Tapping into Talent: Coupling Education and Innovation Policies for Economic Growth[*]

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Abstract

How do innovation and education policy affect individual career choices and aggregate productivity? This paper analyzes the effect of R&D subsidies and higher education policy on productivity growth through the supply of innovative talent. We put scarce talent, higher education attainment, and career choice at the center of a new endogenous growth framework with individual-level heterogeneity in talent, financial resources, and preferences. We link the model to micro-level data from Denmark on the backgrounds of who obtains a PhD and becomes an inventor and the outcomes of a set of policy interventions. We find that R&D subsidies can be strengthened when combined with higher education subsidies, which enable talented but poor youth to pursue a career in research. Education and innovation policies not only alleviate different frictions, but also impact innovation at different time horizons. Education policy is more effective in societies with higher income inequality.

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

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1 Introduction

Talent is a scarce resource and a key input into the innovation and growth process. There are only a handful of people like Marie Curie and Thomas Edison with the potential to produce innovations that transform the way we live. Similarly, certain occupations have greater potential of generating significant spillovers to society. While some occupations (e.g., the production of goods) can be executed by a wide range of people and have limited spillovers, other occupations, such as engineers or scientists in Research and Development (R&D), require talent to push forward the technological frontier and generate spillovers for society. Further, these inventive occupations require not just scarce talent but also training in order to transform individual potential into creative and innovative use. These observations give rise to the following important questions: How do societies select which individuals to allocate to higher education with the potential to become inventors? What frictions prevent individuals from investing in human capital to become an inventor? What policies can alleviate the potential talent misallocation? What are the time horizons over which these policies show their full impact? The answers to these questions are crucial to policy debates in innovation and economic growth, and our study is an attempt to address these questions theoretically, empirically, and quantitatively.

This study provides a framework to connect the supply of talent in the economy and its development to innovation and aggregate growth. We use this framework to study how education and innovation policies affect innovation through its interaction with the supply of inventors. To do this, we first document results on individuals who pursue higher education and become inventors using extensive individual-level micro-data from Denmark. We show that IQ and parental background strongly predict outcomes such as PhD attainment and an individual's innovation. We also document the effect of innovation and education policies and the supply of talent and innovation. Second, motivated by facts on the determinants of education, innovation, and their interaction with public policies, we build an endogenous growth model that centers on the development of scarce talent through higher education and innovation. We calibrate our model to match the empirical results on the determinants of education — IQ, parental background, individual preferences, and the availability of university slots — and the determinants of innovation — education and IQ. We use the calibrated model to study the effects of counterfactual education and innovation policies, which we verify alongside active Danish programs. This framework departs from the endogenous growth literature, which has focused primarily on the firm side of innovation. By putting individuals at the center of our analysis, we stress that the interaction of human capital, innovation, and education policies is essential for understanding economic growth.

The Danish context provides an ideal environment to study the relationship between talent, education, and innovation. To this end, we rely on administrative data, which includes detailed individual information, such as educational attainment, employment and wages, age, and parental background. Crucially, the data also features a measure of individuals' IQ, which we use as a proxy for talent. In order to speak to innovation and the effects of policies, we match the dataset to external patent data from the European Patent Office (EPO) and policy data from the Danish Ministry of Education. A unique feature of this dataset is detailed information on an innovation and education policy change implemented in 2002, which introduced new R&D subsidies and dramatically increased funding to universities and the level of PhD enrollment. This policy change provides an excellent case study to jointly analyze the role of innovation and education policy. We exploit this variation to better isolate the links between talent, education, and innovation.

With this data, we document three main sets of stylized facts. First, we discuss the determinants of higher educational attainment. We show that individuals with higher IQs and higher family incomes are more likely to obtain a PhD. Second, we analyze the determinants of becoming an inventor. We observe that PhD graduates are over ten times more likely to file for a patent than college graduates and about 30 times more likely than individuals with no college education. Individuals with higher IQs are also more likely to file for a patent, even after controlling for education. Third, we document the role of public policies in innovation. Starting in 2002, the Danish Government required the universities to increase the number of PhD slots as part of a larger initiative to support education and innovation in Denmark (Ministry of Education, 2016). We observe that as the number of slots for PhDs increases, the average IQ of the enrolling students falls. We interpret this as evidence that the quality of PhD students is heterogeneous, and expanding PhD slots may draw in a marginal researcher who is less talented than the average researcher from the existing pool. Thus, even though policy can increase the supply of researchers, there is a trade-off between expanding the pool of PhDs and the average talent of PhDs in the economy.

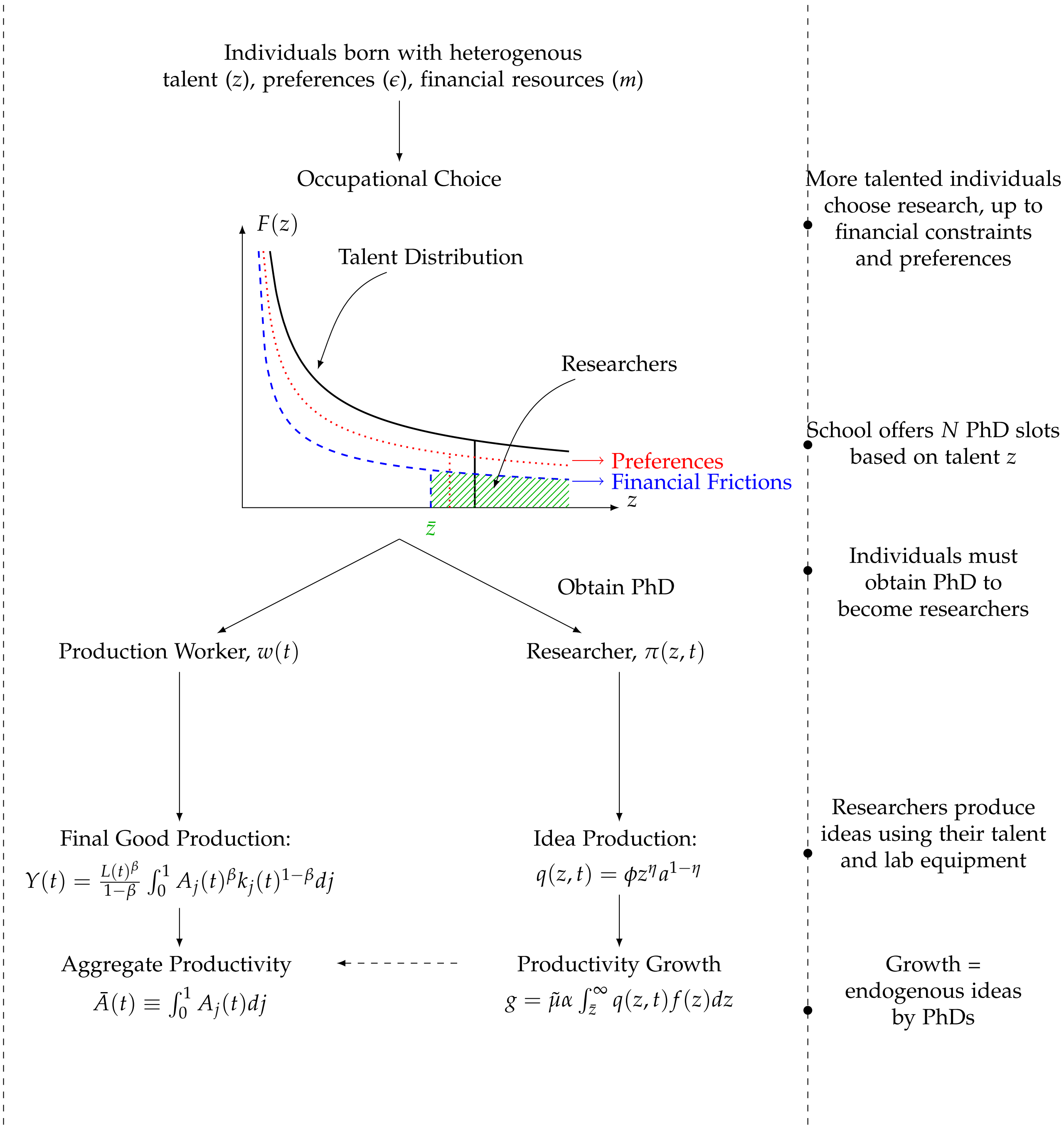
Motivated by the stylized facts in micro-level data from Denmark, we build an endogenous growth model with new elements that connect the development of scarce talent to the innovative capacity of the economy. This model builds in fundamental ingredients that relate human capital to aggregate innovation, speaking to how the supply of innovative talent is formed and how this, in turn, shapes growth. We emphasize five main elements in the theoretical framework: i) talent is necessary for innovation and heterogeneous in quality, ii) higher education is important for innovation, iii) some talented individuals, such as those born to poor families, may not have enough resources to afford higher education and build inventive human capital, iv) regardless of access to resources, some talented individuals may dislike research, and v) there are limited training slots at universities.

In the model, individuals are born with heterogeneous talent, preferences, and family financial resources. They decide, depending on their talent and preferences, whether they want to get higher education and become a researcher and contribute to aggregate innovation or enter the production sector. If they lack the financial resources, they may not get the education necessary for innovation, even if they have sufficient talent and desire. Once in the research sector, individuals produce ideas proportionally to their talent. Schools have a fixed amount of PhD slots, which they give to the most talented individuals who want to get a PhD and have sufficient resources to do it. A fundamental driving force in the model is that talent is local and scarce. The key elements of the model are illustrated in Figure 1.

