a crucial part of our framework, determining the allocation of talent in the innovation pipeline.

Given the IQ-based sorting patterns in Figures 1 and 2, we next examine empirical specifications that control for additional factors influencing occupational sorting, allowing us to jointly assess the relative importance of various determinants of career choice.

We implement a multinomial logistic regression to explore the determinants of career choice for R&D workers, entrepreneurs, and entrepreneur types. We compare the probability that an individual i enters an occupation k against the probability of becoming a production worker [3], as described in equation (1):

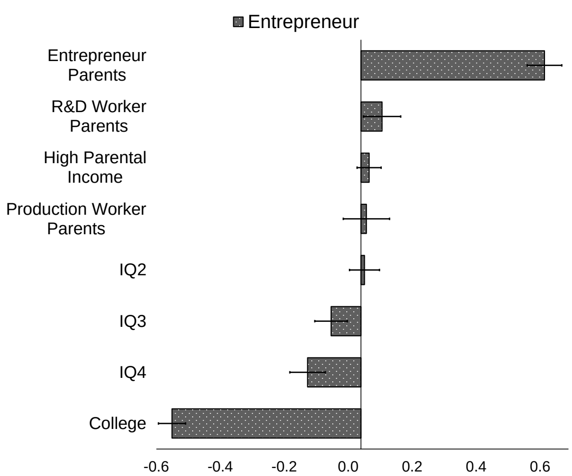
[3]For individuals with multiple occupations during the sample period, we assign each individual i to the occupation k in which they spend the majority of their observed working years. Our results remain consistent when we instead classify occupations based on cross-sectional career observations from a single year. See Appendix B for additional details.

$$\log\left(\frac{P_{i,k}}{P_{i,p}}\right) = \beta_1 college_i + \sum_{j=2}^{4} \omega_i \mathbb{I}\{IQ\ Quartile_i = j\}$$
$$+ \beta_2 entrepreneur\ parents_i + \beta_3 R\&D\ worker\ parents_i$$
$$+ \beta_4 production\ worker\ parents_i + \phi parent\ income_i + \Lambda_{b(i)} + \epsilon_i, \quad (1)$$

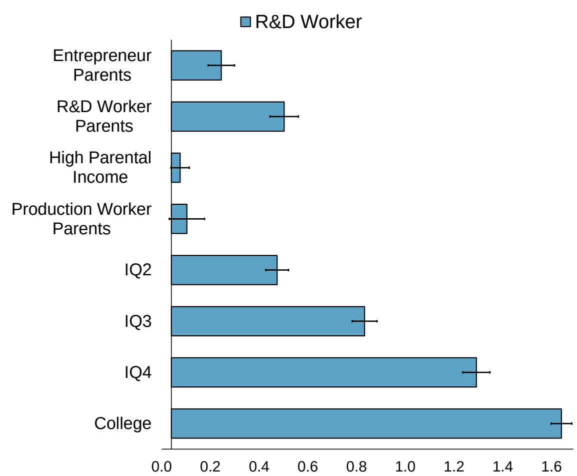
where $P_{i,k}$ is the probability that individual i is in occupation k against the probability of being a production worker, $P_{i,p}$.[4] The independent variables are all binary and indicate individual i's college attainment, her IQ quartile, whether she has a parent entrepreneur[5], a parent R&D worker, a parent production worker, and whether her parents' income belongs to the top half of the income distribution. We include cohort fixed effects $\Lambda_{b(i)}$, where $b(i)$ is the birth cohort of individual i. We plot the coefficients from two regressions with the structure of equation (1) in Figures 3 and 4.

The first specification, in Figure 3, examines the likelihood of becoming an entrepreneur, in panel (A), or an R&D worker, in panel (B), against the baseline case of being a production worker. We plot the estimated coefficients ordered by decreasing magnitude for entrepreneurs, with bands for the standard error.

Figure 3: Multinomial Logit for Career Choice



(a) Entrepreneur



(b) R&D Worker

[4]Appendix C provides the full details underlying this figure.

[5]Parent entrepreneur includes if either parent is an entrepreneur. This is measured as registered self-employment as a primary occupation, as we do not observe firm founding prior to 2001.

Figure 3a shows that the strongest predictor of entrepreneurship is whether an individual has a parent who is an entrepreneur. The estimated coefficient of 0.574 log odds implies that individuals with a parent entrepreneur are 78% more likely to be entrepreneurs, conditional on covariates. Those with more education and higher IQ are less likely to be entrepreneurs overall, as the top IQ quartile is 15% less likely to be an entrepreneur than a production worker, conditional on covariates.

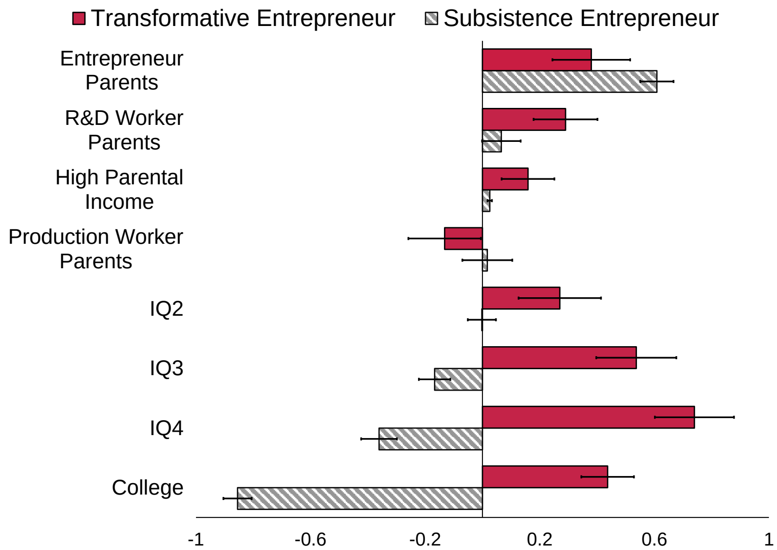
On the other hand, as seen in Figure 3b, there is a strong connection between schooling and IQ and becoming an R&D worker. The top quartile of IQ has 1.25 higher log odds of being an R&D worker over a production worker. This means they are about 2.5 times more likely to be R&D workers than production workers. College additionally makes an individual almost 4 times more likely to be an R&D worker than a production worker. These results highlight the importance of talent and higher education for becoming an R&D worker.

Figure 3 also reveals that high parental income is not a strong factor in determining career choice when controlling for the other covariates. However, parental income could have an indirect impact on occupational sorting through the likelihood of college attendance. In Appendix C, we show that even though parental income does not influence the likelihood of becoming an R&D worker when education is taken into account, it remains a strong predictor of college education, conditional on IQ and parental education levels. This suggests that unequal access to higher education, which is strongly influenced by parental income, serves as a key bottleneck in the pathway to becoming an R&D worker.

In the second specification in Figure 4, we separate the entrepreneurial types and examine the likelihood of becoming a transformative entrepreneur, a subsistence entrepreneur, or an R&D worker against the baseline case of being a production worker. Figure 4 presents the coefficients corresponding to the two entrepreneur types. While parental entrepreneurship remains a key factor for transformative entrepreneurs, IQ and education now also play crucial roles, unlike the case of general entrepreneurship. In particular, college education and the highest IQ quartile are associated with an increase in the probability that an individual is a transformative entrepreneur by 55% and 110%, respectively, conditional on covariates. These results deliver Fact 3, that transformative entrepreneurs have higher IQ and obtain higher education. On the contrary, the probability of becoming a subsistence entrepreneur is negatively associated with higher IQ. This result aligns with the model discussed later, which suggests negative selection by talent into subsistence entrepreneurship.

An important element for our framework is that unequal access to education, which

Figure 4: Entrepreneur Type



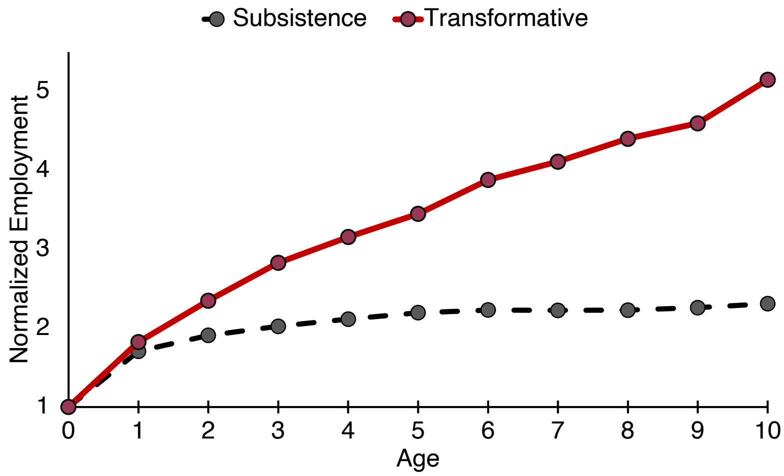
is influenced by both individual IQ and parental income, creates a bottleneck for both R&D workers and transformative entrepreneurs.[6] Not only does education drastically increase the odds of becoming an R&D worker, but it also doubles the likelihood of being a transformative entrepreneur vis-a-vis a subsistence entrepreneur and production worker. This outsized effect of education, which is itself affected by ability and parental income, is an important channel for opportunities into entrepreneurship.

Firms. Are transformative entrepreneurs more likely to produce a successful firm? Figure 5 documents the evolution of employment of firms held by transformative and subsistence entrepreneurs over firm ages. To focus on the differences in their growth patterns, we plot employment, normalizing the initial value to be one, even though transformative entrepreneurs start larger.

We find that transformative entrepreneurs start around twice as large as subsistence entrepreneurs and grow more than 9% faster per year, leading to stark differences in the firm size distribution of the two firm types. As a result, even though transformative entrepreneurs account for only 13% of the workforce hired by startups (firms of age 0), by age ten, they account for 34% of the employment of firms of that age. This finding

[6]The influence of the family economic background on college attainment is an important ingredient in the theoretical model. The literature has documented the link between educational attainment and family income in the case of Denmark, despite the generous government education subsidies; see Nielsen et al. (2010) and Akcigit et al. (2025). We document such a link in the context of our data in Appendix C.

Figure 5: Employment by Entrepreneur Type/Age



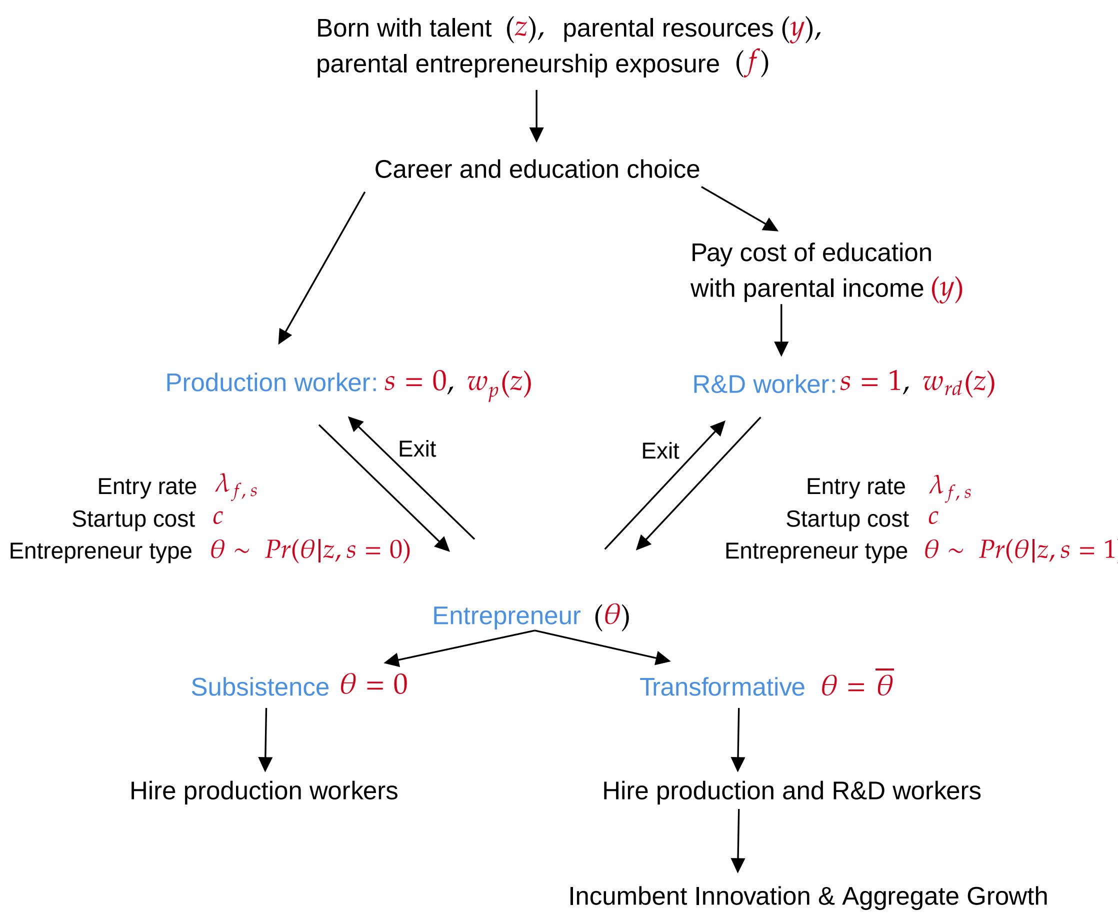
underscores their important role in the overall business dynamism in the economy and disproportionate impact relative to their smaller share of initial entrepreneurship. In Appendix C, we show that transformative entrepreneurs, in addition to being more likely to be innovative, also have higher revenue growth and lower exit rates than subsistence entrepreneurs. These results are robust to different definitions of a transformative entrepreneur.

Empirical Takeaways. Overall, our empirical findings suggest that entrepreneurs are negatively selected on ability and schooling, but those who undertake transformative entrepreneurship—by hiring R&D workers—are positively selected, akin to R&D workers, and run larger, faster-growing firms. Further, parental background in occupation and income shapes educational and entrepreneurial opportunities. Taken together, these results underscore the importance of jointly considering individual attributes—such as IQ, education, and family background—and entrepreneurial type to understand firm dynamics and economic growth. To further unpack these dynamics and their implications for policy, we next introduce a theoretical framework that integrates individual occupational choice, entrepreneurial heterogeneity, and firm life-cycle dynamics.

3 Model

This section develops a life-cycle model of career choice, entrepreneurship, and firm dynamics embedded in an endogenous growth framework, guided by the empirical facts presented earlier. In our model, individuals differ in ability, family income, and exposure to parental entrepreneurship. These differences affect educational decisions and ultimately shape occupational choices, the evolution of firms, aggregate innovation, and economic growth. The model is formulated in continuous time and designed to capture the interplay between talent allocation across occupations and firm growth along a Balanced Growth Path (BGP) equilibrium. In our exposition of the model, we normalize all the growing variables by the final good in the economy to keep the stationary equilibrium values constant, and suppress time subscripts whenever this causes no confusion. Figure 6 illustrates the key elements of the model, from initial career choice between R&D and production worker, to entrepreneurial choice, to the dynamics of firms and innovation.

Figure 6: Model Map



3.1 Environment and Agent Heterogeneity

We consider an economy 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 $\Omega(z, y, f)$. 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 Educational Choice and Occupational Sorting

When individuals are born, they initially decide on an occupation to begin their working career, choosing either to become a production worker or an R&D worker. Production workers do not attend higher education, while an R&D career requires the acquisition of costly education, where the cost is denoted by the parameter c_s. We interpret this cost broadly — not necessarily as tuition fees, but rather as living expenses, books and supplies, the opportunity cost of foregone income during higher education, and other related expenditures. Importantly, we assume that this cost must be paid in advance through parental resources, reflecting a form of financial friction.[7] Therefore, individuals with $y < c_s$ cannot afford schooling, and they become production workers. In addition, individuals have preferences over education characterized by an idiosyncratic preference shock ϵ.

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.[8] Given this structure, the occupation choice problem of an individual with state (z, y, f) who can afford education can be expressed as:

$$\max \left\{ W_0(z, y, f), W_1(z, y, f) - c_s + \epsilon \right\}. \tag{2}$$

Here, $W_s(z, y, f)$, $s \in \{0, 1\}$, which will be derived in the next subsection, denotes the lifetime values associated with a career as a production worker ($s = 0$) and an R&D

[7] The literature has documented the presence of financial frictions and the influence of parental income on access to college education in Denmark, despite the low cost of education compared to other countries; see Nielsen et al. (2010) and Akcigit et al. (2025). We will use the evidence from Nielsen et al. (2010) to calibrate the magnitude of these financial frictions, which play a central role in the allocation of talent within our framework.

[8] Accordingly, in our model, choosing education is effectively equivalent to choosing between a career as a production worker ($s = 0$) or an R&D worker ($s = 1$).

worker ($s = 1$), not accounting for education costs and preference shock. We assume the preference shock follows a logistic distribution with mean χ and scale parameter ς.[9] Given this distributional assumption, the above decision problem implies that the probability of acquiring education and becoming an R&D worker is given by

$$\mathbb{P}\left(s=1|z,y,f\right) = \mathbb{1}(c_s < y) \times \frac{1}{1+\exp\left(\frac{W_0(z,y,f)}{\varsigma} - \frac{W_1(z,y,f)-c_s+\chi}{\varsigma}\right)}. \tag{3}$$

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) 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 distribution of preference shocks, reflects the trade-off between the lifetime values of being a production worker $W_0(z,y,f)$ and an R&D worker $W_1(z,y,f)$, adjusted for schooling costs c_s and average preference for schooling χ. A higher ς increases the role of idiosyncratic preferences, making the decision more dispersed and less deterministic.

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 occupation of production worker or R&D worker, corresponding to $s = 0$ and $s = 1$ respectively. We allow for heterogeneity in how ability affects worker productivity across occupations by assuming that a worker with ability 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 of production worker ($s = 0$) or R&D worker ($s = 1$). Consequently, the wage income per period is given by

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

where ω_s denotes the wage *per efficiency unit* for a production worker ($s = 0$) and an R&D worker ($s = 1$), which will be determined in equilibrium by the set of entrepreneurs and their firms, which we turn to in the following section.

[9] In this setting, a negative value for χ can be interpreted as disutility from education.

3.3 Entrepreneurial Opportunities and Startup Decisions

In addition to earning wage income, agents receive random opportunities to become entrepreneurs and earn profits from running a firm over the course of their life cycle. This opportunity arrives at rate $\lambda_{f,s}$, which depends on whether the agent comes from an entrepreneurial family ($f = 1$) or not ($f = 0$), and on her education level $s \in \{0, 1\}$. When the entrepreneurship opportunity arises, the agent draws an entrepreneur type θ from a distribution $\Pi(\theta|z, s)$ that depends on the agent's ability and education. The drawn type θ determines the entrepreneur's efficiency in utilizing R&D workers, which will be explained further in the next section. We assume θ can take two possible values, $\theta \in \{0, \bar{\theta}\}$. The types $\bar{\theta}$ are *transformative entrepreneurs*: they hire both production workers and R&D workers, and the latter enables them to engage in innovation activity in an attempt to expand their firms. The types $\theta = 0$ are only involved in production and do not innovate, but they may still grow their firms exogenously.

An individual's decision to transition from worker to an entrepreneur involves comparing the benefits of starting a firm — net of a stochastic entry cost c_e — with the continuing value of remaining a worker.[10] If she decides to become an entrepreneur, 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, the lifetime value of the workers solves the following equation:

$$
\begin{aligned}
\rho W_s(z, y, f) = {} & \omega(z, s) \\
& + \lambda_{f,s} \left[\mathbb{E}_{c_e,\theta} \left(\max \left\{ V_e(\theta) - c_e, W_s(z, y, f) \right\} \right) - W_s(z, y, f) \right] \\
& + \psi \left[0 - W_s(z, y, f) \right]
\end{aligned} \tag{4}
$$

where ρ is the discount rate.[11] The left-hand side, $\rho W_s(z, y, f)$, represents the required return on the worker's lifetime value at the discount rate r, which equals the sum of three distinct components. First, the worker earns a per-period wage, $\omega(z, s)$, based on their ability and education. Second, workers have the option to transition into entrepreneurship when opportunities arrive at the rate $\lambda_{f,s}$; the term inside brackets captures the expected additional benefit from potentially becoming an entrepreneur, considering both the entrepreneurial payoff $V_e(\theta)$ (defined explicitly in the next section)

[10] 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).

[11] Due to the normalization of value functions by the final good, the value function is discounted with ρ rather than interest rate r. For details, see Appendix A.1 for the household decision and A.4 for normalization.

net of entry costs c_e, and the continuation value of remaining a worker $W_s(z, y, f)$. This expectation is taken over the distributions of the entry cost and entrepreneurial type θ. Finally, the last term accounts for mortality: workers exit the economy at rate ψ, at which point their lifetime value drops to zero. We next turn to describe what entrepreneurs do in detail and the resulting firm dynamics.

3.4 Entrepreneurship and Firm Dynamics

The firm side of the model builds on the framework of Klette and Kortum (2004) to capture the dynamics of innovation and firm growth. In our setting, each firm is owned and managed by an entrepreneur and is conceptualized as a portfolio of product lines that generate profits via employing production workers.[12] Entrepreneurs start their firms with a single product line, reflecting the minimal initial scale of new firms. Firms invest in innovation—using R&D workers as input—to expand their portfolios by improving product quality. While innovation grows firm value, this growth is offset by competition from incumbents and entrants that displace product lines. As a result, firm value evolves endogenously with the capture of new product lines and the loss of existing ones.

The firm's dynamic decision is characterized by its choice of innovation effort, which determines the arrival rate of new product lines. A firm with n product lines and entrepreneur type θ produces innovations at rate

$$X(n, \theta) = \theta l_{rd}^{\sigma} n^{\eta}, \tag{5}$$

where l_{rd} denotes the efficiency units of R&D labor hired by the firm, σ captures the elasticity of innovation with respect to R&D labor, and η governs returns to scale in the number of product lines.[13] The parameter θ reflects entrepreneurial innovation capability: transformative entrepreneurs have $\theta = \bar{\theta} > 0$ and actively invest in R&D, while subsistence entrepreneurs have $\theta = 0$ and therefore do not attempt to innovate and do not hire any R&D workers. Given this technology, the cost of producing innovation effort X is given by the cost of R&D worker it requires:

[12] These product lines are used as inputs to produce the final good in the economy. We provide further details in Appendix A.2.

[13] The inclusion of n in the innovation function reflects that firms with more product lines have a larger base of knowledge and resources, enhancing their capacity to generate innovations. We assume $\sigma + \eta \leq 1$, i.e., we allow for decreasing returns to scale in innovation production function, motivated by the evidence provided by Akcigit and Kerr (2018).

$$C(X; n, \theta) = \omega_1 \left(\frac{X}{\theta n^\eta} \right)^{\frac{1}{\sigma}}$$

where ω_1 is the wage per efficiency unit of R&D labor.

When innovation is successful, the firm improves the quality of a random product by a factor γ and captures it from another firm, thereby increasing its portfolio by one product. Symmetrically, each product line the firm owns is at risk of being displaced by other firms and entrants at the rate τ. We refer to τ as *business reallocation rate*, which is endogenously determined in equilibrium and taken as given by the firm.

The value of a firm with n product lines and type θ is denoted by $V(n, \theta)$ and satisfies the following Bellman equation:

$$\begin{aligned} \rho V(n,\theta) = {} & \pi n \\ & + \tau n \left[V(n-1,\theta) - V(n,\theta) \right] \\ & + \max_X \left\{ X \left[V(n+1,\theta) - V(n,\theta) \right] - \omega_1 \left(\frac{X}{\theta n^\eta} \right)^{\frac{1}{\sigma}} \right\} \\ & + \upsilon n \left[V(n+1,\theta) - V(n,\theta) \right] \\ & + \psi \left[0 - V(n,\theta) \right]. \end{aligned} \tag{6}$$

The first term on the right-hand side, πn, captures the total flow profits generated by the n product lines.[14] The next term reflects the loss in value due to competition by other incumbents and new entrepreneurs, where each product line faces the risk of being displaced at the rate τ. The maximization component represents the change in the firm value through innovation; by choosing an optimal innovation effort X, or equivalently, how many R&D workers to hire, and paying the corresponding cost, the firm expands its portfolio (increasing the number of product lines from n to $n+1$). The next term captures exogenous factors that may contribute to firm growth at the rate ν per product line. Finally, the last term accounts for the exit due to the death of the entrepreneur, in which case the value of the firm goes to 0. Note that since firms enter with a single product line, the value of choosing entrepreneurship introduced in the previous section satisfies $V_e(\theta) = V(1, \theta)$.

Firm exit occurs either through exogenous death of the entrepreneur or endogenously when all product lines of the firm are lost due to competition from other firms. In the latter case, the entrepreneur shuts down the firm and returns to the labor market

[14]Details on the product market and the resulting profits πn are provided in Appendix A.2.

in her previous occupation. Together, the 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.

3.5 Labor Market Clearing and Stationary Equilibrium Distributions

One of the main novel elements of this framework is connecting the origins of the supply and demand sides for innovation. This section discusses the labor market clearing that enables this general equilibrium treatment. On the supply side of the labor market, recall that each individual with ability z who works as a production or R&D worker supplies z^{α_s} efficiency units of labor, and the total number of such workers is determined by agents' educational choices early in life and their entrepreneurial decisions over the life cycle. On the demand side, firms demand $\frac{1}{\omega_0\gamma}$ efficiency units of production worker per product line they own, which is derived in Appendix A.2. Demand for R&D workers, on the other hand, is determined by firms' innovation effort choice X implied by firms' dynamic problem (6).

Let $\Phi_s(z,y,f)$ denote the density of individual workers with talent z, parental income y, family entrepreneurship background f, and schooling $s \in \{0,1\}$. Let $\Psi(n,\theta)$ denote the joint distribution of active firms by number of product lines n and entrepreneurial type θ. Labor market clearing then requires that

$$\sum_{\theta}\sum_{n}\frac{1}{\omega_P\gamma}n\,\Psi(n,\theta) = \sum_{f}\int_z\int_y \Phi_0(z,y,f)\,z^{\alpha_0}dzdy \tag{7}$$

for production workers, and

$$\sum_{\theta}\sum_{n}\left(\frac{X(n,\theta)}{\theta n^{\eta}}\right)^{\frac{1}{\sigma}}\Psi(n,\theta) = \sum_{f}\int_z\int_y \Phi_1(z,y,f)\,z^{\alpha_1}dzdy \tag{8}$$

for R&D workers. To solve for these labor market-clearing conditions, we need to characterize both the worker and firm distributions, $\Phi_s(z,y,f)$ and $\Psi(n,\theta)$. We provide the derivation of these distributions in Appendix A.5.