The model is tractable and delivers certain intuitive results. Higher incomes in research make individuals more likely to work in the research sector. Innovation is limited by the availability of educational slots, talent, and the forces that generate a match of talent to education. Talented people might not end up going into research due to either a dislike of research or a lack of resources to afford education. The latter of these two, lack of financial resources due to parental background, delivers an inefficiency in the allocation of talent. This inefficiency is linked to economic growth through idea production in the research sector. The reader should note that, unlike earlier growth models, the innovation capacity of a society is primarily affected not only by the quantity but also by the quality of the researcher pool, consistent with the relationship between talent and innovation. Our model also enables intuitive policy counterfactuals, as it delivers analytical solutions for the balanced growth path impact of innovation and education policies.

The framework is not only well-suited to connect to individual-level data on talent and family background, but also to understand the outcomes of policy interventions from the Danish government. From 2002-2013, the Danish government pursued a set of aggressive policies aimed at promoting innovation

Figure 1: Summary of the Model



and education through the "Innovation Danmark" program. We highlight how different policies affect the economy through different channels. For instance, an R&D subsidy boosts profits in the research sector, pulling talented individuals with enough resources into research. A subsidy to education, on the other hand, enables access to the research sector to talented and interested individuals who would otherwise lack the financial resources to access higher education due to their family background. The Danish government also required universities to increase their PhD slots. Our model highlights that this type of policy introduces a trade-off between an increase in the pool of researchers in the economy and a decline in the average talent of researchers, because the marginal individual pulled into the research sector is less talented than the existing pool of researchers. This is consistent with the empirical evidence in the micro-data.

Before proceeding to policy counterfactuals, we validate our model by illustrating its ability to match out-of-sample moments. First, the model delivers surprising results on selection into higher education depending on parental income. Individuals who enroll in a PhD with wealthier parents have higher IQs than individuals with poorer parents. This result from the model is confirmed in the data. Second, we evaluate the introduction of policies implemented in the Danish education and innovation market. We run these policies through the model and observe the predicted change in the IQ and innovation of PhDs. We then compare the model-predicted changes to the data and find a close match. After confirming the ability of the model to match out-of-sample moments, we proceed to innovation and education policy counterfactuals that alter the policy mix. We highlight four main findings.

First, we show that, in steady state, education policy is more effective dollar per dollar than R&D policy. A 10% R&D subsidy has a long-run effect on the growth rate of 6.4%, compared to the same allocation for education policy has an effect on growth of 9.6%.[1] Both policies take time to see their full effect.

Second, there is a pecking order among educational subsidies, R&D subsidies, and expanding the slots for education. The optimal policy mix depends on the size of the budget the government has to allocate to research. If the government has limited funding (less than 0.6% of GDP in our calibration), our framework suggests it should only allocate to educational subsidies to improve the talent pool by enabling access to education for talented individuals from poor families. For intermediate budget levels between 0.6% and 1.2% of GDP, the government should mix only R&D and educational subsidies. For example, given a budget of 1% of GDP, the optimal allocation is to use 58% of the budget for educational subsidies and 42% for R&D subsidies and no allocation of funds for expanding educational slots. With a larger budget, the government should mix subsidies to education, subsidies to R&D, and an expansion in the supply of education slots. Given a budget of 2% of GDP, it is optimal to allocate 35% to education subsidies, 46% of the budget to R&D subsidies, and 19% to expanding the educational slots available. The fact that there is an optimal mix highlights the role of the complementarities of the policies in their contribution to economic growth. The increase in slots expands the size of the talent pool in the economy, while R&D and education subsidies sort talented individuals who either had better options in the production sector or could not afford higher education into the research sector.

Third, our analysis suggests that education policy is more effective in more unequal societies in stimulating innovation. We analyze the responsiveness of policy under different levels of financial access to education. In an environment with a more equal distribution of family income, more individuals can afford schooling; thus, subsidizing the cost of education is less effective in stimulating economic growth.

[1] By % in this case, we refer to percent changes from the baseline growth rate.

In an extreme case, in an economy where everyone can afford education, educational subsidies have no effect, as individuals who want to pursue a career in research will do so regardless. On the other hand, in an economy where many individuals cannot afford education, educational subsidies are the most effective policy tool for innovation.

Fourth, we solve for the transitional dynamics of our model and find that it takes time for all of these policies to show their full effect. We find that R&D subsidies are the most effective policy for innovation in the short run. On impact, R&D policy stimulates the purchase of R&D inputs other than human capital (e.g., lab equipment) by the existing researchers, which translates into relatively more innovation. Education policy, on the other hand, has limited effectiveness in the short run, but is more effective in the medium to long run. It takes about nine years for educational subsidies to surpass R&D policy in terms of its overall growth effect for an equivalent government expenditure.

We highlight some overarching themes from these results. First, education policy is an integral component of a policymaker's toolkit for overall innovation. It cannot be thought of separately from its impact on the allocation of talent into research. Second, the model suggests a framework to think about how inequality and educational opportunity affect economic growth. Third, when observing the aggregate response to any policies, policymakers need to exert patience as each of these policies takes time for their full effects to be realized.

The rest of the paper proceeds as follows. We complete this section with a review of the literature. Section 2 discusses the institutional background in Denmark, the data, and the empirical stylized facts. Section 3 describes the theory, starting with the environment and equilibrium, and moving to theoretical counterfactuals on the introduction of policies and the frictions they alleviate. Section 4 describes the calibration and illustrates the ability of the calibrated model to match out-of-sample moments. Section 5 performs the quantitative policy counterfactuals. Section 6 concludes.

Related Literature

This paper primarily builds on and extends the theoretical and empirical literature on innovation and endogenous growth. One of the main departures of our analysis is the focus on individuals instead of firms. In our model, as in the classical endogenous growth models, ideas are the main source of economic growth (Romer, 1990; Aghion and Howitt, 1992), and idea production is heterogeneous in terms of quality, as in Akcigit and Kerr (2018). Our departure from this literature is focusing on the individual sources of economic growth and embedding realistic frictions grounded in the micro-data.

The relationship between scarce talent and aggregate innovation has received lively discussion in recent papers. Aghion et al. (2017, 2023a), Akcigit et al. (2017), and Bell et al. (2018) find that parental backgrounds influence who becomes an inventor in Finland, historical US, and modern US, respectively. Through name-matching between modern and historical data, Celik (2023) also finds that a child's likelihood of becoming an inventor is determined in part by family wealth. We verify this finding in the case of Denmark. The allocation of talent to innovative occupations has important implications for economic growth, as Waldinger (2016) finds that human capital is much more important than physical capital for innovation in both the short and long run. We put human capital at the center of this framework, recognizing that human capital must be built from raw talent.

Understanding the role of human capital in aggregate innovation can help enrich discussions on the interaction between R&D policy and economic growth. Standard growth models of R&D in firms assume the supply of scientists is elastic in steady state (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Klette and Kortum, 2004) and predict large effects of R&D subsidies on economic growth. However, there is empirical evidence that the general equilibrium effects of R&D policy are minimal (Goolsbee, 1998; Wilson, 2009). Our analysis enriches this discussion and provides a more micro-founded analysis of the scientists in research. We introduce a framework that includes matching of individuals to occupations (Rosen, 1981), financial frictions (e.g., Jovanovic, 2014, Celik, 2023), and talent heterogeneity (e.g., Jaimovich and Rebelo, 2017). Our new ingredients provide a quantitative framework that links this primarily theoretical work to empirical studies on the impact of R&D policy.

Empirically, economists have found that R&D subsidies increase firm innovation levels (Hall and Van Reenen, 2000; Bloom et al., 2002). Fiscal policies and public R&D investments also have positive effects in partial equilibrium (Moretti and Wilson, 2014; Azoulay et al., 2018). However, there is also evidence that this is much weaker in general equilibrium. For instance, Wilson (2009) finds that R&D subsidies simply pull innovative activity away from states that do not have subsidies, creating small aggregate effects. Moretti and Wilson (2014) find that R&D subsidies often simply lead to scientist reallocation across states. Dimos and Pugh (2016) review the literature and find mixed effects of public expenditure on R&D spending. Bloom et al. (2019) discuss this literature and suggest a potential combination of policies, which this current paper explores. In particular, we find that innovation policy is much more effective when combined with education policy, in line with empirical work that has noted optimal innovation allocation (David et al., 2000).

The elasticity of the supply of human capital in research is an important component for explaining the interaction between innovation and R&D policy, as noted by Goolsbee (1998) and Romer (2000). Goolsbee (1998) finds that R&D subsidies mostly transmit to scientist wages. With an inelastic supply of scientists, this price effect does not transmit significantly to overall innovation. Even if human capital is elastic in the long run, it takes time to build and entering individuals may have different talent than the existing pool. We build a model that formalizes these empirical observations and connects them through education and innovation.

In linking educational opportunities and frictions to growth, we take theoretical motivation from work dating back to Loury (1981), and developed by Glomm and Ravikumar (1992), Galor and Zeira (1993), and Fernandez and Rogerson (1996). These works modeled the interaction between private investment and public investment in education, which may diverge due to financial resources and financial opportunity. Benabou (1996) shows that income distributions and the distribution of wealth and power in society can have significant growth effects. More recent work has shown that credit constraints are relevant for pursuing higher education (e.g., Lochner and Monge-Naranjo, 2011, 2012; Dahl and Lochner, 2012). Hoxby and Turner (2015) also highlight the importance of information and knowledge about education opportunities. These forces may generate intergenerational income inequality and hold back opportunities for talented individuals. Our paper complements this work by building in a direct link between credit constraints and macroeconomic outcomes through educational opportunity. Further, applying empirical evidence on talent and talent development allows us to quantify these channels.

Education is a key channel of opportunity for individuals to lift their skills and contribute to economic growth. The framework in this paper complements an extensive empirical literature on the role of education in developing the workforce of an economy. Many papers find significant effects of schooling attendance on earnings (Angrist and Krueger, 1991; Ashenfelter and Krueger, 1994; Ashenfelter et al., 1999; Card, 1999) and connected education and the development of cognitive skills and human capital to economic growth (Mankiw et al., 1992; Hanushek and Kimko, 2000; Barro, 2001; Krueger and Lindahl, 2001; Hanushek and Woessmann, 2008; Hanushek, 2016). Further, schooling may have different effects depending on students (Aakvik et al., 2003) and the topics (Toivanen and Vaananen, 2016). Fujimoto et al. (2023) find that broadening educational access can have limited effects due in part to negative talent selection, which connects to a message in our paper that expanding educational slots may bring in worse fits for higher education. Kirkeboen et al. (2016) show how the chosen fields of students have an important impact on future earnings and are consistent with endogenous occupational choice based on comparative advantage. One central occupational choice is whether to take an innovative career. Previous papers have noted the importance of education for innovation (Aghion et al., 2009, 2017; Toivanen and Vaananen, 2016; Bianchi and Giorcelli, 2019; Aghion et al., 2023b; Biasi and Ma, 2022), and the role of education and human capital formation for long-run economic growth (Mincer, 1984; Barro, 2001). Grossman et al. (2017) find that increased education over time is a key component of sustaining balanced growth. College graduates and PhDs make up a large share of inventors as Aghion et al. (2017) find in Finland, and which we also find in the case of Denmark. We connect this literature to work on R&D in order to link the development of talent to policies for economic growth.

Given its scarcity, the allocation of talent to specific occupations is central to the production of ideas and growth of an economy. Murphy et al. (1991) note how occupational choice is an important force in economic growth in the context of rent-seeking versus entrepreneurship. Using survey data, Arts and Veugelers (2020) show that individuals with a strong taste for science make better inventors. Rosen (1981) discusses how, in a world without financial frictions or heterogeneous preferences, high-ability individuals will sort into careers with the highest returns to talent. Willis and Rosen (1979) show evidence based on this fact in the sorting of ability to college attendance, Topel and Ward (1992) study this in the context of early career occupational switches, while Aghion et al. (2018) and Pearce (2020) show this in the context of teams, and Prato (2022) studies sorting of inventors by ability across countries. Burchardi et al. (2020) find that migrants make important contributions to aggregate growth. However, this is complicated by frictions in the allocation of individuals to occupations. Celik (2023) finds that misallocation of talent to non-inventing occupations has a first-order effect on economic growth. Hsieh et al. (2019) find that better occupational allocation for minorities and females over the last 50 years has contributed to aggregate growth, which complements literature that has addressed this with rising female labor force participation (Greenwood et al., 2005). We also find frictions in occupational allocation have significant implications for economic growth.

We unite these facts on skill, education, occupational sorting, and innovation into an endogenous growth framework with talent heterogeneity, education, financial frictions, preferences, and physical capital for R&D (e.g., lab equipment). These forces enable realism when it comes to addressing how education and innovation policies interact with talent and human capital in the economy, allowing us in turn to establish a connection to the data and evaluation of the transmission of policies to innovation and economic growth at different horizons, through the lens of policy experiments in Denmark. We next turn to the institutional environment in Denmark, the data we apply, and the key facts that inform our model.

2 Institutional Background, Data, and Stylized Facts

This project relies on Danish micro-data with individuals and firms. We primarily make use of individual identifier data and extensive innovation and education policies in Denmark from Denmark's Statistics Office (DST) and external data sources from 2002-2013. The Danish context provides a laboratory to understand the effects of specific economic policies targeted towards higher education and R&D. This section describes the institutional background, data, and key stylized facts that connect talent, education, innovation, and policy.

2.1 Institutional Background

This section provides details on the institutional background for higher education in Denmark and the relevant education and innovation policies. We direct particular attention to PhDs due to their outsized role in innovation and the fact they were an important target in the policies introduced in this time period.

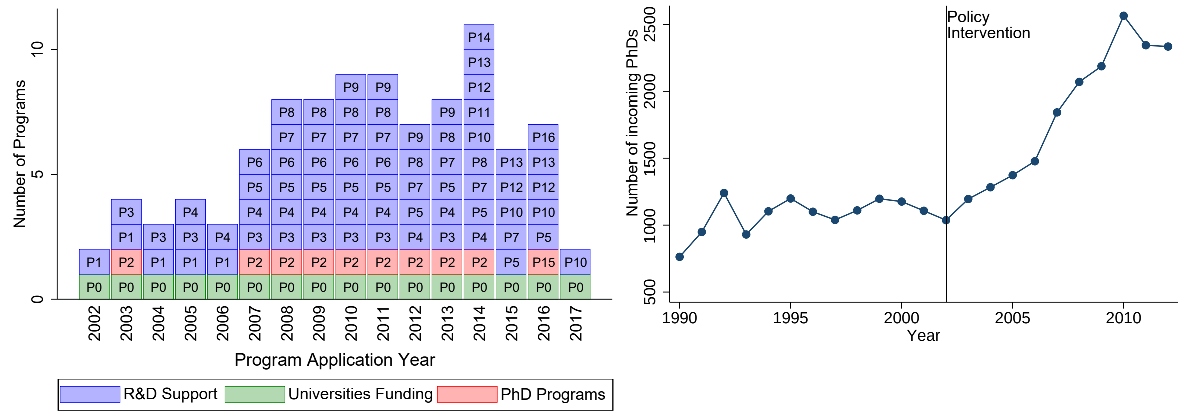
A PhD is the highest level of educational attainment in the Danish education system, and the Danish Ministry for Education and Research considers it a key element for supporting scientific capacity in Denmark (Ministry of Education, 2016). A typical PhD program has a duration of three years and begins after the completion of a 2 years Master's program. There are multiple ways of financing a PhD, including University basic funding, external grants, and funding from research councils or foundations.

The Danish Government has introduced a number of education and innovation policies since 2002. These policies were united in order to build "a comprehensive strategy for the development of Denmark into a leading global growth and knowledge society" (Jensen et al., 2012). On the education side, alongside targets for education attainment at lower levels, the goal was to increase the provision of higher education in order to establish a highly qualified recruitment base of researchers in both the private and public sectors. On the innovation side, the objective of the new R&D programs was to make Danish companies among the most innovative in the world. The "Innovation Danmark" database contains information on several education, research, and innovation programs since 2002. Figure 2a displays the number of active programs in the "Innovation Danmark" database by year. Each box represents an active program in the particular year. The identifiers inside each box represent the program instrument listed in Online Appendix A. Each color code signifies a program that addresses a different element of the market for idea production – R&D subsidies (blue), educational slots expansion (green), and educational subsidies for PhDs (red).

As part of the investment in higher education, the government required universities to increase PhD enrollment. This feature of the institutional environment motivates our modeling choice of a fixed number of university slots, which can be expanded through government policy. Universities were required to increase the annual intake of PhD students to a target number of 2,400 students, particularly within natural science, technology, medical and health science, and ICT (Ministry of Education, 2016). PhD enrollment, which had been relatively stable at about 1,200 individuals in the years up to 2002, started to increase gradually and reached about 2,400 in 2012, as displayed in Figure 2b. This was accompanied by increased funding for universities in the form of educational and research grants.

We will use these programs to discuss both qualitative and quantitative counterfactuals that resemble these policies. In the process, we group the various programs into three main categories: (i) R&D subsidies, (ii) subsidies to the cost of education, and (iii) increase in PhD slots. In Section 5, we will discuss the

Figure 2: Innovation and Education Policies in Denmark



(a) "Innovation Danmark" Programs

(b) Increase in PhD Enrollment in Denmark

Source: DST, Note: In Panel (A), the figure displays the research and education programs active in the "Innovation Danmark" database each year. Each box represents an active program in the particular year. The identifiers inside each box represent the program instrument listed in Online Appendix A. Color codes refer to the role of policies in terms of R&D support to firms (blue), grants for PhD students (red), and subsidies to universities to expand educational slots (green). In Panel (B), the graph plots the number of incoming PhDs by year in Denmark from 1990-2012.

quantitative implications of the policies, making use of a calibrated version of our model from Section 4. Next, we present additional details about the data and stylized facts that connect talent, education, and innovation.

2.2 Data

The empirical and quantitative analysis in this project is built on detailed micro-level data from the Denmark Statistical Office (DST). For data on individuals, we rely on the Integrated Database for Labor Market Research (IDA), where each individual in Denmark is assigned a unique identifier and is observed on an annual basis. From different subsets of this dataset, we can leverage information on individuals' highest completed education, background family characteristics (e.g., parental income), employment status, occupation, and income. In addition, the firm-linked (FIDA) dataset connects individuals to their place of employment (a unique employer identifier) each year. This comes with firm-level data such as sales, profits, and employees.

In addition to the individual-level data in IDA, we make use of further internal data on an individual's academic pursuits. The PHD dataset contains detailed information on individuals who enrolled in a PhD program. PHD contains information on most students' subject of PhD, date of enrollment, and date of graduation. Further, this data describes the funding source of their education and can be linked to individuals' socioeconomic background.

We combine these datasets with IQ data provided from the Danish military test, Borge Prien's Prove, which is required for conscripts at age 18.[2] We interpret the IQ measure as a proxy for an individual's

[2] Studies have indicated this data is a reliable measure of cognitive ability in a similar sense to IQ, e.g. Hartmann and Teasdale (2005). Teasdale (2009) reviews the literature. In Online Appendix E, we present a robustness exercise to take into account the fact that IQ is a noisy measure of talent.

talent. The test data goes back to 1995 and, with tests mostly taken at age 18, it provides information on most males entering the workforce or college after 1995. In total, we have approximately 500,000 observations for males with IQ data.