3.6 Aggregate Business Reallocation and Innovation

The process of business reallocation across firms is central to the dynamics of our model. It is driven by both new entrepreneurs' and incumbent firms' activities. The overall rate of business reallocation, denoted by τ, is given by

$$\tau = \sum_{\theta} e_{\theta} + \sum_{\theta} \sum_{n} \left[X(n,\theta) + \nu n \right] \Psi(n,\theta)$$

where e_{θ} denotes the entry rate into type-θ entrepreneurship, capturing the contribution of entrants to business reallocation, while the second term reflects the incumbent firms' innovation efforts as well as exogenous factors that contribute to business reallocation across firms.

Whereas τ measures the overall flux of business activity—including both new firm entry and incumbent expansion (innovative or otherwise)—only some of those changes lead to direct quality improvements in our model. Thus, τ captures the entire process of reallocation across the economy, encompassing both innovating and non-innovating firms. In contrast, we define τ_g as *aggregate innovation rate*, which captures the portion of these reallocative events that actually raise product quality and thereby contribute to aggregate growth:

$$\tau_g = \sum_{\theta} s_{\theta}^{I} e_{\theta} + \sum_{\theta} \sum_{n} X(n,\theta) \Psi(n,\theta) \tag{9}$$

where s_{θ}^{I} is a parameter representing the share of entry by θ-type entrepreneurs that leads to a quality improvement upon entry. This parameter is calibrated using empirical evidence to reflect the relative importance of entrants on the overall growth of the economy. Consequently, τ_g governs growth via successful innovations, and τ governs the broader reallocation of resources across the economy.

Finally, the aggregate growth rate of the economy is expressed as[15]

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

where $\gamma > 1$ is the step of product quality improvements achieved through innovation. We finish our model description by defining the equilibrium of this economy.

Definition 1 *A Balanced Growth Path (BGP) equilibrium is a collection of value functions* $\{W_s(z,y,f),\ V(n,\theta)\}$*, policy functions (e.g., education choice, entrepreneurial entry, R&D intensity), wages* $\{\omega_0, \omega_1\}$*, and distributions* $\{\Phi_s(z,y,f),\ \Psi(n,\theta)\}$ *satisfying the following:*

1. ***Workers' Optimization.*** *Each agent solves the problem* (2) *and the Bellman equation in* (4)*, choosing whether to pay the education cost and become an R&D worker or to*

[15] The derivation of the growth rate is given in Appendix A.3.

become a production worker that does not require education, and whether to transition to entrepreneurship upon an opportunity.

2. ***Firms' Optimization.*** *Each entrepreneur with state* (n, θ) *solves the firm problem in* (6)*, determining R&D effort (if transformative) to maximize firm value.*

3. ***Market Clearing.*** *The supply of production and R&D labor—driven by individuals' occupational choices—matches the total labor demanded by firms, as specified in equations* (7) *and* (8).

4. ***Stationary Distributions.*** *The distributions* Φ *and* Ψ *over individuals and firms remain invariant over time, consistent with endogenous transitions and entry/exit, satisfying* (18) *and* (20) *in Appendix A.5.*

5. ***Balanced Growth.*** *Let* $\gamma > 1$ *be the quality step per successful innovation and* τ_g *the aggregate innovation rate. Output grows at*

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

endogenously determined by equilibrium innovation and entrepreneurship.

Model Takeaways. Our framework unifies the career choices of individuals—whether to become a production worker, R&D worker, or entrepreneur—with firm-level innovation and underlines how they jointly shape economic growth through innovation. Specifically, it illustrates that talent allocation across occupations—determined by individual ability, educational opportunities, and family background—critically influences the supply of innovative talent (R&D workers) and the emergence of transformative entrepreneurs. A central implication of this model is that the synergy between higher-ability transformative entrepreneurs and the supply of educated R&D workers is essential for sustaining growth. Moreover, the model highlights that financial constraints limiting access to education can lead to significant talent misallocation, reducing both the number of transformative entrepreneurs and R&D workers. Consequently, alleviating these barriers through targeted policies can substantially boost innovation, improve occupational sorting, and accelerate overall economic growth.

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 and promote innovation.

4.1 Functional Forms and Identification

We begin with a description of the estimation procedure. Our model has 27 parameters, 11 of which are calibrated externally and presented in Table 1.

Table 1: Calibrated Parameters

Parameter	Description	Value	Source
ρ	Discount rate	0.050	Standard
ψ	Death rate rate	0.025	40-year career
σ	Curvature on innovation production function	0.500	Akcigit and Kerr (2018)
σ_z	SD of talent distribution	0.224	Data
σ_y	SD of family income distribution	0.619	Data
$\rho_{z,y}$	Correlation of talent and family income	0.144	Data
μ_y	Mean of family income distribution	0.461	Nielsen et al. (2010)
p_f	Probability parent entrepreneur	0.080	Data
c_s	Education cost	0.275	Data
γ	Innovation step size	1.250	De Loecker et al. (2020)
s_θ^I	Share of entrants with improvement upon entry	0.25	Data

Notes: These parameters are independently identified in the data or literature.

We set the discount rate ρ to 5 percent. Following the microeconometric literature on innovation, we set the curvature of innovation production function to $\sigma = 0.5$, indicating a quadratic cost function; this captures diminishing returns to labor inputs in research.[16] The death rate ψ is set to 0.025, implying 40 years of expected working life. The innovation step size (γ=1.25) indicates that successful innovations increase productivity by 25%, calibrated from markup data from De Loecker et al. (2020). The share of innovative entrants s_θ^I is directly measured in the data as the share of entering

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

firms that improve upon the median productivity upon entry in their given industry. The education cost parameter (c_s) is directly measured in the data as the opportunity cost from foregone earnings during the years of higher education relative to lifetime earnings.

We assume that z and y follow a bivariate lognormal distribution with mean parameters μ_z and μ_y, standard deviation σ_z and σ_y, and correlation $\rho_{z,y}$. The standard deviations of talent (proxied by IQ) and family income are measured directly from data, as is their correlation. The talent mean parameter, μ_z, is normalized, as its level is not separately identified. The family income mean parameter, μ_y, is calibrated to match the share of individuals who are credit constrained (30%) from Nielsen et al. (2010), who study higher education in Denmark and estimate the number of individuals in the population who face credit constraints for education based on the response of college enrollment to changes in student aid arising from a Danish reform. This moment is central to our quantification of the effect of financial frictions on college access. Finally, the probability of parent entrepreneurship is calibrated to $p_f = 0.08$, representing the baseline rate of entrepreneurship in the previous generation.

The remaining 16 parameters are estimated jointly by matching 41 moments from the data to model-generated moments, which are presented in Table 3 and Figure 7. We combine individual-level moments with firm-level moments to connect these two core features of our framework. These moments focus on ability distributions across occupations, the performance of transformative and subsistence entrepreneurs, and the aggregate growth rate. Each set of moments is chosen for its economic relevance to the key mechanisms of the model.

To begin with, we target R&D workers and entrepreneurs share by IQ deciles to discipline the parameters that determine the returns to each occupation, such as α_s. Motivated by our empirical evidence, the probability of drawing a type $\bar{\theta}$ and becoming a transformative entrepreneur depends both on ability z and investment in schooling s, according to the following functional form:

$$\Pi(\bar{\theta}|z,s) \equiv \mathbb{P}(\theta = \bar{\theta}|z,s) = \frac{\varphi + \iota \times s}{1 + \exp\left(-\kappa\left(z - \zeta\right)\right)},$$

where φ, κ, ζ, and ι are parameters that we estimate by targeting the share of transformative entrepreneurs by IQ deciles and by education. Overall, φ captures the baseline probability of transformative entrepreneurship, while ι and κ govern the role of education and ability respectively, and ζ represents a threshold parameter. We calibrate $\bar{\theta}$ by matching the life-cycle growth profile of transformative entrepreneurs, captured through the average firm size by age. We allow subsistence firms to grow exogeneously at rate ν, which we pin down by comparing the growth trajectories of subsistence and transformative firms by age.

We assume that schooling and parental entrepreneurship background interact additively in the arrival rate,

$$\lambda_{f,s} = \lambda_f + \lambda_s,$$

and we further normalize $\lambda_s = 0$ for uneducated individuals ($s = 0$) such that we only estimate the additional entrepreneurial opportunity due to education. The entry cost c_e is drawn from a Pareto distribution with shape parameter ϖ and a scale parameter fixed at 1.[17] We identify these parameters by targeting the share of entrepreneurs with and without entrepreneurial parents and the differences in entrepreneurship rates across education groups.

A core component of our firm dynamics framework is the innovation production function in equation (5). To identify the curvature of the innovation production function with respect to the size of the firm η, we run the following firm-level regression, which connects the R&D employment to the total workforce for a firm j at time t:

$$\ln(R\&D\ Worker_{jt}) = \beta_0 + \beta_1 \ln(Total\ Worker_{jt}) + \varepsilon_{jt}. \tag{10}$$

This relationship describes how firm-level innovation scales with size and helps us identify the returns to scale pattern in innovation: if $\beta_1 = 1$, R&D employment scales proportionally with total employment corresponding to $\sigma + \eta = 1$ in the model. $\beta_1 < 1$, on the other hand, indicates decreasing returns to scale in innovation. Therefore, this regression coefficient helps identify the parameter η, which governs how the number of product lines contributes to the firm's innovation capacity, conditional on the calibrated value of σ. As a result, our framework allows for decreasing returns to innovation at the firm level, as long as the R&D workforce does not scale one-to-one with firm size. This is consistent with the economy's need to have a robust pool of entrepreneurs to absorb R&D workers without hitting diminishing returns. We now turn to the estimation results to connect the moments to the underlying parameters.

[17]The arrival rate λ and the scale parameter of the entry cost cannot be separately identified; hence we set the latter to 1.

4.2 Estimation Results

In this section, we present the internally estimated parameters in Table 2 and the moments that identify them in Table 3 and Figure 7.

Table 2: Estimated Parameters

Parameter	Description	Value
$\lambda_{f=1}$	Entrepreneurship arrival rate w/ entrepreneur parent (%)	0.05
$\lambda_{f=0}$	Entrepreneurship arrival rate w/o entrepreneur parent (%)	0.02
$\lambda_{s=1}$	Contribution of education to entrepreneurship arrival rate (%)	0.1
$\bar{\theta}$	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
φ	Entrepreneurial type draw function	0.354
α_1	Wage function - R&D workers	0.545
α_0	Wage function - Production workers	0.495
m	Entrant cohort mass	0.181
η	Product line share in innovation function	0.338
χ	Utility from education	-3.153
ς	Education preference shock scale	0.389
ϖ	Pareto shape parameter for entry cost	2.571
ν	Exogenous arrival rate of products (subsistence firms)	0.125

Notes: All parameters are estimated jointly.

We describe some of the key results from our estimation. For the entrepreneurship arrival rate by parent entrepreneurial exposure, λ_f, we find $\lambda_{f=1} = 0.05\%$ and $\lambda_{f=0} = 0.02\%$, which capture the critical role of family background—individuals with entrepreneur parents are 2.5-times more likely to have an opportunity to become an entrepreneur. The contribution of education to entrepreneurship arrival rate ($\lambda_{s=1} = 0.1\%$) also indicates that educated workers are much more likely to have entrepreneurial opportunities. The parameter $\iota = 3.358$ further amplifies the effect of education on entrepreneurial opportunities. Our estimation of this parameter suggests that, on average, education increases the likelihood of being a transformative entrepreneur as opposed to subsistence by about 69 percentage points. The estimated wage parameters for R&D workers ($\alpha_1 = 0.545$) and production workers ($\alpha_0 = 0.495$) capture the earnings premium for R&D workers, which is part of what draws higher-IQ individuals into an R&D career. The value for the product line share in innovation ($\eta = 0.338$) implies that, for each percentage increase in firm size, the innovation rate increases by only about 0.84 percent, resulting in decreasing returns in innovation. Together, these parameters illuminate how family background, education, and labor market structures interact to shape entrepreneurial outcomes and economic mobility.

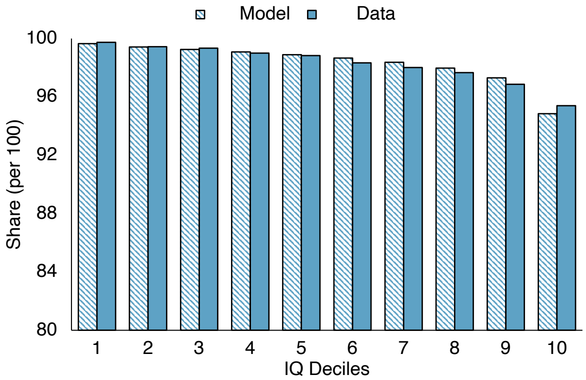
Table 3: Moments

Description	**Model**	**Data**
R&D workers share by IQ	In Figure 7	
Entrepreneurs share by IQ	In Figure 7	
Transformative entrepreneur share by IQ	In Figure 7	
R&D workers share in highest family income decile	0.027	0.028
Entrepreneur share by entrepreneur parent	0.10	0.10
Entrepreneur share by non-entrepreneur parent	0.06	0.06
Entrepreneur family share	0.08	0.08
Average firm size at age 10 - Subsistence entrepreneur	2.30	2.27
Average firm size at age 10 - Transformative entrepreneur	4.96	5.08
Share of transformative entrepreneurs within production workers	0.006	0.007
Share of transformative entrepreneurs within R&D workers	0.05	0.05
R&D workers log wage premium - highest to lowest IQ decile difference	0.09	0.09
Regression coefficient in equation (10)	0.38	0.36
Aggregate growth rate (%)	1.00	1.00

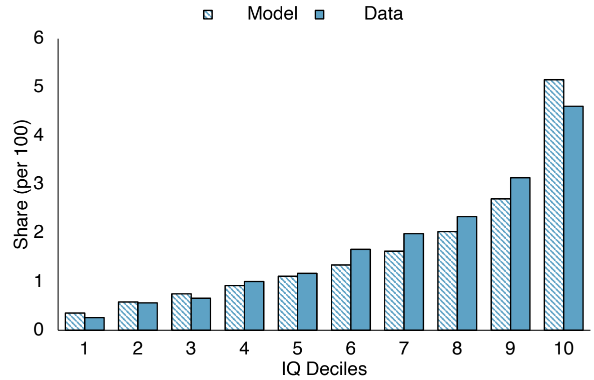
Notes: Moments jointly input into estimation. Average firm size moments are relative to entry size.