Lastly, we turn our focus to innovation, using information about policy interventions and innovation outcomes. DST provides details on R&D project funding following the expansion of government R&D support starting in 2002. We observe both funding through the broad "Innovation Danmark" program and specific R&D subsidies. The innovation program also has information on funding to education, which will be a key component of our policy discussion.

We combine DST data with innovation data made available through patents at the European Patent Office (EPO). Using a disambiguation algorithm provided by the DST, we are able to match about 75% of inventors on patents from Denmark to the individual information in the IDA dataset. We use these patents as our primary measure of innovation.

While all background data is available from 1980-2013 (i.e., age, education, sex, country of origin), the intersection of the datasets covers the years 2001-2013, which we will use for our analysis. This leaves us with approximately 32 million employer-employee observations, 10,000 inventors, and 37,000 unique PhDs.

The extensive data enables us to document the key elements of educational and occupational choices as well as innovative outcomes. Detailed parental data enables a study of the determinants of who becomes a PhD based on their background. Further, due to a host of policy tools the Danish government utilized over the main sample period, we have information related to policy instruments. Next, we use this data to document the stylized facts, which will also serve as motivation and quantitative tests for the model.

2.3 Stylized Facts

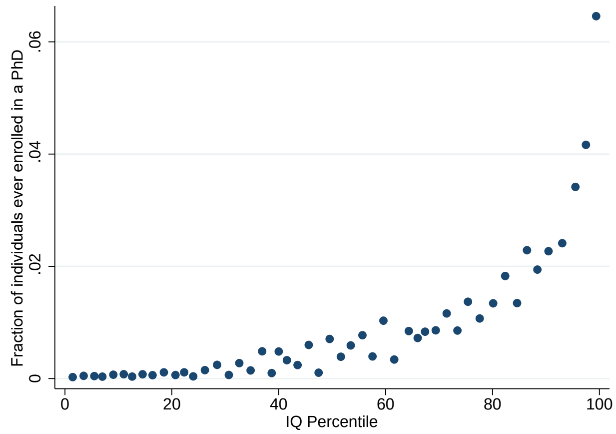
This section describes the stylized facts that connect talent, education, and family background to innovation and policy. We present our results in three groups. First, we document the role of talent and parental income in determining educational attainment. Second, we turn to innovation, documenting the role of education and talent as determinants of patenting. Third, we analyze the role of policy, evaluating the Danish reform to increase PhD enrollment and the corresponding change in incoming talent and overall innovation. These facts will also motivate the building blocks of our model, frame our quantitative investigation, and provide out-of-sample moments to test the model.

Determinants of Educational Attainment

We start by documenting the role of IQ and parental background as determinants of educational choice. Figure 3 presents the relationship between ability, proxied by IQ, and the likelihood of doing a PhD. The figure displays the fraction of individuals who enroll in a PhD at any time in their life per each IQ percentile.

We find a striking positive relationship between IQ and PhD attainment, where individuals with higher IQ are more likely to obtain a PhD. The relationship between IQ and the probability of becoming a PhD is convex; for each increase in an IQ percentile, an individual is increasingly more likely to enroll in a PhD. While the lowest IQ percentile has essentially zero probability of enrolling in a PhD, the median percentile has about 0.5%, and the top percentile has about a 6-7% probability of enrolling. Hence, more talented people are more likely to enroll in a PhD.

Figure 3: Probability of Enrolling in a PhD and IQ Percentile



Source: DST, Note: This figure displays the fraction of individuals who enroll in a PhD by IQ percentile bin.

In addition to IQ being an important determinant of advanced education, we relate the socioeconomic background of parents to the child's likelihood of obtaining a PhD. Figure 4 displays the fraction of individuals who enroll in a PhD at any point in their life as a function of their father's age-adjusted income percentile. We measure father's income in the year 2000 and exclude mother's income in order to avoid the higher variance in female labor force participation in Denmark. We provide a robustness check in Online Appendix E that includes the income of both parents.

Figure 4: Probability Child Enrolls in a PhD and Father's income percentile

Source: DST, Note: This figure displays the fraction of individuals who enroll in a PhD by father's income percentile bin. Income percentile is age-adjusted and measured in year 2000.

Figure 4 shows that children of higher-income fathers are more likely to enroll in a PhD. This interesting fact could be driven by multiple forces. First, this could be due to the limited financial resources faced by individuals born to poorer fathers. Second, talent or skill transmission across generations could also be responsible for this relationship. In order to tease out the intergenerational talent transmission margin, we next document the link between parental income and child IQ.

How is talent related to parental income? To answer this question, we correlate a child's IQ with their father's income percentile and we find a positive relationship. However, the correlation between parental income and IQ is 0.18, which is a significant departure from a perfect correlation of 1 and indicates imperfect sorting of talented children to high-income parents.

To jointly assess the importance of talent and parental income for PhD attainment, we perform regressions that include both variables as predictors. Our findings, presented in Online Appendix C, show that talent and father's income separately impact the propensity to enter a PhD. In the same section, we also show that parental income is still an important determinant of child's PhD even conditioning on parents who have a PhD, as a way to control for the transmission of information about career opportunities from parents.

Finally, we note that not all talented individuals born from rich families choose to obtain a PhD. Even when we consider individuals in the top 1% of the IQ distribution who are also children of the richest 5% of fathers, we still observe that about 90% do not enroll in a PhD program. This result motivates us to include in our model some distaste for research that drives individuals who could obtain a PhD into the production sector.

To summarize the main findings on the determinants of obtaining a PhD, we find that:

- IQ is a key determinant of whether an individual enrolls in a PhD.
- IQ is correlated with parental income but not perfectly.
- Parental income matters for PhD attainment both through IQ transmission and on its own, implying that some talented individuals may face financial hardship that prevents them from enrolling in higher education even though they are born with a high IQ.
- Not all individuals with high IQ and high parental income choose to pursue a PhD.

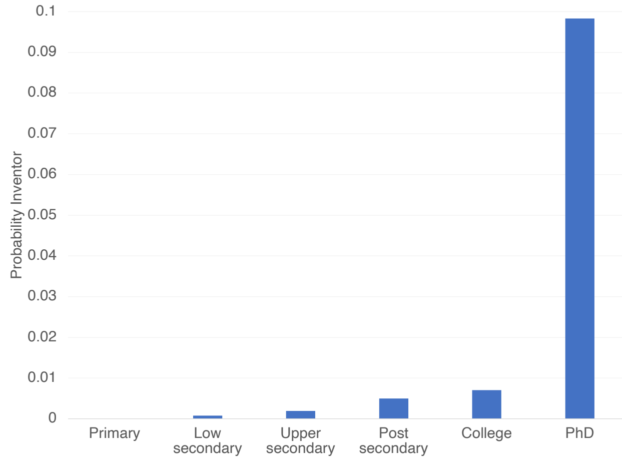
These findings motivate the features of the education block of our model, where individuals need to have sufficiently high talent and parental resources to obtain a PhD. Further, some individuals may prefer a career outside of research and choose not to pursue a PhD even if they have high enough talent and resources.

Determinants of Being an Inventor

We now turn to analyzing the determinants of becoming an inventor. Figure 5 plots the fraction of individuals who are inventors (i.e., who have at least one patent) as a function of their highest level of educational attainment, described by the six education categories in Denmark: primary, lower secondary, upper secondary, post-secondary, college, and PhD.

The link between education and becoming an inventor is monotonically increasing. Most interestingly, individuals with PhDs are disproportionately more likely to become inventors. College graduates are also more likely to be inventors than those without a college degree. In particular, the probability that a PhD graduate has a patent is 9.8%, while the probability a college graduate has a patent is 0.7%. When we compare PhDs to the population with no college education, we find an even larger difference in the probability of being an inventor, approximately 30 times larger for PhDs than for the general population. This fact illustrates the tight link between higher education and innovation, motivating the focus on PhDs in our analysis.

Figure 5: Probability of Being an Inventor by Education Level



Source: DST, Note: Fraction of individuals who file at least one patent by education level. The education level indicates the highest level of education obtained amongst the adult population.

We also find that individuals with higher IQs are more likely to become inventors even when we condition on education. To formally test the importance of IQ and education as predictors of innovation, in Online Appendix C, we document the results of a regression that includes both IQ and education as predictors of becoming an inventor, and we find that the two elements are separately strongly associated with the propensity to innovate.

Public Policy and Innovation

Our last set of empirical facts documents the role of public policies in innovation. Starting in 2002, the Danish Government required the universities to increase the number of PhD slots as part of a larger initiative to support education and innovation in Denmark, as discussed in Section 2.1. Figure 6 shows the number of individuals enrolled in a PhD over time (blue line) and the average IQ of enrolled PhD students (red line).

We observe that as the number of slots for PhDs increases, the average IQ of the enrolling students falls.[3] This indicates that the quality of enrollees is heterogeneous, and expanding slots may draw in a marginal researcher who is less talented than the average researcher from the existing pool. Thus, even though policy can increase the supply of researchers, there is a trade-off between expanding the pool of PhDs and the average talent of PhDs in the economy.

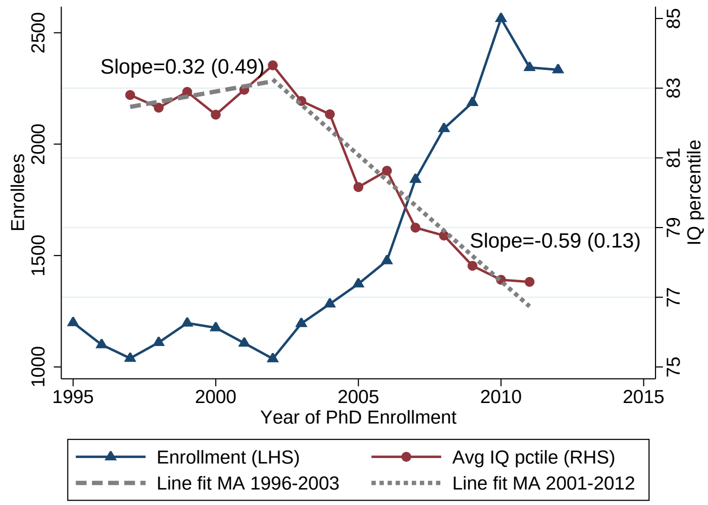
As a result of the increase in the supply of PhDs, we would expect to find an increase in overall innovation from newer PhD cohorts but less innovation per person, as the average IQ declines in the larger cohorts. Indeed, we find these results, which are documented and discussed in further detail in the Online Appendix C.4.[4]

Overall, some of our results confirm what the previous literature has shown on family background determinants of who becomes an inventor (Akcigit et al., 2017; Bell et al., 2018) and the importance of IQ for innovation (Aghion et al., 2017). We add new facts to this growing literature, such as the relationship

[3]The coefficients of a regression of IQ on year are significantly negative in the post-period. We also find a trend break and threshold break through Wald and threshold tests.

[4]We further discuss how these results cohere with the model in Section 3.

Figure 6: PhD Enrollment and Average IQ of Enrolled PhD Students



Source: DST, Note: This figure plots PhD enrollment in Denmark (blue line, RHS y-axis) over the years 1995-2015 and IQ of enrolled students with a three-year moving average (red line, LHS y-axis).

between IQ and PhD enrollment, as well as the link between the incoming cohort size and average IQ (as shown in Figure 6). All facts related to the interaction between IQ and PhD are introduced and used to discipline a model for the first time in the growth literature.

This section presented empirical facts about the determinants of being an inventor, obtaining a PhD, and the interaction of public policy and innovation. These facts motivate the key components of the model, which focuses on three key forces determining educational attainment and occupational sorting: ability, parental income, and preferences. The model will then provide a framework to study the effects of public policy on the composition of the PhD pool, innovation, and economic growth.

3 Model

The three sets of facts above highlight the importance of ability and family background to obtain a PhD and innovate. To speak to these facts, we build an endogenous growth model centered around talent development and allocation to link human capital formation to the innovation production function. Individuals are heterogeneous in talent, parental resources, and career preferences. When individuals are born, they choose whether to enter the production sector or research sector as in Figure 1. In order to enter the research sector, they must first obtain a PhD. Universities have a fixed number of slots that they give to individuals who (i) have sufficiently high talent, (ii) choose to take a career in research, and (iii) are able to afford the cost of education.

In the research sector, individuals produce and sell ideas to maximize income. On the production side, the model features a competitive final good production market and intermediate goods monopolists, who buy ideas from researchers in a market for ideas to improve the quality of their output. Innovation drives the growth in aggregate output and productivity through the improvement of intermediate goods quality. The economy is open to trade in the goods sector and capital markets, which implies that the interest rate is exogenous, but the idea production sector is closed to trade, as in Grossman and Helpman (1991).

The model is tractable and connects to the empirical facts discussed in the introduction and explored in Section 2.3. We provide an analytical solution to the steady state of the model and then discuss transitional dynamics from the introduction of subsidies. This framework is amenable to the introduction of various policies, which we explore theoretically in Section 3.2. In Section 4, we bring the model closer to the data by matching its quantitative features in order to inform policy counterfactuals.

3.1 Environment and Equilibrium

In this section, we will describe the basic environment and equilibrium. Our focus will be on a Balanced Growth Path (BGP) equilibrium where all aggregate variables are growing at the same rate g. We open the model discussion with occupational and educational choice and then turn to a discussion of the research and final goods markets, and close the model with the discussion of the balanced growth path.

Preferences, Career and Education

A unit mass of individuals live in a small open economy. Time is continuous and individuals are born and die at rate δ. Individuals garner hand-to-mouth log utility and attempt to maximize lifetime utility with discount rate ρ. Individuals consume the final good and make educational or career choices based on the expected value of occupations. Given the death rate δ, individuals' overall discounting is $\delta + \rho$.

Individuals are born with heterogeneous talent (z), family resources (m), and career preferences (ϵ), which determine sorting into two different occupations. There is a mass of production workers L and a mass of researchers N, such that:

$$L + N = 1.$$

Production workers work in final good production, while researchers need to first obtain a PhD and then they will work in the research sector.

At the education stage, PhD slots are limited and the university offers a PhD slot to a share N of individuals born in each cohort. The university attempts to offer the slots to the most talented individuals and is aware of the distribution of preferences, financial constraints, and talent. As a result, there is an equilibrium threshold $\bar{z}$ such that the university admits individuals with talent z greater than $\bar{z}$ that fills a class of size N, considering that some individuals above the threshold will decline the PhD offer based on their preferences and finances. In line with the facts about the determinants of education, the individual's education and career choice depends on (i) talent, (ii) financial resources, and (iii) preferences. We discuss these three forces in order.

First, individual talent, z, is distributed according to a Pareto distribution with c.d.f. $F(z) = 1 - \left(\frac{z_{min}}{z}\right)^{\theta}$ and we assume that $z_{min} = 1$. Thus, the fraction of individuals of a given cohort above the school's threshold $\bar{z}$ will be $1 - F(\bar{z}) = \bar{z}^{-\theta}$.

Second, obtaining a PhD is costly: upon starting a PhD, an individual must pay an upfront cost of education κ.[5] Motivated by the evidence in Section 2.3 (and noted in work such as Lochner and Monge-Naranjo, 2011, 2012), we assume that many individuals cannot afford education and must rely on parental

[5]We interpret this cost more broadly than tuition, in that it includes the opportunity cost of foregone income that might be required by individuals to support their families. We note that in our data PhD students earn on average only 74% the income of comparable individuals in the labor market, measured as the ratio of the average income of PhD students to the average income of individuals without a PhD in the same age and talent group. The lower income while in the PhD program could cause more severe hardship to individuals from poorer families.

resources to cover the upfront cost of education. In line with our empirical facts, we assume that talented individuals are more likely to have wealthier parents. We thus introduce the following reduced-form relationship to capture the correlation between talent and parental income.

We assume that for a fraction μ of individuals, talent is proportional to their parents' income, so that more talented children are matched to richer parents and the child's IQ percentile is the same as their parents' income percentile. For the remaining fraction $(1-\mu)$ of individuals, parental resources are independent of their talent. For these individuals, we assume that income is distributed as a Pareto with shape parameter $\tilde{\theta}$. To pin down the scale of the parental income distribution, we assume that if income were equally distributed, all students could afford education. This is equivalent to assuming that the scale parameter of the parental income Pareto distribution takes value $\frac{\tilde{\theta}-1}{\tilde{\theta}}\kappa$. As a result, due to the properties of the Pareto distribution, the probability that these individuals can afford education is $\left((\tilde{\theta}-1)/\tilde{\theta}\right)^{\tilde{\theta}}$.

Thus, the share of individuals in a given cohort that can afford education, $\tilde{\mu}$, is given by:

$$\tilde{\mu} \equiv \mu + (1-\mu) \times \left(\frac{\tilde{\theta}-1}{\tilde{\theta}}\right)^{\tilde{\theta}}. \tag{1}$$

The first term on the right-hand side indicates the fraction μ of potential students above the school's cutoff with talent proportional to parental income; these individuals have high talent and are matched to high-income parents, so they can afford education.[6] The second term indicates the $(1-\mu)$ fraction of individuals with talent independent of parental income, so that they can afford education with probability $\left(\frac{\tilde{\theta}-1}{\tilde{\theta}}\right)^{\tilde{\theta}}$.

Note that this structure allows us to capture the correlation between talent and parental income without keeping track of the intergenerational income distribution.[7] The degree of correlation between parental income and children's talent is captured by the parameter μ. This links to a literature that has pointed to how educational opportunities may be shaped by previous generations wealth in ways that potentially generate inefficiencies in the private market and induce intergenerational inequality (Loury, 1981; Glomm and Ravikumar, 1992; Fernandez and Rogerson, 1996).

Third, even an individual with high talent and sufficient parental resources may not choose to become a researcher because of career preferences. We assume that individuals have heterogeneous preferences for working in the production sector, captured by a variable ϵ. If an individual has sufficient talent and parental resources to obtain a PhD, she will compare the alternative of becoming a researcher and earning profits $\pi(z,t)$ or a production worker and earning a wage $w(t)$. The preference for being a production worker enters additively as $\ln(\epsilon)$. We assume $\epsilon^{\rho+\delta} \sim U(0, Ez)$, thus the preference shock scales with individual talent with coefficient E. This assumption captures the idea that more talented individuals, while facing higher returns in the research sector, also have larger outside options in the production

[6] For ease of exposition, we present the case where all individuals with a proportional match of IQ to parental income who are above the school cutoff can afford education. This is true for the parameter values that we obtain from our calibration. In Online Appendix B.5, we derive key model equations for the case where some of the individuals who are in the left tail of the talent distribution and with talent proportional to parental resources cannot afford the cost of education.