The estimation matches the specific moments and the occupational distribution quite well. The key moments in our model are targeted to match empirical regularities in entrepreneurship, innovation, and career dynamics. The shares of R&D workers, entrepreneurs, and transformative entrepreneurs by IQ are matched across the ability distribution (discussed below). We precisely match the impact of parental background, with entrepreneurs' children being significantly more likely to become entrepreneurs themselves (0.10 vs 0.06 for non-entrepreneurs' children). Our model accurately captures firm growth dynamics with subsistence entrepreneurs reaching average sizes of 2.30 employees at age 10 (vs 2.27 in data), while transformative entrepreneurs grow substantially larger (4.96 in the model vs 5.08 in the data). The model successfully reproduces the critical role of education in fostering transformative entrepreneurship, with educated entrepreneurs being eight times more likely to build transformative firms (0.05 vs 0.006 for uneducated). We match the change in wage premium over the IQ distribution for R&D workers (0.09 log difference), the relationship between occupation and entrepreneurial outcomes (0.36 regression coefficient in the data vs 0.38 in the model), and the aggregate growth rate (1%).

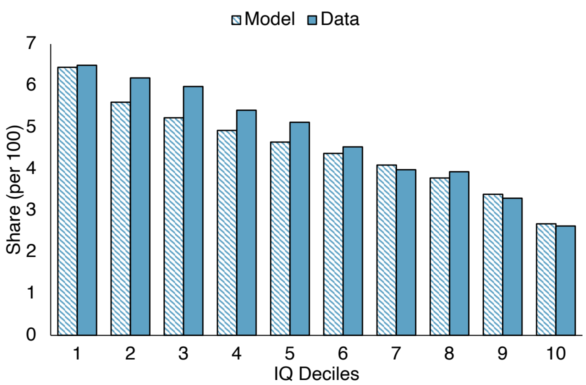
Figure 7: Talent Allocation across Types



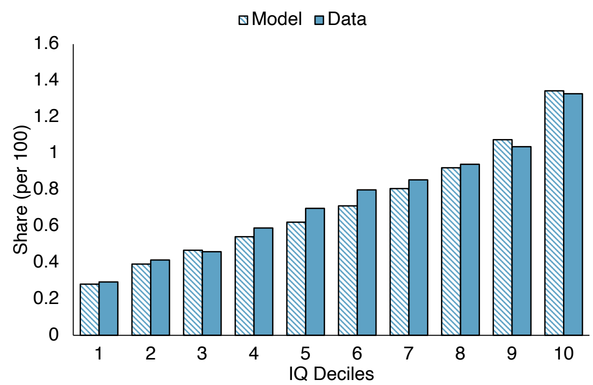
(a) Production Worker



(b) R&D Worker



(c) Non-transformative entrepreneur



(d) Transformative entrepreneur

On the career choice side, Figure 7 shows 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.

4.3 Untargeted Moments

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, which was not directly targeted in the data. Panel A of Table 5 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 regarding the higher propensity of entrepreneurs with an R&D background to be transformative compared to those with a production worker background.

Table 4: 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	0.12	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 occupation background. Panel B of Table 5 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 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.

Finally, we examine the dynamics of firm size by entrepreneurial type. Figure 8 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.[18]

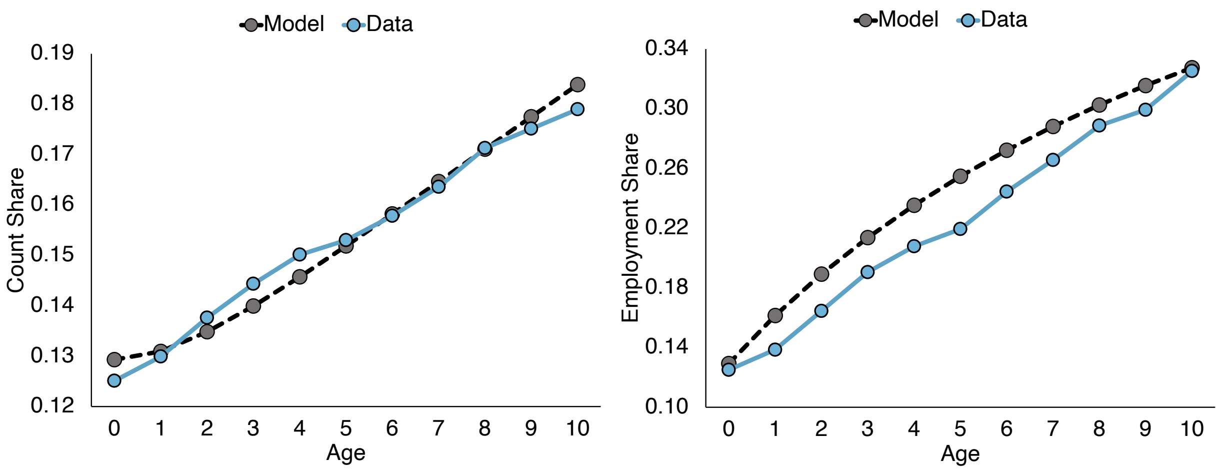
The pattern is monotonically increasing, as transformative entrepreneurs account for a share of firms that increases from about 13% at age 0 to 18% at age 10, and a share of total employment that increases from about 13% at age 0 to more than 30% at age 10. The model and the data are closely aligned, highlighting the increasing importance of transformative entrepreneurs throughout the firm life cycle, which will be central to understanding misallocation and evaluating policy counterfactuals.

4.4 Education and Entrepreneurship

One of the novel components at the center of this framework is the study of the pipeline for transformative entrepreneurs. Before turning to the counterfactual analysis, we

[18]We normalize the initial count of firms to adjust for the share of all individuals in the economy.

Figure 8: Untargeted Moments: Share of Transformative Entrepreneurs



(a) Share of Transformative Entrepreneurs

(b) Employment Share of Transformative Entrepreneurs

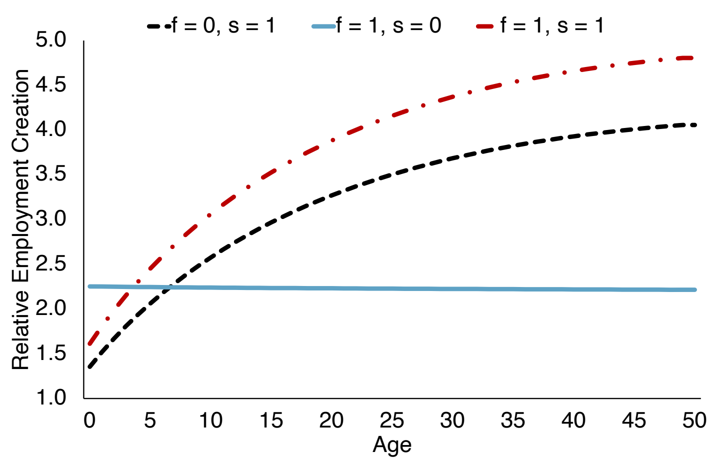
turn to the importance of education for entrepreneurship and firm dynamics. The quantified model suggests education is not just important for the creation of R&D workers, but also for the role of entrepreneurs. To highlight the role of education, we run a counterfactual exercise where we shut down the effect of higher education on the arrival rate of a transformative entrepreneurial idea. Specifically, we set the parameters $\lambda_{s=1} = 0$ and $\iota = 0$, neutralizing the higher education 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 assumptions.

Table 5: Importance of Education for Entrepreneurship

	Baseline	**No Educational Impact on Entrepreneurship**	**Change(%)**
Growth (%)	1.00	0.92	-7.95
		Occupation Shares	
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

Table 5 presents the results of this counterfactual analysis, illustrating the impact of removing the effect of higher 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%. This shows the crucial role of education in driving growth through entrepreneurship. Second, the share of R&D workers decreases by 8.55%, representing a combination of forces due to the symbiotic relationship between entrepreneurs and R&D workers. The occupational decision of an 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 higher education and transformative entrepreneurship reduces the perceived benefits of higher education, thereby discouraging individuals from choosing careers in R&D. In addition, the demand for R&D workers declines, given that there are fewer transformative entrepreneurs. These results emphasize the critical role of education in shaping the innovation pipeline within our framework.

Figure 9: Firm Life Cycle by Schooling and Parental Entrepreneurship



To further illustrate the role of schooling and family background, Figure 9 presents the impact of education and family exposure to entrepreneurship on the unconditional expected employment creation for an individual by age. The lines represent three groups of individuals: (i) those with parental exposure to entrepreneurship and no higher education (f=1, s=0, solid blue line); (ii) those with education attainment but no parent entrepreneurs (f=0, s=1, dashed black line); (iii) those with education and with parental entrepreneurship exposure (f=1, s=1, dashed-dotted red line). Each line shows the unconditional expected job creation for an individual from each group, relative to those without schooling or parent entrepreneurs (f=0, s=0). As a result, these lines include both the probability of starting a firm and the expected size of such a firm. The figure shows that individuals who have both parent entrepreneurs and higher education are the largest contributors to job creation.

There are three important observations from Figure 9. First, for entrepreneurs without higher education, parental exposure leads to over twice as much job creation throughout the life cycle. This effect is due to the higher propensity of becoming entrepreneurs for individuals with a parent entrepreneur. Second, we observe that individuals with schooling exhibit a steeper job creation profile. Higher education increases the likelihood that these individuals will draw a transformative type, conditional on having an entrepreneurial opportunity. Thus, in the first few years following their education (ages 0-5), they are more likely to delay starting a firm if they draw a low type compared to individuals without higher education. This is because they expect a greater chance of drawing a high type in the future. As a result, individuals with higher education show lower job creation in the early years but higher job creation in the central and later stages of their careers. Finally, the fact that individuals with both higher education and parental exposure to entrepreneurship have the steepest employment creation profile highlights that the interaction of parental entrepreneurship and schooling is central to the contribution of transformative entrepreneurs to job creation.

5 Talent Allocation and Policy Counterfactuals

In this section, we use our quantitative framework to examine the allocation of talent in the innovation pipeline, focusing on how individual career choices and firm dynamics interact, as well as the related policy implications. We begin with a positive analysis of the impact of financial frictions on both career choice and firm dynamics. Next, we explore policy tools that can foster growth by improving the allocation of talent across occupations and promoting the development of startups and firms.

5.1 Talent (Mis)Allocation

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. Such barriers can spill over to the rate of transformative entrepreneurship, given the large impact of education on the probability of becoming a transformative entrepreneur. These considerations raise the following questions: Are there missing R&D workers and missing entrepreneurs in the economy due to the inability to pursue education because of family income?

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 attend school. We do not subsidize their schooling directly, as they must still pay the education cost, which enters their discounted lifetime earnings, but they are not financially constrained. The results of this exercise are illustrated in Table 6, 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 6: Alleviating Financial Frictions in Education Access

	Baseline	**No Financial Frictions**	**Change (%)**
Growth (%)	1.00	1.11	11.08
		Occupation Shares	
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

Alleviating the frictions in access to education would increase the R&D workers population share by 15.2%, transformative entrepreneurs by 7.5%, and the growth rate by 11.1% relative to the baseline. Unequal access to education represents a bottleneck for various career paths due to the financial frictions that hinder access. As a result, alleviating these frictions can have a significant impact on talent allocation to entrepreneurship and innovation, enabling talented individuals from lower-income families to pursue careers as R&D workers and transformative entrepreneurs.

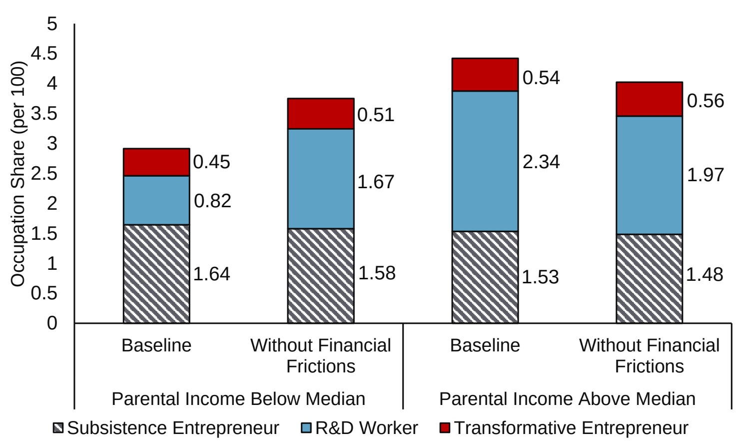
In our framework, the education channel operates on both the demand of R&D talent by transformative entrepreneurs and the supply of R&D talent through the career choice of R&D workers. Alleviating financial frictions increases both the demand and the supply for talent. The supply channel quantitatively 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. We thus focus on the supply-side effect of financial frictions, allowing the share of R&D workers to increase while keeping the demand side fixed at the steady state. Table 7 reports the results from this exercise, showing that the growth rate increases by only 6.6%, compared to 11.1% when both supply and demand adjust. Thus, the supply side can only generate about 60% of the total general equilibrium effect. These results underscore the complementarity of R&D workers and transformative entrepreneurs in the innovation pipeline. Merely increasing the number of inventors is insufficient; there must be a corresponding rise in job opportunities created by transformative entrepreneurs to fully unlock their potential and drive maximum growth.