[7] Our setup abstracts away from individual consumption-savings decisions and does not generate an endogenous wealth distribution. The assumptions on parental income allow us to capture rich features, such as the correlation between talent and parental income, while keeping the model tractable so that we can provide an analytical solution for the balanced growth path equilibrium. As a result, we capture the interaction between child schooling and parental income net of savings.

sector.[8] Thus, the lifetime value function, $V(z, \epsilon, b)$, for an individual born in cohort b with talent z and preference ϵ is given by:

$$V(z, \epsilon, b) = \max\{V^{phd}(z, b), V^{worker}(b) + \ln(\epsilon)\}, \tag{2}$$

where $V^{phd}(z, b)$ is the value of becoming a researcher for an individual with talent z and $V^{worker}(b)$ is the value of becoming a production worker. The lifetime value of being a PhD for individuals with talent z in cohort b is given by

$$V^{phd}(z, b) = \int_b^\infty e^{-(\delta+\rho)(t-b)} \ln(\pi(z, t))dt.$$

This equation indicates that individuals discount at rate at $\delta + \rho$ the lifetime path of their income, which they consume with log utility hand-to-mouth. Similarly, the individual value of being a production worker (without including the preference shock) is as follows:

$$V^{worker}(b) = \int_b^\infty e^{-(\delta+\rho)(t-b)} \ln(w(t))dt.$$

Given wages and profits, forward-looking individuals decide whether they want to obtain a PhD. Some individuals who would prefer to choose a research career may be prevented from obtaining it due to a lack of financial resources or talent. To understand the forces determining the individual decision and school cutoff, we turn to the research production and labor market in order to characterize wages and profits.

Research Production

Once individuals make their career choice, those who pursue a PhD work as researchers and produce ideas to sell to intermediate goods producers. At each time t, a researcher produces a set of ideas using as inputs her own talent and lab equipment, which is purchased at the marginal cost $\bar{A}$. This research production can be interpreted as the production of ideas in academic institutions or firms.[9] For each total quantity of ideas, a fraction ϕ are implemented successfully.[10] Thus, an individual with talent z who purchases a units of lab equipment produces a bundle of ideas q:

$$q = \phi z^\eta a^{1-\eta}.$$

The number of ideas produced is increasing in the researcher's talent and in the amount of lab equipment. The parameter $\eta \in [0, 1]$ denotes the individual's share in idea output. Given the per unit price of ideas p,

[8] While our model does not feature income heterogeneity in the production sector, in reality, more talented individuals have higher wages outside of research and thus higher outside options. Assuming that the career preference shock scales with talent allows us to proxy for higher outside options in the private sector for more talented individuals. This assumption also implies that, conditional on sorting into research, individuals from higher-income families have higher talent, because they need a higher premium to overcome a higher preference shock on average. We use this prediction to indirectly test our assumption in the data, where we find that this surprising result is confirmed, as we document in Figure 10.

[9] We abstract away from the relationship between researchers and firms or academic institutions in producing research output.

[10] Another way of interpreting ϕ can be as the common R&D productivity in the economy.

a researcher with talent z chooses the amount of lab equipment a to maximize her profits,[11]

$$\pi(z) = \max_{a \geq 0} \left\{ p\phi z^{\eta} a^{1-\eta} - \bar{A}a \right\}.$$

The profit maximization of the researcher delivers, for a given z, optimal lab equipment a, quantity of innovation q, and profits π:

$$a(z) = z\left((1-\eta)\phi\frac{p}{\bar{A}}\right)^{\frac{1}{\eta}} \tag{3}$$

$$q(z) = \phi z\left((1-\eta)\phi\frac{p}{\bar{A}}\right)^{\frac{1-\eta}{\eta}} \tag{4}$$

$$\pi(z) = \frac{\eta}{1-\eta} z\left((1-\eta)\phi\frac{p}{\bar{A}}\right)^{\frac{1}{\eta}} \bar{A}. \tag{5}$$

The resulting profits determine the value of being a researcher and will inform an individual's occupational choice. We now turn to the final good production to characterize the wages of production workers and then to intermediate goods producers who buy ideas.

Final Good Production

The final good $Y(t)$ is competitively produced at time t using production labor L and a continuum of intermediate goods k_j:

$$Y(t) = \frac{1}{1-\beta} L(t)^{\beta} \int_0^1 A_j(t)^{\beta} k_j(t)^{1-\beta} dj,$$

where $A_j(t)$ represents the quality of the intermediate good j at time t. The price of the final good is normalized to 1. The time indices will be suppressed henceforth when it does not cause confusion. The profit of the final goods producer is equal to their total output minus the prices they pay for intermediate goods $P_j k_j$ and wages paid to labor wL. This leads to demand for the intermediate good as follows:

$$P_j = L^{\beta} A_j^{\beta} k_j^{-\beta}. \tag{6}$$

The marginal cost of producing each intermediate good for the monopolist is ψ in terms of the final good and the monopolist maximizes profits subject to the demand curve as follows:

$$\Pi_j = \max_{k_j, P_j} \left\{ P_j k_j - \psi k_j \right\}, \textit{ subject to (6)}.$$

The resulting equilibrium profits for the intermediate good producer can be shown to be linear in the quality A_j such that:

$$\Pi_j = \pi_I L A_j,$$

where $\pi_I \equiv \beta \left[(1-\beta)/\psi\right]^{\frac{1-\beta}{\beta}}$. We define aggregate productivity in the economy, $\bar{A}$ as the average quality of intermediate goods: $\bar{A} \equiv \int_0^1 A_j dj$. In line with the literature (Akcigit and Kerr, 2018), we assume that

[11] Later in this section, we show that the price p is independent of the intermediate good producer to whom a researcher sells the idea.

$\psi = 1 - \beta$.[12] It follows that the wage of unskilled workers and aggregate output are linear in aggregate TFP as follows:

$$w = \frac{\beta}{1-\beta}\bar{A} \tag{7}$$

$$Y = \frac{1}{1-\beta}L\bar{A}. \tag{8}$$

Given their profit $\pi_I L A_j$, intermediate goods monopolists have incentives to invest in technology. They can increase their productivity (A_j) by buying ideas from researchers. We now turn to the process of purchasing an idea to characterize prices.

The Market for Ideas

The intermediate goods monopolists buy ideas from researchers. A bundle of ideas q increases the intermediate good's productivity by a step size $q\bar{A}$, such that a monopolist with technology A_j can increase the quality to $A_j + q\bar{A}$.

The surplus or change in value from buying an idea is appropriated by the researcher. The intermediate goods producers pay unit price p_j, which is the unit value of innovation, for a bundle of ideas q that arrive at rate x.[13] Without loss of generality, we assume that researchers are randomly matched to intermediate goods producers.[14] Let us denote the value of owning a product line A_j as $V(A_j)$, which looks as follows:

$$rV\left(A_j\right) = \pi_I L A_j + x\left[V\left(A_j + q\bar{A}\right) - V\left(A_j\right) - p_j q\right]. \tag{9}$$

This continuous time Hamilton-Jacobi-Bellman has the following interpretation: the left-hand side equates the safe flow return, $rV(A_j)$, to the risky return on the right-hand side, which has the following components. The first term is the per-period profit flow $\pi_I A_j$; the second term captures the change in firm value due to the increased quality by $q\bar{A}$ minus the total cost of the idea to the firm, $p_j q$.

Proposition 1 *The equilibrium value function of monopolist j takes the following form:*

$$V(A_j) = \frac{\pi_I}{r} L A_j,$$

and the unit price of an idea p_j is equal to:

$$p_j = p = \frac{\pi_I}{r} L\bar{A}. \tag{10}$$

Proof. Since the researcher appropriates all of the surplus from the idea sale, then the surplus to the intermediate goods producer from purchasing the idea is 0, i.e.,

$$V\left(A_j + q\bar{A}\right) - V\left(A_j\right) - p_j q = 0 \tag{11}$$

Conjecture the following form of the value function from Equation (9): $V(A_j) = vA_j + \omega\bar{A}$. Substituting the guess into Equation (9), it follows in a straightforward manner that $v = \frac{\pi_I L}{r}$ and $\omega = 0$. Substituting

[12] This is without loss of generality as the model structure is the same regardless, and a combination of ψ and β can be used to target profits in Section 4.

[13] The rate x does not need to be pinned down in order to solve for the price of the idea.

[14] The exact market structure in the market for ideas is irrelevant because the value function is linear in A_j, so that the return to an additional unit of productivity is the same across all intermediate goods producers and independent of their current level of productivity. See Akcigit et al. (2018).

this result into Equation (11) delivers the unit price p_j described in Equation (10). ■

Note that the per unit price of an idea is independent of buyer j. The interpretation of this price is that the flow gain associated with an idea bundle q is $q\pi_I L\bar{A}$ and r encapsulates the discounted sum of this gain. Alternatively, it can be interpreted as the discounted value of innovation to buying firms. With the price of ideas closing the model, we can characterize the research pool and growth rate of the economy.