Table 7: Synergy between R&D Workers and Entrepreneurs

	Baseline	**No Change in Entrepreneurship (PE)**	**Demand and Supply Adjust (GE)**
Growth (%)	1.000	1.066	1.111

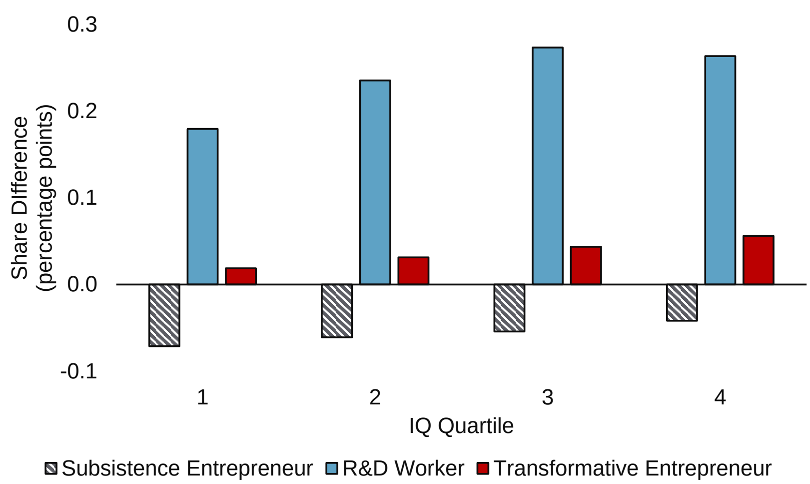
Figure 10: Alleviating Financial Frictions by Family Background



Returning to the full general equilibrium effects of alleviating financial frictions, Figure 10 shows the share of individuals who choose an occupation as subsistence entrepreneur, R&D worker, or transformative entrepreneur depending on their parental background. We group individuals by parental income above or below the median. The figure compares the occupational shares in the baseline and in the counterfactual with no financial frictions for individuals with low-income and high-income parents. The figure illustrates that, without financial frictions, the share of R&D workers increases for individuals with low parental income, but it decreases for those with high parental income, 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 intergenerational talent correlation. In addition, we note that the share of transformative entrepreneurs increases for individuals with both low and high parental income. This result is due to direct and indirect effects. First, alleviating financial frictions improves access to education, which directly increases the arrival rate of transformative entrepreneurship. Second, the increased supply of R&D workers further stimulates transformative entrepreneurship. 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 11 shows the change in the share of individuals in each occupation between the baseline and the counterfactual with no financial frictions.

Figure 11: Alleviating Financial Frictions by IQ



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 high-IQ 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. This result highlights that alleviating financial friction improves the allocation of talent to innovative careers in the economy.

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 12 explores how talent misallocation affects the dynamics of firms and innovation, comparing the counterfactual BGP without financial frictions discussed above (blue solid lines) to the baseline case (gray dashed lines).

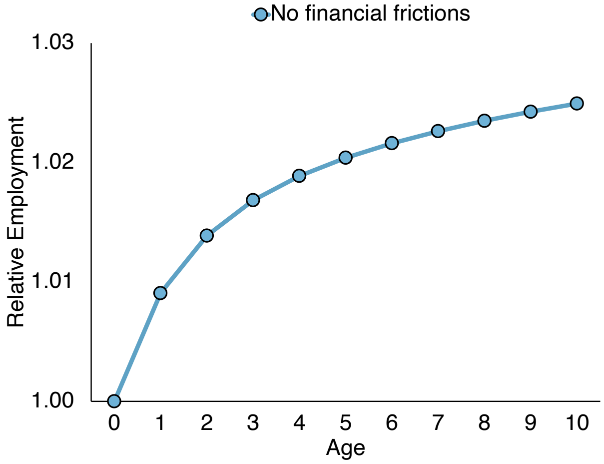
Panel (A) shows the average employment of transformative entrepreneurs by firm age relative to the baseline. The alleviation of financial frictions increases average employment for transformative entrepreneurs, which goes up by 1% for firms of age 1 and by almost 3% for firms of age 0. Next, we split this effect into the share of firms of each entrepreneur type and the share of employment. Panel (B) evaluates the share of transformative entrepreneurs with and without financial frictions by firm age. Panel (C) shows the employment share of transformative entrepreneurs in the economy with and without financial frictions. These pictures show that alleviating financial frictions increases both the share of firms that are transformative and the share of employment that they account for. This change in the composition of firms toward transformative types is the driver of the increase in innovation and aggregate growth when financial barriers to education access are lifted.

This result complements previous work (Akcigit et al., 2025) in showing the connection between financial frictions and innovation but expands on how the educational channel has a direct impact on entrepreneurship and firm dynamics. This new channel may lend itself to novel policy implications. Motivated by this observation, in the next section, we investigate how different policies can improve the allocation of talent, firm growth, and the innovative capacity of the economy.

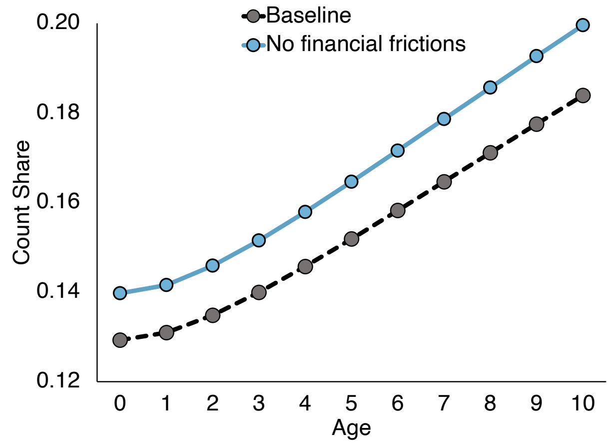
5.2 Comparing Alternative Policies

This section studies 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. Keeping fixed the budget of the policymaker, we consider four different possible instruments for innovation: subsidize R&D, entrepreneurship, transformative entrepreneurship, or education.

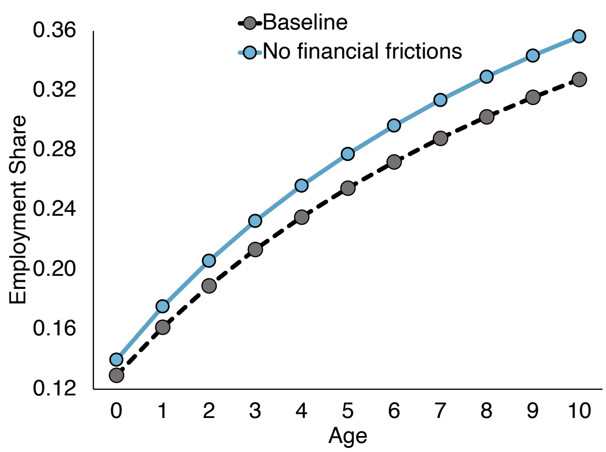
Figure 12: Alleviating Financial Frictions: Firm Outcomes



(a) Average Employment of Transformative Firms



(b) Share of Transformative Firms



(c) Employment Share of Transformative Firms

We assume that the government levies a lump sum tax to finance the policies by balancing the budget in every period. The four different policies have a specific mapping to the quantified model: (i) subsidy to the entry cost for all entrepreneurs (*Uniform Startup Subsidy*), (ii) subsidy to the incumbent firms for their R&D expenses (*R&D Subsidy*), (iii) subsidy to the entry cost only for transformative entrepreneurs (*Innovative Startup Subsidy*), and (iv) subsidy to the cost of education for those who cannot afford it (*Education Subsidy*). We compare alternative BGP equilibria with policies that use the same total government budget. Table 8 reports the results for a government budget equivalent to 0.05% of GDP. The first row of the table reports the change in the growth rate under each policy, while the other rows report the change in the share of each occupation.

Table 8: Policy Outcomes for Equivalent Budget of 0.05% of GDP

	Uniform Startup Subsidy	R&D Subsidy	Innovative Startup Subsidy	Education Subsidy
Growth (% Change wrt Baseline)	0.11	2.31	4.38	16.14
	Occupations Shares (% Change wrt Baseline)			
Production Workers	-0.01	-0.04	-0.08	-0.33
R&D Workers	-0.02	2.86	4.04	22.26
Subsistence Entrepreneurs	0.76	-0.74	-1.45	-5.27
Transformative Entrepreneurs	0.50	1.49	6.69	10.84

There are several key takeaways from Table 8. First, a uniform entrepreneurship subsidy appears largely ineffective, as it primarily attracts subsistence entrepreneurs, subtracting them from R&D and production, without significantly increasing the number of transformative entrepreneurs. Because subsistence entrepreneurs neither hire R&D workers nor significantly expand, they do not propel the innovation process, so the economy's long-run growth rate remains only slightly above the baseline.

In contrast, an R&D subsidy for incumbents spurs moderate innovation in the economy, increasing the demand for R&D workers and also resulting in a modest increase in the share of transformative entrepreneurs. However, its overall impact on growth is limited compared to some other policies in Table 8 primarily for two reasons. First, there are decreasing returns to innovation at the firm level implied by our estimation results. Second, this policy does not *directly* affect how many people can become R&D workers or transformative entrepreneurs.

Unlike the uniform startup subsidy, the innovative startup subsidy targets transformative entrepreneurs who plan to hire R&D workers. Lowering these entrepreneurs' startup costs leads to an appreciable increase in the share of transformative firms, fueling faster innovation, greater demand for R&D labor, and higher overall growth. Although this policy does not help incumbents as much as the R&D subsidy, it effectively boosts the formation of growth-oriented, transformative startups, which accounts for a noticeable rise in the growth rate.

Both the R&D subsidy and the innovative startup subsidy can stimulate innovation to some extent, but neither tackles the root cause of the primary friction — the unequal access to education faced by those who cannot afford it. In contrast, subsidizing the cost of education proves far more effective given the same budget. By helping more individuals afford higher education, it expands both the pool of potential R&D workers and the set of individuals who can found transformative firms. The heightened supply of R&D workers supports incumbent innovation, while the broader set of educated individuals fosters more transformative startups in the first place. Because this policy strengthens both sides of the market for innovation (the supply of R&D labor and the demand for it), it creates the largest increase in growth relative to the other three subsidies.

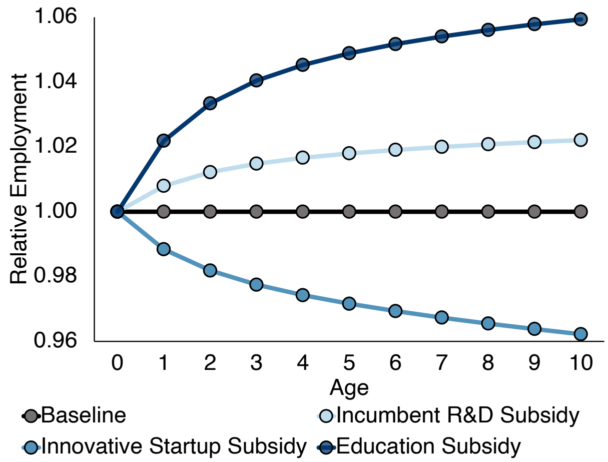
Overall, Table 8 highlights that innovation and entrepreneurship respond strongly to policies that expand human capital (education) or that specifically target growth-oriented startups. These policies create a more pronounced "multiplier" effect by simultaneously deepening the labor pool for R&D and boosting transformative entrepreneurship, thereby accelerating aggregate productivity growth more effectively than indiscriminate entry or incumbent-only R&D subsidies.

Policies and Firm-level Outcomes. Each policy also impacts the growth of firms, and thus, job creation and innovation spillovers at the firm level. This result is illustrated in Figure 13, which shows firm outcomes in the baseline (gray lines), and under the three policies that proved effective in increasing growth: the R&D subsidy (pale blue), innovative startup subsidy (medium blue), and education subsidy (dark blue).

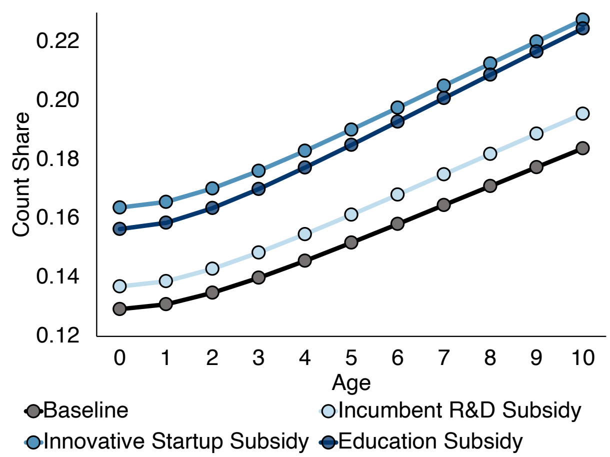
Panel (A) shows the average employment of transformative entrepreneurs by firm age relative to the baseline. An R&D subsidy achieves an expansion in average employment of transformative firms of about 2%, which mostly accrues in the early part of the firm life cycle. Education subsidies increase the average employment of transformative firms not just initially (by 2% at age 1) but also as the firm ages, up to 6% at age 10. An innovative startup subsidy instead reduces the average employment of innovative firms because it increases the share of transformative entrepreneurs more than the share of R&D workers, resulting in less innovation per transformative firm and flatter life-cycle growth.

Panels (B) and (C) show, respectively, the share of transformative firms and the employment share of transformative firms under different policies by firm age. All three main policies boost the share of transformative firms and their employment share at any age. The innovative startup subsidy increases the share of transformative firms the most, followed closely by the education subsidy. However, the latter is the most effective instrument to boost the employment share of transformative firms, which increases to about 40% for firms of age 10 compared to about 30% in the baseline.

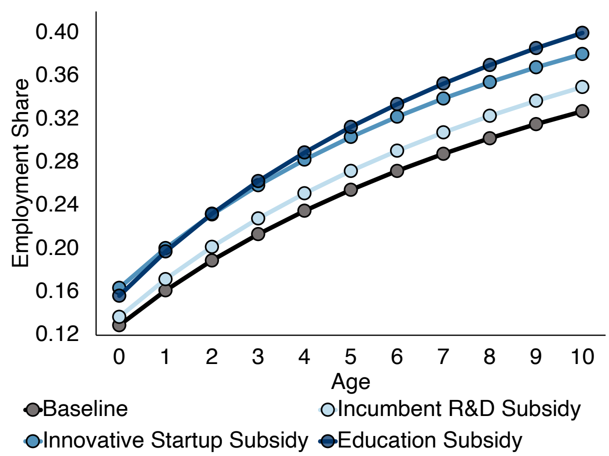
Figure 13: Firm Outcomes under Policies



(a) Average Employment of Transformative Firms



(b) Share of Transformative Firms



(c) Employment Share of Transformative Firms

The overarching takeaway is that education subsidies consistently outperform other policy interventions across all measured outcomes, suggesting that they may be the most effective approach to fostering high-impact entrepreneurship, while direct R&D support and startup subsidies offer more modest but still positive effects.

Optimal Policy Mix. So far, a clear hierarchy of policy effectiveness has emerged, based on interventions amounting to 0.05% of GDP. Education policy tends to be the most effective, but innovative entry policies also show high effectiveness. Next, we will consider the potential interactions and complementarity between policies: certain policies may become more effective when implemented alongside others. We explore policy interactions at increasingly larger budgets in Table 9.

Table 9: 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

Table 9 illustrates the optimal allocation of a given budget across three policy areas to maximize growth as budget levels increase from 0.05% to 0.70% of GDP. Our results reveal a clear prioritization pattern: at lower budget levels (0.05-0.50% of GDP), funding is split between education subsidies and innovative startups, with education receiving the majority share at the smallest budget but steadily decreasing as the budget increases, while support for innovative startups grows substantially.

As the budget expands beyond 0.5% of GDP, incumbent R&D begins receiving allocation, from a 5% share at a budget of 0.6 % of GDP to a 13.9% share with a 0.7% GDP budget. Meanwhile, the education subsidy share continues to decline, and innovative startups maintain the dominant share (though slightly reduced from its peak). This strategic shift in budget allocation produces progressively stronger innovation outcomes, with the percent change in innovation growing from 20% at the lowest budget level to 75% at the highest, suggesting that policymakers should prioritize education and innovative startups when resources are constrained, and then move to support established firms' R&D when substantial funding is available. This result connects to the broad interplay between education and transformative entrepreneurship at the center of our analysis.

6 Conclusion

This paper highlights the fundamental role of the symbiotic relationship between entrepreneurs and inventors in driving technological progress, innovation, and long-run economic growth. By examining the distinct pathways to becoming an inventor or an entrepreneur, and the role that entrepreneurs play in hiring and managing inventive talent, we contribute to a deeper understanding of how innovative firms emerge and scale. In particular, we connect the concept of the transformative entrepreneur to the broader literature on talent allocation and economic dynamics.

Our contribution is twofold. First, we present new empirical evidence on entrepreneurial careers and firm dynamics. We show that while the likelihood of becoming an R&D worker rises with IQ, the likelihood of becoming an entrepreneur declines with it. However, for transformative entrepreneurs—those who actively hire R&D workers and pursue innovation—IQ and educational attainment are strongly predictive. Parental background remains a powerful determinant of entrepreneurship in general, but talent and education appear to be key filters for the most growth-oriented entrepreneurs.

Second, we develop a quantitative endogenous growth model that incorporates these empirical patterns and captures the feedback loop between transformative entrepreneurs and skilled R&D workers. Our analysis reveals that financial constraints in access to education, particularly for talented individuals from low-income backgrounds, represent a key bottleneck for innovation. These frictions limit the development of both the supply of innovative workers and the demand from transformative entrepreneurs. Among various policy tools, we find that education subsidies are more effective in addressing these root frictions than uniform startup subsidy or incumbent R&D subsidies, producing greater gains in both innovation and aggregate growth.

In short, unlocking an economy's innovative potential requires strengthening both sides of the market: the supply of skilled R&D talent and the demand of transformative entrepreneurs. This underscores the importance of policies that promote inclusive access to higher education and improve the allocation of talent in the economy. Although the central role of the entrepreneur has long been recognized, this paper offers a new foundation - empirical, theoretical, and quantitative - to understand how entrepreneurs and inventors jointly shape the future of modern economies.

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Appendix

A Model Appendix

A.1 Representative Household

Our economy admits representative households for each cohort of agents with characteristics of ability, parental income, and parental entrepreneurship, (z, y, f). The household values the consumption of the final good of the cohort with the following preferences:

$$U_0 = \int_0^\infty e^{-\rho t} \ln C_t dt, \tag{11}$$

where $\rho > 0$ is the discount factor and $C(t)$ denotes consumption at time t. The representative household earns wage income from production and R&D workers, as well as interest income at rate r from asset holdings A_t, which correspond to the total value of firms owned by entrepreneurs within the cohort. Given this specification, the representative household maximizes utility as defined in equation (11), subject to the flow budget constraint,

$$\dot{A}_t + C_t = rA_t + I_{p,t} + I_{rd,t},$$

where $\dot{A}_t$ is the time derivative of the assets, $I_{p,t}$ and $I_{rd,t}$ denote the wage income of production workers and R&D workers within the cohort, respectively. This problem delivers the standard Euler equation:

$$\frac{\dot{C}_t}{C_t} \equiv g_c = r - \rho, \tag{12}$$

where g_c is the growth rate of consumption, which is equal to the growth rate of the final good, g, in the BGP equilibrium. We next discuss final good production and derive its growth rate.

A.2 Product Market Structure and Static Profits

Consider a representative firm that produces the final good, denoted by Y_t, using a continuum of intermediate inputs $y_{j,t}$. The production technology is Cobb-Douglas in logs:

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

The measure of available product lines is unity, although not all lines are necessarily active at any given time[19]. $\mathcal{N}$ denotes the active set of product lines. We normalize the price of the final good to one without loss of generality. Cost minimization problem implies that the representative final-goods producer allocates an identical expenditure, Y_t, to each active intermediate variety j

$$p_{j,t}y_{j,t} = Y_t, \ \forall j \in \mathcal{N}$$

Intermediate Production. An intermediate goods firm is defined as an entity holding a collection of product lines. These firms are the key objects of interest, which are run by entrepreneurs in our theoretical framework. Each intermediate good $y_{j,t}$ is produced via a linear technology:

$$y_{j,t} = q_{j,t}l_{j,p,t}, \tag{13}$$

where $l_{j,p,t}$ denotes the effective units of production labor allocated to line j, and $q_{j,t}$ is the productivity level at which intermediate good is produced by the firm at date t. Consequently, the marginal cost of producing line j is $\frac{w_{0,t}}{q_{j,t}}$, where $w_{0,t}$ represents the wage rate per efficiency unit of production workers.

Firms can augment their portfolios by innovating on a product line. Successful innovation upgrades the quality of intermediate j by a factor $\gamma > 1$, increasing q_j to γq_j. We assume Bertrand competition between the latest innovator and the previous incumbent: upon innovating, the entrant captures the entire market for that intermediate and sets a price equal to the former incumbent's unit cost:

$$p_{j,t} = \frac{\gamma w_{0,t}}{q_{j,t}}. \tag{14}$$

Under this pricing rule, the market is fully served by the new innovator. This implies that each product line j is produced by a single intermediate good firm that has the highest productivity $q_{j,t}$.

Static Profits. The associated static profit for an intermediate line j is

$$\pi_{j,t} = \ p_{j,t}\, y_{j,t} \ - \ w_{0,t}\, l_{j,p,t} \ = \ \frac{\gamma - 1}{\gamma}\, Y_t. \tag{15}$$

[19]Product lines may become inactive due to the death of entrepreneurs, for instance.

It follows that the labor demand for line j is

$$l_{j,p,t} \;=\; \frac{1}{\omega_{0,t}\,\gamma},$$

where we define $\omega_{0,t} \equiv \frac{w_{0,t}}{Y_t}$. Note that, at any point in time, this static problem is identical across all product lines a firm owns. If a firm holds n such lines, its total static profit equals $\pi_t\, n$. There is no heterogeneity in static profits across entrepreneur types in our framework; differences instead arise in each type's propensity to innovate and expand the firm's portfolio.

Next, we derive the final good output as a function of aggregates. Let $L_{P,t}$ be the aggregate demand for production labor. It satisfies

$$L_{P,t} \equiv \int_{\mathcal{N}} l_{j,p,t} dj = \frac{\phi}{\omega_{0,t}\gamma}$$

where $\phi \equiv |\mathcal{N}|$ defines the measure of active product lines.

As firms set a price equal to $p_{j,t} = \frac{\gamma w_{0,t}}{q_{j,t}}$, we get

$$\begin{aligned}
\ln(Y_t) &= \int_{\mathcal{N}} \ln(y_{j,t}) dj \\
&= \int_{\mathcal{N}} \ln(p_{j,t} y_{j,t}) dj - \int_{\mathcal{N}} \ln(p_{j,t}) dj \\
&= \ln(Y_t)\phi - \ln(w_{0,t}\gamma)\phi + \int_{\mathcal{N}} \ln(q_{j,t}) dj \\
&= \ln(Y_t)\phi + [\ln(L_{P,t}) - \ln(\phi) - \ln(Y_t)]\,\phi + \int_{\mathcal{N}} \ln(q_{j,t}) dj \\
Y_t &= \phi^{-\phi} L_{P,t}^{\phi} Q_t
\end{aligned}$$

where $Q_t \equiv \exp\left(\int_{\mathcal{N}} \ln(q_{j,t}) dj\right)$ is the aggregate productivity index.

A.3 Aggregate Growth Rate

In previous section, we show that $Y_t = \phi^{-\phi} L_{P,t}^{\phi} Q_t$. Since $L_{P,t}$ and ϕ are constant in stationary equilibrium, the growth rate of aggregate output Y_t equals the growth rate of the aggregate productivity index Q. We can express $\ln Q_t$ after an instant Δt as

$$\begin{aligned}
\ln Q_{t+\Delta t} &= \int_0^1 \left[\tau_g \Delta t \ln\left(\gamma q_{jt}\right) + (1 - \tau_g \Delta t) \ln q_{jt}\right] dj \\
&= \tau_g \Delta t \ln(\gamma) + \ln Q_t
\end{aligned}$$

where τ_g is aggregate innovation rate defined in equation (9) and higher order terms in Δt are omitted. By subtracting $\ln Q_t$ from both sides, dividing by Δt, and taking the limit as $\Delta t \to 0$, we get

$$g = \frac{\dot{Q}_t}{Q_t} = \lim_{\Delta t \to 0} \frac{\ln Q_{t+\Delta t} - \ln Q_t}{\Delta t} = \ln(\gamma)\,\tau_g.$$

where $\dot{Q}_t$ denotes the time derivative of aggregate productivity index.

A.4 Normalization of Value Functions

In this section, we derive the normalized value function for the firms given in equation (6).[20] We start with the unnormalized firm value $\tilde{V}_t(n,\theta)$, given by

$$\begin{aligned} r\tilde{V}_t(n,\theta) - \frac{\partial \tilde{V}_t(n,\theta)}{\partial t} &= \pi n Y_t \\ &+ \tau n \left[\tilde{V}_t(n-1,\theta) - \tilde{V}_t(n,\theta)\right] \\ &+ \max_X \left\{ X\left[\tilde{V}_t(n+1,\theta) - \tilde{V}_t(n,\theta)\right] - w_{1,t}\left(\frac{X}{\theta n^\eta}\right)^{\frac{1}{\sigma}} \right\} \\ &+ \upsilon n \left[\tilde{V}_t(n+1,\theta) - \tilde{V}_t(n,\theta)\right] + \psi\left[0 - \tilde{V}_t(n,\theta)\right], \end{aligned} \tag{16}$$

where the term $\frac{\partial \tilde{V}_t(n,\theta)}{\partial t}$ reflects the fact that the value of the firm changes over time. We normalize the value function with the final good Y_t such that

$$\tilde{V}_t(n,\theta) \equiv V(n,\theta)Y_t.$$

Substituting the above definition into the left side of the value function above yields the following,

$$\begin{aligned} r\tilde{V}_t(n,\theta) - \frac{\partial \tilde{V}_t(n,\theta)}{\partial t} &= rV(n,\theta)Y_t - \frac{\partial\left(V(n,\theta)Y_t\right)}{\partial t} \\ &= rV(n,\theta)Y_t - \frac{\dot{Y}_t}{Y_t}V(n,\theta)Y_t \\ &= (r-g)V(n,\theta)Y_t \\ &= \rho V(n,\theta)Y_t, \end{aligned} \tag{17}$$

[20] The normalized value functions for workers in equation (4) can be derived similarly and is therefore omitted for brevity.

where g is the growth rate of the final good and $r - g = \rho$ from the household maximization problem in equation (12). Finally, by substituting the last term into the unnormalized value function, canceling the final good from both sides, and defining normalized efficiency wage for R&D workers as $\omega_1 \equiv \frac{w_{1,t}}{Y_t}$, we arrive at the normalized value function in equation (6).