Balanced Growth Path Equilibrium

We next describe the solution to the occupational choice problem along a balanced growth path where all aggregate variables are growing at the same rate g. Forward-looking individuals observe the research and final good production market and make their career choice as described in Equation (2).[15] This equation governs how the research market influences occupational choice and the school cutoff $\bar{z}$. Let $\hat{w}$ and $\hat{\pi}z$ denote the detrended values of being a production worker and a researcher with talent z respectively.[16] Then, along the balanced growth path, the values of a production worker and a researcher of talent z are:

$$V^{worker}(b) = \frac{\ln(\hat{w})}{\rho+\delta}, \qquad \text{and} \qquad V^{phd}(z,b) = \frac{\ln(\hat{\pi}z)}{\rho+\delta}.$$

Using these expressions to solve Equation (2), we obtain that the fraction of individuals in a given cohort who prefer the research sector, α, is also time-invariant and independent of z [17]:

$$\alpha \equiv \Pr\left(V^{phd} > V^{worker} + \ln(\epsilon)\right) = \frac{1}{E}\frac{\hat{\pi}}{\hat{w}}. \tag{12}$$

We return to the fixed set of slots N that the school holds for students, also recalling the three elements that determine entry into PhD. Individuals who prefer working in the research sector, α, have talent above the school cutoff ($z \geq \bar{z}$), and with sufficient financial resources, $\tilde{\mu}$, will enter the PhD filling up the N slots:[18]

$$N = \Pr(z \geq \bar{z}) \times \tilde{\mu} \times \alpha. \tag{13}$$

The occupational choice and school cutoff determine the availability of researchers in the economy.[19] We can solve for the partial equilibrium expression for the school cutoff, $\bar{z}$, by plugging Equations (1) and (12) into Equation (13) to obtain:

$$\bar{z} = \left[\frac{\tilde{\mu}}{NE}\frac{\hat{\pi}}{\hat{w}}\right]^{\frac{1}{\theta}}. \tag{14}$$

Given prices and wages, Equation (14) delivers a partial equilibrium expression for the school cutoff $\bar{z}$. Higher research profits ($\hat{\pi}$) and lower production wages ($\hat{w}$) pull in more talent and induce a higher cutoff for the university. In addition, preferences for production and lack of financial resources reduce the propensity of individuals to enter the research market. The larger the mean of the preference shock for working outside the research sector (through larger E), the lower the school has to make the cutoff. If

[15]Online Appendix B solves this equation and shows that the solution to the occupational choice problem is time-invariant.

[16]We look for a balanced growth path of the economy where the growth rate of final output g is constant. Then, the expressions for the detrended values $\hat{w}$, and $\hat{\pi}z$ are such that: $w(t) = \hat{w}A_0 e^{gt}$; $\pi_H(z,t) = \hat{\pi}zA_0 e^{gt}$.

[17]See Online Appendix B for derivation.

[18]In Online Appendix B we show that financial constraints and preferences are independent of z.

[19]Notice that, given that population size is constant, along the balanced growth path the share of individuals in a cohort who enroll in a PhD, N, is equal to the share of researchers in the population.

there are fewer individuals lacking financial resources (higher $\tilde{\mu}$), the school would have a higher cutoff for the same number of enrollees.

Next, we solve for the general equilibrium allocation of talent in the economy. From Equations (5) and (7) we obtain the values for the detrended variables $\hat{\pi}$ and $\hat{w}$. Plugging these two variables into Equation (14) allows us to solve for the analytical general equilibrium expression for the school's cutoff, which contains the elements of the financial frictions $\tilde{\mu}$, preferences E, slots N, as well as the other fundamental parameters in research and final good production, described in the following proposition.

Proposition 2 *The threshold $\bar{z}$ to enter the research sector is time-invariant and is given by:*

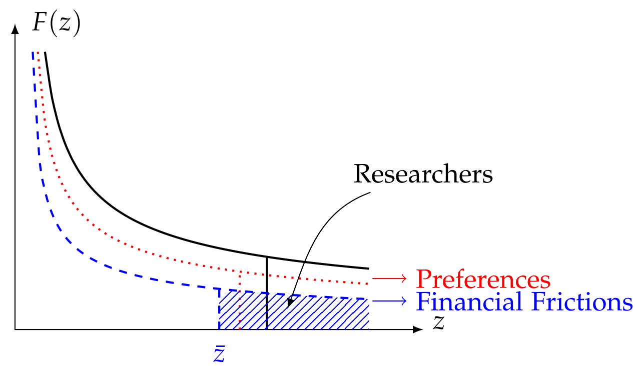
$$\bar{z} = \left[\frac{\tilde{\mu}}{NE}(1-\beta)\eta \left((1-N)\frac{\phi}{r}((1-\eta)\pi_I)^{1-\eta} \right)^{\frac{1}{\eta}} \right]^{\frac{1}{\theta}}, \tag{15}$$

Proof. See Online Appendix B. ∎

We note that the cutoff is increasing in the returns to innovation (π_I), the rate of successful innovation (ϕ), and the size of the market (L). Additionally, $\bar{z}$ is more responsive to these three forces the larger η is, governing the importance of talent in idea production. On the other hand, the cutoff is decreasing in the mean of the preference shock (E), the number of education slots, N, and the interest rate r. All these factors affect the talent cutoff as a function of the shape of the talent distribution, θ.

Figure 7 illustrates the allocation of PhD slots, which determine the research pool. The school accepts lower-quality students as a result of the lack of financial resources (low $\tilde{\mu}$) and heterogeneous preferences (high E). If all individuals prefer a career in research and can afford education, the school's cutoff would be at the black vertical line (highest talent pool). When some high-talent people prefer a career in production due to a distaste for research, this shifts the cutoff to the red vertical dashed line. In addition, when some high-talent people cannot afford education, this shifts the cutoff even further down to the blue vertical dashed line (lowest talent pool). This latter case generates the misallocation of talent in society.

Figure 7: The pool of educated researchers



Having characterized $\bar{z}$, we now characterize the growth rate of the economy as a function of the research market producing ideas. The ideas produced by researchers shape the growth rate of aggregate productivity, $\bar{A}(t)$, by increasing the quality of intermediate goods, as described in the following proposition.[20]

Proposition 3 *The aggregate growth rate of the economy is given by:*

$$g = \bar{z}N\frac{\theta}{\theta-1}\left(\phi\left((1-\eta)\frac{\pi_I(1-N)}{r}\right)^{1-\eta}\right)^{\frac{1}{\eta}}. \tag{16}$$

Proof. See Online Appendix B.2. ■

Equation (16) delivers growth as a function of fundamental parameters and $\bar{z}$. We note that g is increasing in the quantity of researchers, N, and the quality of researchers, which itself is a function of $\bar{z}$. It is increasing in the fraction of effective ideas in the economy, ϕ, and the price of ideas. The parameters for the share of talent in research production, η, and the shape of the talent distribution, θ, interact with g through both the production of ideas conditional on the talent pool and its effect on the talent pool, $\bar{z}$. Preferences and financial resources affect the growth rate through the talent threshold $\bar{z}$.

Recall from Equation (8) that aggregate final good output is linear in productivity. Thus, if aggregate productivity grows at rate g, final good output also grows at rate g. We now summarize the characteristics of the balanced growth path of the economy, on which the economy's growth rate is constant and the cutoff $\bar{z}$ is time-invariant.

Definition 1 *: **Balanced Growth Path.** A balanced growth path consists of a constant growth rate g, paths for the wage w, research profits $\pi(z)$, optimal lab equipment $a(z)$, new ideas $q(z)$, price of ideas p and cutoff $\bar{z}$ such that:*

1. *Lab equipment $a(z)$, idea qualities $q(z)$, and profits $\pi_H(z)$, are given by Equations (3)-(5).*
2. *The path for the unskilled wage solves Equation (7);*
3. *The school's cutoff is given by Equation (15);*
4. *Aggregate productivity $\bar{A}$ and aggregate output Y grow at rate g, described in Equation (16).*

We note that the BGP equilibrium can be solved analytically and is unique. The novelty of this balanced growth path is summarized by the talent cutoff (human capital quality $\bar{z}$) and slots (quantity N) as the central determinants of growth. Talent allocation, in turn, depends on the frictions and preferences of potential researchers, their educational and occupational decisions, as well as the supply of education slots.[21] This concludes the characterization of the balanced growth path equilibrium. Next, we will discuss the implications of innovation and education policies.

3.2 Policy Intervention: Innovation and Education Policies

The balanced growth path equilibrium provides a framework to address the steady state response of the economy to the introduction of policies, which we describe in this section.[22] In Section 5, we discuss transitional dynamics as the economy responds to policy in the short run from its initial steady state.

[20] We focus on growth coming from endogenous innovation, but discuss an extension where people outside the research market also produce ideas with an exogenous arrival rate in Online Appendix E.

[21] There are no strategic decisions, so the cutoff represents a unique equilibrium given the constraints, preferences, and talent of agents.

[22] We thus continue without the t index in this analysis.

We compare three types of interventions: R&D subsidies, educational financing subsidies, and expanding university slots. Each subsidy affects the economy through different channels. An R&D subsidy stimulates innovation through both (i) expanding the expenditures on lab equipment from the existing pool of researchers and (ii) improving the talent of new researchers by increasing the returns to the research, and thus attracting into the research sector talented individuals who would otherwise choose production work. A subsidy to education enables talented individuals from poor families, who would otherwise be unable to afford education, to enter the research sector. Finally, increasing the number of PhD slots expands the pool of researchers that create new ideas in the economy. We assume that the government finances these policies with a proportional tax τ on intermediate firms' profits.

We now introduce each of the three types of policies (R&D subsidies, education subsidies, and university slots expansion) and analyze how they affect the equilibrium growth rate of the economy. We will then discuss the quantitative effect of these subsidies in Section 5.

3.2.1 R&D subsidy

The government can stimulate research efforts with an R&D subsidy. We assume that the government subsidizes the price of ideas that are being purchased by firms from researchers by a rate s, so that researchers receive a total compensation of $p(1+s)$ per unit of ideas.