A.5 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.5.1 Firm Size Distribution

The equilibrium mass of firms is denoted by $\Psi(n, \theta, s|z, y, f)$ where firms are indexed by size $n \in \{1, 2, 3, ...\}$, entrepreneur type $\theta \in \{0, \bar{\theta}\}$, entrepreneur's education s and characteristics (z, y, f). We denote the relevant marginal distribution, i.e., integrated version over education and worker characteristics, as $\Psi(n, \theta)$. In stationary equilibrium, the firm mass satisfies a set of conditions that regulate entry, transition, and exit:

$$\begin{aligned}
\tau\Psi(1, \theta, s|z, y, f) + \psi \sum_{n=1}^{\infty} \Psi(n, \theta, s|z, y, f) &= e(\theta, s|z, y, f) \qquad (18) \\
[X(n, \theta) + \tau + v + \psi]\, \Psi(1, \theta, s|z, y, f) &= \tau 2\Psi(2, \theta, s|z, y, f) + e(\theta, s|z, y, f) \\
[X(n, \theta) + (\tau + v)\, n + \psi]\, \Psi(n, \theta, s|z, y, f) &= [X(n, \theta) + v(n-1)]\, \Psi(n-1, \theta, s|z, y, f) \\
&\quad + \tau(n+1)\Psi(n+1, \theta, s|z, y, f), \quad n \geq 2
\end{aligned}$$

where $e(\theta, s|z, y, f)$ denotes the density of firm entry, given by:

$$e(\theta, s|z, y, f) = \lambda_{f,s} \Pi(\theta|z, s) \times \mathbb{P}\left[V_e(\theta) - c_e > W_s(z, y, f)\right] \Phi_s(z, y, f), \qquad (19)$$

and integrating it over the entrepreneur's education and worker characteristics gives

$$e_\theta = \sum_{f \in \{0,1\}} \sum_{s \in \{0,1\}} \int_z \int_y e(\theta, s|z, y, f) dz dy.$$

The first equation in (18) describes the entry of firms, ensuring that the inflow of new firms balances the outflow due to business reallocation τ and the mortality of the entrepreneur ψ. The right-hand side represents the entry flow, which depends on the arrival rate of entrepreneurship 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. 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 business reallocation. The next equation describes a similar evolution of mass of firms with size $n \geq 2$, where firms experience growth due to innovation or exogenous reasons and shrink due to competitive forces.

Equation (19) defines the density of firm entry with entrepreneur type θ due to individuals with ability z, parental income y, family background f, and education status s. The term $\lambda_{f,s}$ captures the arrival rate of entrepreneurial opportunities based on family background and education. The term $\Pi(\theta|z,s)$ denotes the probability of drawing entrepreneur type θ conditional on ability and education. The expression $\mathbb{P}\left[V_e(\theta) - c_e > W_s(z,y,f)\right]$ is the probability that the value of starting a firm exceeds the value of remaining a worker. Finally, $\Phi_s(z,y,f)$ is the density of individuals with characteristics (z,y,f) and education status s. Altogether, the equation gives the mass of individuals who receive an opportunity, draw type θ, find it profitable to enter, and have the corresponding characteristics.

A.5.2 Worker Distribution and Occupational Flows

The distribution of workers is represented by $\Phi_s(z,y,f)$, the unnormalized probability density function of worker characteristics (z,y,f) in occupation production worker or R&D worker, corresponding to $s \in \{0,1\}$. In equilibrium, worker outflows (due to transitions to entrepreneurship and mortality) must be equal to inflows (occupation choice of newborn and transitions out of entrepreneurship). The unnormalized density of workers satisfies:

$$\left(\sum_\theta e(\theta,s|z,y,f) + \psi\right)\Phi_s(z,y,f) = m\mathbb{P}\left(s|z,y,f\right)\Omega(z,y,f) + \sum_\theta \tau\Psi(1,\theta,s|z,y,f). \quad (20)$$

Equation (20) relates the unnormalized density of workers, $\Phi_s(z,y,f)$, in occupations of production or R&D, to two distinct inflows: new entrants making initial occupation choices based on their characteristics, represented by $m\mathbb{P}(s|z,y,f)\Omega(z,y,f)$, and existing entrepreneurs returning to worker status, denoted by $\sum_\theta \tau\Psi(1,\theta,s|z,y,f)$. These inflows must exactly offset occupational outflows in BGP, which occur due to the entry into entrepreneurship—captured by $\sum_{\theta} e(\theta, s|z, y, f)$—and worker mortality at rate ψ.

B Data Appendix [21]

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 origins, 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 the military test, Borge Prien's Prove, which is required for males in Denmark at age 18. We merge these datasets together, which enables tracking individuals across their lifetime across firms and occupations.

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 this project combines various datasets from the Danmark Statistical Office. We observe a crosswalk for all individuals to their parents. Given the income and occupation database, we are able to link individuals to parental income and occupation observations.

Our measure of entrepreneurs, indicating business founders with at least one registered employee, captures 147,087 firms and 24,281 transformative firms. For firm-level analysis, we leverage the entire firm distribution (including entrepreneurs without IQ information). For IQ$\times$ firm analysis, we leverage observations that have both IQ and firm information (17,669 firms). Below, we detail the main datasets used in the DST

[21] Denmark Statistical Office data were obtained by Ufuk Akcigit under the purview of University of Chicago licenses. The remaining co-authors, Harun Alp, Jeremy Pearce and Marta Prato, did not have any unauthorized access to this data while working on this paper.

server in an itemized fashion. We proceed by discussing the core datasets and what they provide.

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 (500,000 total).

For internal data to the DST, we leverage the IDA, which 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. Leveraging IDA alongside BEF, we connect individuals to their parents' characteristics, including the 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 are linked to 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 occupations over time. We also connect individuals and firms to their patents to speak to innovation at the individual and firm levels. 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 individuals behind the firm and their employees. This link is done primarily through the IVPS/IVPE entrepreneurship databases, which provide information on the primary founders 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 from 2001-2013.[22] We identify the primary business founders of 28% of the total registered firms.

[22]We define a firm as an entity with a firm identifier and at least one registered employee.

B.3 Occupations

As noted in the main text, our analysis focuses on four distinct occupations. In this section, we provide additional details on occupation definitions, particularly for the R&D category, which determines how R&D workers and transformative entrepreneurs are classified.

An R&D worker is defined as an individual who is in an R&D occupation for at least half of their working life. The R&D occupation, in turn, is determined by the patenting intensity of different occupations. Our baseline framework looks at occupations where workers have a 1% patenting intensity rate or higher. Table B1 lists the top five most common R&D occupations in the economy by inventor rate and employment share, respectively. The empirical findings are qualitatively robust to considering alternative cutoffs to classify R&D occupations, such as a patenting intensity of 2% or 0.5%.

Next, a transformative entrepreneur is defined as an entrepreneur who hires at least one R&D worker. In the next section, we show that the firm-level results are robust across variations of this definition, such as hiring an R&D worker in the first year since starting the firm, in the first five years, or ever in the life of the firm.

Table B1: 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

C Empirical Appendix

This section extends the analysis from the main text, focusing on robustness and additional facts on career choice, entrepreneurship, and firm dynamics.

C.1 Career Determinants

This section provides additional results on occupational sorting and transformative entrepreneurship. We start by providing more details on the specification underlying the figures in Section 2. Next, we expand on the role of parental background in education decisions. Finally, we assess the robustness of our empirical findings to alternative definitions of occupations and firms used in the primary specifications.

Tables from Main Text Figures. Table C2 displays the coefficients corresponding to the multinomial logistics regressions from the estimation of equation (1) presented in Figures 3 and 4. "Model 1" indicates the first specification, that distinguishes entrepreneurs and R&D workers from production workers. "Model 2" represents the second specification, which additionally includes the split between transformative and subsistence entrepreneurs.

Model 1 shows distinct patterns across different occupational choices. For R&D workers, higher IQ is strongly positively associated with choosing this occupation, with coefficients increasing monotonically from quartile 2 (0.434) to quartile 4 (1.252), while parental income on its own has no significant effect. College education has a large positive effect (1.601) on R&D work. By contrast, for entrepreneurs, higher IQ has a negative association, noted in the 3rd (-0.093) and 4th quartile (-0.167), and college education is strongly negative (-0.591), suggesting average entrepreneurs follow a different human capital accumulation path.

Model 2 shows distinct patterns across different occupational choices. For transformative entrepreneurs, higher IQ is strongly positively associated with choosing this occupation, with coefficients increasing monotonically from quartile 2 (0.270) to quartile 4 (0.740), while parental wealth shows a significant positive effect (0.159). College education has a substantial positive effect (0.437) on transformative entrepreneurship. Parental background also plays an important role, with parental entrepreneurship (0.380) and parental R&D work (0.291) both having significant positive effects, while parental business ownership shows no significant association. These results suggest that transformative entrepreneurs represent a distinct group from regular entrepreneurs, with selection patterns more similar to R&D workers regarding human capital requirements but with additional importance placed on parental wealth, indicating that both ability and access to resources are crucial factors for transformative entrepreneurial activity.

Table C2: Logistic Regressions for Figures 3 and 4

	IQ Quartile (baseline: Q1)			Parental Income
Occupation	Q2	Q3	Q4	High vs. Low
R&D Worker	0.434***	0.793***	1.252***	0.036
	(0.077)	(0.074)	(0.071)	(0.039)
Entrepreneur	0.011	-0.093**	-0.167***	0.025
	(0.029)	(0.031)	(0.034)	(0.023)

	College	Parent Entrepr.	Parent R&D	Production Worker Parent
R&D Worker	1.601***	0.205***	0.463***	-0.064
	(0.048)	(0.060)	(0.043)	(0.050)
Entrepreneur	-0.591***	0.574***	0.066	0.017
	(0.026)	(0.033)	(0.035)	(0.044)

Model 2

	IQ Quartile (baseline: Q1)			Parental Income
Occupation	Q2	Q3	Q4	High vs. Low
R&D Worker	0.436***	0.799***	1.261***	0.038
	(0.077)	(0.074)	(0.071)	(0.039)
Subsistence	-0.003	-0.167***	-0.361***	0.005
Entrepreneur	(0.030)	(0.033)	(0.038)	(0.025)
Transformative	0.270**	0.537***	0.740***	0.159**
Entrepreneur	(0.087)	(0.085)	(0.084)	(0.056)

	College	Parent Entrepr.	Parent R&D	Production Worker Parent
R&D Worker	1.606***	0.203***	0.466***	-0.064
	(0.048)	(0.060)	(0.043)	(0.050)
Subsistence	-0.855***	0.609***	-0.003	0.084
Entrepreneur	(0.030)	(0.035)	(0.041)	(0.053)
Transformative	0.437***	0.380***	0.291***	-0.132
Entrepreneur	(0.056)	(0.083)	(0.068)	(0.077)

Notes: Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The models are multinomial logit estimations with a production worker as the base category (0). Cohort fixed effects included in both models but not reported. Parent Entrepr. = parent was self-employed, Parent R&D = parent worked in R&D, Production Worker Parent = parent was not R&D or self-employed.

Schooling. Individuals' schooling is an essential input to their career development process. In this section, we focus on two core determinants of schooling: family income and IQ. Both covariates may affect an individual's propensity to obtain education through ability and financial frictions or opportunities. We perform a simple regression that examines the propensity of an individual to attend college as a function of their family income and IQ . Equation (21) provides the specification, as follows:

$$s_i = \alpha + \alpha_1 IQ_i + \alpha_2 ParInc_i + \Lambda_{b(i)} + \epsilon_i. \tag{21}$$

Equation (21) is a linear probability model, where s_i is an indicator of individual i's college attainment (0 or 1); IQ_i is the IQ in percentiles (going from 0 to 1); $ParInc_i$ is the parental income is percentile (going from 0 to 1), based on the income in 2000; $\Lambda_{b(i)}$ is a control for the cohort $b(i)$ of the individual. Table C3 reports the results from the above regression.

Table C3: Probability of College Attendance

	(1) College	(2) College
IQ	0.389***	0.359***
	(0.002)	(0.002)
Parental Income	0.154***	0.121***
	(0.002)	(0.002)
Parent College		0.081***
		(0.001)
Observations	442587	442587

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C3 shows that IQ has a substantial positive effect on college attendance, with coefficients of 0.389 and 0.359 in columns (1) and (2), respectively, indicating that a one standard deviation increase in IQ raises college probability by approximately 36-39 percentage points. Parental income also positively influences college attendance, with effects of 0.154 and 0.121, suggesting that higher family resources significantly increase educational attainment opportunities. Column (2) additionally controls for parental education, showing that having college-educated parents independently increases a child's probability of attending college by 8.1 percentage points while slightly reducing the magnitude of both IQ and parental income coefficients. These results suggest that, while cognitive ability remains the strongest predictor of college attendance, both financial resources and inter-generational transmission of educational preferences play important roles.

Table C4: Probability of becoming an R&D Worker

	(1) R&D Worker	(2) R&D Worker
IQ	0.021***	0.021***
	(0.001)	(0.001)
Parental Income	0.005***	0.005***
	(0.001)	(0.001)
Parent College		0.001
		(0.000)
Observations	442587	442587

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In our model, there is a one-to-one correspondence between college attainment and R&D occupation. Thus, we repeat the regression in equation (21), considering the outcome variable of becoming an R&D worker. Table C4 displays the results for the probability of becoming an R&D worker, with both columns revealing more modest but still highly significant effects. IQ shows a consistent positive effect of 0.021 across both specifications, indicating that higher cognitive ability increases the likelihood of R&D careers, though with a substantially smaller magnitude than its effect on college attendance. Parental income has a small but significant positive effect of 0.005, suggesting that family resources play a minor role in R&D career selection. Interestingly, in column (2), parental college education shows no statistically significant effect on R&D career choice (coefficient of 0.001), unlike its substantial impact on college attendance. This pattern suggests that while cognitive ability remains important for specialized R&D careers, the inter-generational transmission of preferences and advantages mainly operates through increased college attendance rather than directly influencing occupational selection into R&D work. The overall findings indicate that R&D workers are primarily selected based on ability rather than family background characteristics.

C.2 Firm Dynamics

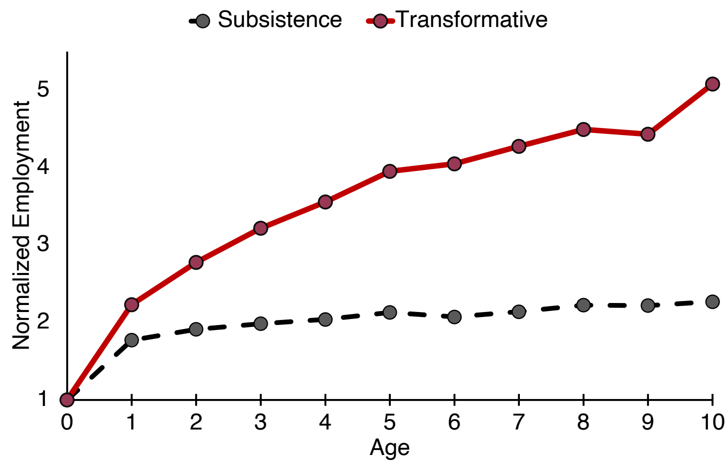
This section provides more details on entrepreneurship types. We first examine entrepreneurial characteristics across different organizational forms and industries, highlighting the sharp contrasts between transformative and subsistence entrepreneurship. Regression analyses reveal that transformative entrepreneurs possess significantly higher cognitive abilities and educational attainment, particularly in knowledge-intensive sectors, while also benefiting from greater parental wealth and education. Industry-specific selection patterns demonstrate considerable heterogeneity, with technology and professional services attracting individuals with the highest human capital, while retail and personal services show less pronounced selection effects. The data further reveals how non-corporate and corporate entrepreneurship differ in their selection mechanisms, with corporate ventures typically founded by entrepreneurs with stronger educational backgrounds and industry experience.

The section then analyzes firm dynamics through comparative life-cycle patterns between transformative firms (those hiring R&D workers) and subsistence enterprises. Illustrated through Figures C1-C3, transformative firms demonstrate substantially stronger trajectories in employment growth (increasing five-fold over ten years) and revenue generation (reaching seven times their initial levels), while maintaining lower exit rates in later years compared to subsistence firms that plateau after modest initial growth. Additional analyses explore how founder characteristics correlate with venture performance metrics, including productivity, innovation intensity, and survival rates, documenting significant sorting effects where high-ability entrepreneurs disproportionately select industries with higher returns to ability. This comprehensive approach provides insights into both selection mechanisms and subsequent firm performance patterns that characterize entrepreneurial activity.

Figures C1-C3 present a comparative analysis of firm life cycles between transformative entrepreneurship (defined as firms hiring an R&D worker) and subsistence entrepreneurship. All figures display measures of growth over the first ten years of operation, with the initial size normalized to one at age zero.

In Figure C1, we consider a definition of transformative entrepreneur as hiring an R&D worker in the first five years of operation (as opposed to ever in the life of the firm, which is our baseline definition in the main text). The figure shows that both transformative and subsistence firms start with the same baseline (normalized) employment at age 0 and diverge in their growth trajectories. Transformative entrepreneurs exhibit substantially stronger employment growth, increasing five-fold by age 10, compared

Figure C1: Firm life cycle, with transformative definition based on first 5 years



to subsistence firms, which plateau at approximately twice their initial size after the first year. The growth path for transformative firms shows higher growth throughout the decade, while average subsistence firms maintain relatively flat employment levels after their initial modest expansion.

Figure C2: Firm life cycle, Revenue

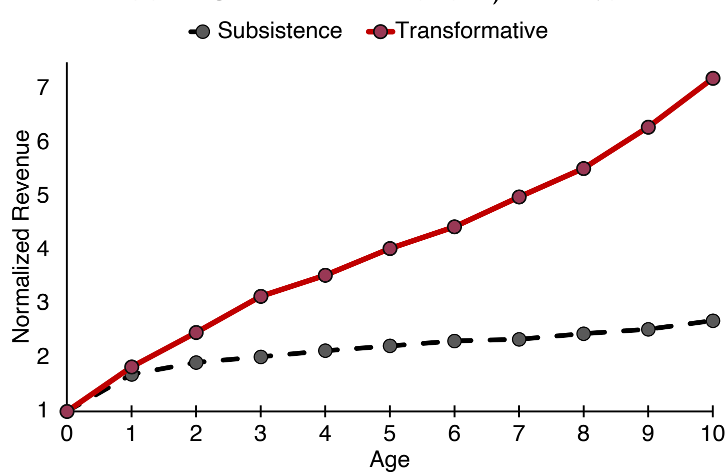


Figure C2 illustrates the revenue performance of both firm types over the same ten-year period. The revenue trajectories closely mirror the employment patterns, with both firm types starting from the same normalized baseline at founding. Transformative firms demonstrate dramatic revenue expansion, reaching more than seven times their initial revenue by year 10. In contrast, subsistence enterprises show only modest revenue growth, reaching approximately 2.5 times their starting level. The revenue gap between the two firm types widens substantially after year 1, with transformative firms exhibiting a steeper, nearly linear growth trajectory throughout the observation period. This revenue differential becomes particularly pronounced in later years, highlighting the cumulative advantage that transformative firms develop over time. These two figures are consistent with the idea that transformative entrepreneurs, through creative destruction, become a larger share of the economy with age.

Figure C3: Firm life cycle, Exit Rates

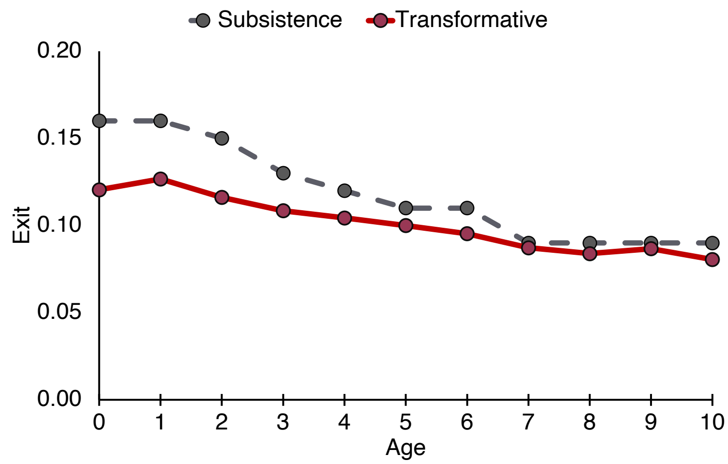
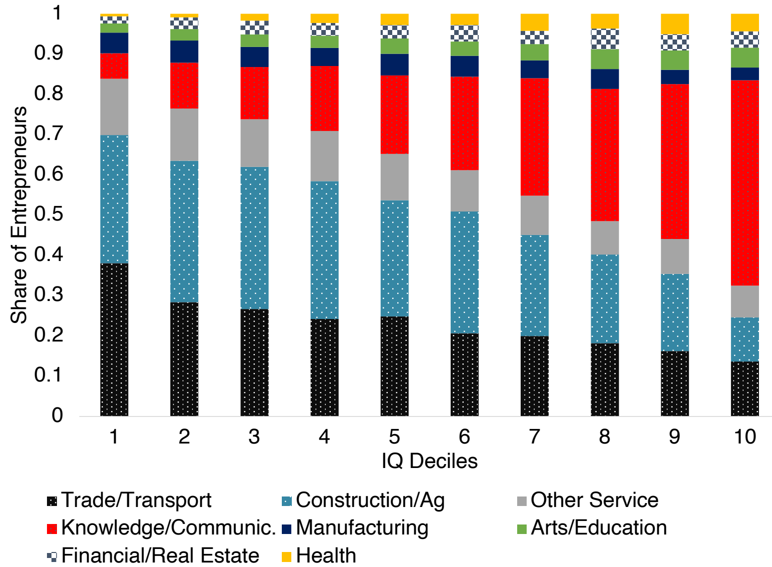


Figure C3 depicts exit rates for both firm types over the first decade of operation. We define exit as the firm having zero employment or firm records. Both transformative and subsistence firms experience relatively high exit probabilities in their early years, with subsistence firms starting at a higher initial exit rate of approximately 16% compared to 12% for transformative firms. The exit rates for both firm types generally decline with age, reflecting a selection effect where surviving firms become increasingly stable. Subsistence firms show a steeper initial decline in exit rates during the first five years, after which both firm types converge to similar exit probabilities of around 8-9% by year 8. Notably, transformative firms demonstrate slightly lower exit rates overall, suggesting that their investments in R&D and growth are connected to greater firm stability and longevity.

Figure C4 illustrates the distribution of entrepreneurs across different industries based on IQ deciles. The graph reveals a clear pattern of industry sorting by cognitive ability, with significant shifts in industry composition moving from lower to higher IQ deciles.

In the lowest IQ deciles (1-4), traditional sectors dominate entrepreneurial activity, with Trade/ Transport and Construction/ Agriculture representing the largest shares. As IQ increases, there is a marked decline in these sectors' representation, with Trade/Transport dropping from nearly 40% in the first decile to only about 12%

Figure C4: Firm Industry by Entrepreneur IQ



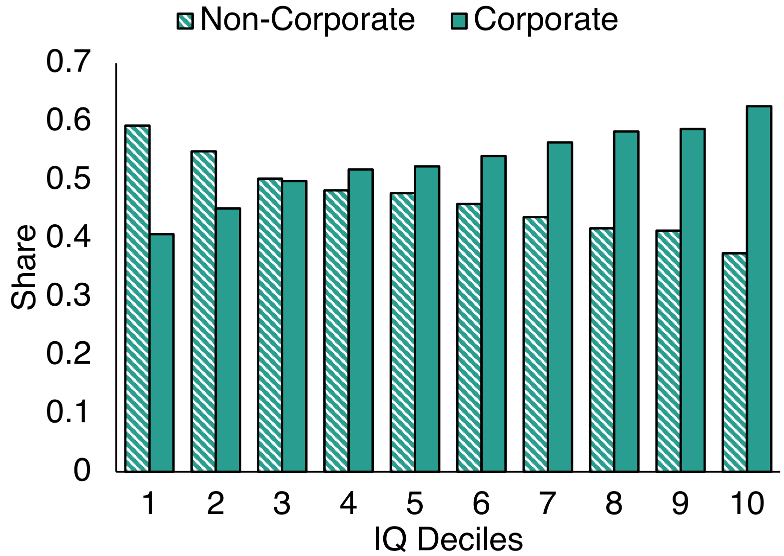
in the tenth decile. Construction/Agriculture follows a similar downward trend as IQ increases.

Conversely, knowledge-intensive industries show a strong positive relationship with IQ. The Knowledge/Communication sector demonstrates the most dramatic increase, expanding from a minimal presence in the lowest IQ decile to becoming the dominant industry category for entrepreneurs in the highest IQ deciles (8-10), where it represents approximately 50% of all entrepreneurial activity. Other high-skill sectors, including Financial/Real Estate, Health, and Arts/Education, also show modest but consistent increases in representation as IQ rises, collectively accounting for a much larger share of entrepreneurship in the top IQ deciles compared to the bottom ones.

This pattern suggests significant sorting of entrepreneurial talent across industries based on cognitive ability, with higher-IQ individuals disproportionately selecting into knowledge-intensive sectors that likely offer greater returns to cognitive skills, while lower-IQ entrepreneurs predominantly enter traditional industries with potentially lower barriers to entry and cognitive skill requirements.

Figure C5 shows the distribution of entrepreneurs across IQ deciles (1-10) by company type, with blue representing non-corporate entrepreneurs and orange representing corporate entrepreneurs. The y-axis shows the share of entrepreneurs, which always totals to 1 (or 100%) for each IQ decile. We note a stark trend: as IQ decile increases from 1 to 10, the proportion of non-corporate entrepreneurs steadily decreases (from about 60% in decile 1 to about 37% in decile 10), while the proportion of cor-

Figure C5: Corporate and Non-Corporate firms by entrepreneur IQ



porate entrepreneurs correspondingly increases. This suggests that entrepreneurs with higher IQ are more likely to establish corporate entities, while those with lower IQ are more likely to operate non-corporate businesses. The shift is gradual but consistent across all deciles, indicating a strong correlation between measured cognitive capacity and the formal business structure entrepreneurs choose. This is consistent with our main message of the paper, as transformative entrepreneurs tend to be more formal and serious about firm structure and expansion.