More formally, the R&D subsidy increases the school's cutoff as follows:[23]

$$\bar{z} = \left[\frac{\tilde{\mu}}{NE}(1-\beta)\eta \left((1-N)\frac{\phi}{r}(1+s)(1-\tau)((1-\eta)\pi_I)^{1-\eta} \right)^{\frac{1}{\eta}} \right]^{\frac{1}{\theta}},$$

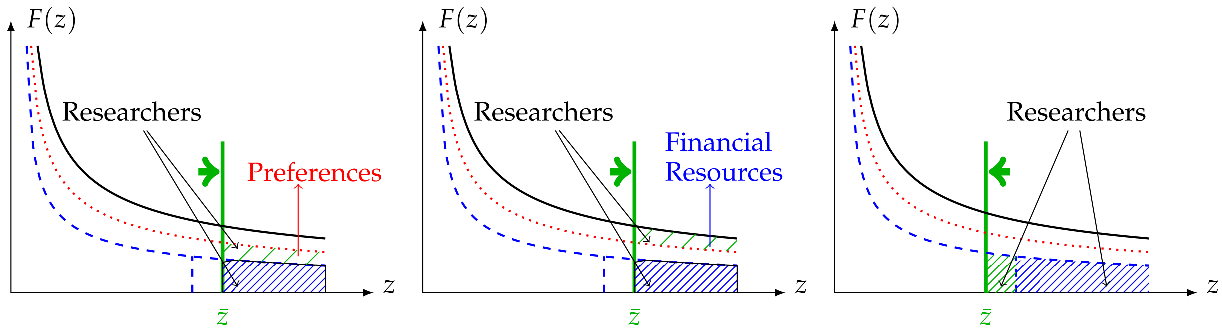
where, recall $\pi_I = \beta \left[(1-\beta)/\psi \right]^{\frac{1-\beta}{\beta}} = \beta$. The resulting growth rate is described by the following expression:

$$g = \bar{z}N\frac{\theta}{\theta-1}\left(\phi \left((1-\eta)\frac{(1+s)(1-\tau)\pi_I(1-N)}{r} \right)^{1-\eta} \right)^{\frac{1}{\eta}}.$$

In our model, R&D subsidy has two effects, as can be seen in the above expressions. First, it has a direct effect, which appears in the expression of the growth rate, of boosting research profits. Thus, given the existing pool of talent, researchers will have the incentive to produce more ideas by purchasing more lab equipment. When the subsidy rate goes up, the growth rate g goes up as a function of the relative importance of lab equipment in the research production function, captured by $1-\eta$. In the extreme case, as $\eta \to 1$, the subsidy has no direct effect on the growth rate. Second, and more interestingly, there is a new channel in our framework where subsidies to R&D indirectly affect the growth rate by increasing the threshold $\bar{z}$. The subsidy increases the return to being a researcher through increasing research profits, hence making the research sector more attractive. This will attract talented individuals into the research sector who would otherwise choose the production sector, resulting in an increase in the average talent of researchers. However, poor individuals who cannot afford education will not be affected by the subsidy. This mechanism is depicted in Figure 8a, where the shaded green region represents the group of people who initially prefer the production sector and then decide to enter research, resulting in an increase of the education cutoff $\bar{z}$.

[23] Please see Online Appendix B.3 for the formal derivation.

Figure 8: Policy and Talent Allocation



(a) R&D Subsidy (b) Subsidy to Cost of Education (c) Increase in PhD Slots

3.2.2 Subsidy to Cost of Education

The government can introduce a subsidy s_κ to the cost of education, such that students pay a net cost $(1-s_k)\kappa$ to enroll in a PhD program. This policy has a direct impact on the fraction of people who can afford education. This means that the probability that an individual can afford education is:

$$\tilde{\mu}_\kappa = \mu + (1-\mu)\left(\frac{\tilde{\theta}-1}{\tilde{\theta}(1-s_\kappa)}\right)^{\tilde{\theta}}.$$

This subsidy allows some talented individuals born in poor families to pay for education and enter the research sector, thus increasing the average quality of researchers. This is illustrated in Figure 8b, where the shaded green area indicates individuals who could not afford education but can access the research sector with the education subsidy. As a result, the schools' cutoff increases as follows:

$$\bar{z} = \left[\frac{\tilde{\mu}_\kappa}{NE}(1-\beta)\eta\left((1-N)\frac{\phi}{r}(1-\tau)((1-\eta)\pi_I)^{1-\eta}\right)^{\frac{1}{\eta}}\right]^{\frac{1}{\theta}},$$

The increase in the average quality of researchers affects the growth rate through $\bar{z}$:

$$g = \bar{z}N\frac{\theta}{\theta-1}\left(\phi\left((1-\eta)\frac{(1-\tau)\pi_I(1-N)}{r}\right)^{1-\eta}\right)^{\frac{1}{\eta}}.$$

We note that with educational subsidies there is no direct effect of the subsidy on the growth rate. The entire effect of the subsidy comes through $\tilde{\mu}_\kappa$, which allows talented individuals born in poor families to afford education and, as a result, it increases $\bar{z}$ and thus increases the growth rate. We also note an effect of the increased tax rate to finance the subsidy that lowers the returns to innovation. Up to this point, we analyzed the two subsidies holding the number of researchers fixed; we now turn to an expansion in the supply of researchers.

3.2.3 Increasing the number of PhD slots

Another policy tool discussed in the Ministry of Education (2016) report is the expansion of university slots. When the university increases the share of educational slots per cohort from N to N_s, more people flow into the research sector. As a result, we obtain the following expression for the university's cutoff with the new number of slots N_s:

$$\bar{z} = \left[\frac{\tilde{\mu}}{N_s E}(1-\beta)\eta \left((1-N_s)\frac{\phi}{r}(1-\tau)\left((1-\eta)\pi_I\right)^{1-\eta} \right)^{\frac{1}{\eta}} \right]^{\frac{1}{\theta}},$$

Increasing the number of slots reduces the cutoff $\bar{z}$, because it induces individuals with less talent to enter into research. This result operates through two direct effects, which are amplified by general equilibrium mechanisms. First, as there are more available slots, the school admits less talented individuals to fill them, as captured by the N_s in the denominator of the equation. Second, increasing the slots reduces researchers' profits through a market size effect, as seen in the term $(1-N_s)$. The market size effect means that research profits increase when there is a larger market to sell ideas to, which can be noted in the price of an idea in Equation (10). As the number of researchers increases, the number of production workers declines, and there is a smaller downstream market size for innovation. The decline in research profits then induces some talented individuals to choose the production sector rather than the research sector, reducing the average talent of the research pool. The tax τ further reduces research profits, amplifying the decline in marginal talent.

The decline in average inventors' talent is illustrated in Figure 8c, where the green shaded area indicates the additional individuals brought into the research sector by the increase in slots and the resulting decrease in the talent threshold $\bar{z}$.

The increase in the number of slots delivers the following equation for the growth rate of the economy:

$$g = \bar{z}N_s\frac{\theta}{\theta-1}\left(\phi\left((1-\eta)\frac{(1-\tau)\pi_I(1-N_s)}{r}\right)^{1-\eta}\right)^{\frac{1}{\eta}}.$$

When the number of slots increases, the growth rate is affected through four channels. First, growth is affected by the increase in the number of people producing ideas, N_s; second, by a reduction in their average quality, $\bar{z}$; third, there is a reduction in lab equipment investment due to the reduced market size effect, $(1-N_s)^{\frac{1-\eta}{\eta}}$; finally, there is an additional reduction in lab equipment due to the tax τ to finance the increased slots. All these interesting channels will have implications for policy design, which we will study quantitatively in Section 5. In order to do that, we first turn to calibrating the fundamental parameters that enable our study of counterfactuals and external checks on the model fit.

4 Calibration

This section describes the calibration and fit of the model. We use the empirical facts from Section 2.3 to discipline the parameters that govern the key forces in the model, such as the link between education, career choice, innovation, and growth. The goal of the calibration is to use the calibrated parameters to quantify the impact of counterfactual policies on growth, which we analyze in Section 5.

Section 4.1 discusses the matching process and the fit with targeted moments. Section 4.2 evaluates how the model performs with non-targeted moments, including leveraging the policy experiment in Denmark.

4.1 Calibration Technique

To calibrate our model, we perform a Simulated Method of Moments (SMM) matching exercise to back out the parameters. We describe the quantitative moments we target in the data and the calibrated parameters in Tables 1 and 2, respectively.

Our model has 12 parameters: $\{\rho, r, \delta, \beta, N, \mu, \eta, \theta, \tilde{\theta}, \phi, \psi, E\}$.[24] We refer to the literature for three parameters $\{\rho, r, \beta\}$ and directly match two with the data (N, δ). For the seven remaining parameters, we select seven informative empirical moments (M^E) from our stylized facts in Section 2.3. We simulate a BGP equilibrium and calibrate it to the data prior to the 2002-2003 policy introduction for the relevant moments in order to focus on the PhD distribution before any major government intervention. We then utilize the SMM to jointly calibrate the seven parameters. To do so, we minimize the distance between model-simulated moments, $M(\Theta)$, and their empirical counterparts, M^E, by searching over the parameter space Θ, using a simulated annealing algorithm, as follows:

$$\min_{\Theta} \sum_{i=1}^{7} (M_i^E - M_i(\Theta))^2.$$

We now proceed with a detailed explanation of the various steps in the calibration.

4.1.1 External Calibration

The production side of our model is very similar to the existing literature. The key departure in our framework is how an individual's life cycle and career choice relate to aggregate innovation. To calibrate the parameters on the production side, we follow the literature and set $\psi = 1 - \beta$ in line with Akcigit and Kerr (2018), set $r = \rho$, and set the discount factor to 97% ($\rho = 0.03$).

4.1.2 Internal Calibration

We first match the number of researchers (N) and the death rate (δ) directly to the data. We set the number of researchers to be equal to the share of PhDs as a fraction of the adult working population before the major policy interventions in our data, which is 1%. We set the death rate to generate an expected working life of 40 years, which implies a value of $\delta = 0.025$.

For the remaining seven parameters $\{\eta, \theta, \phi, \beta, E, \mu, \tilde{\theta}\}$, we target seven moments (M1-M7) jointly. Even though the parameters are identified together, below we provide a heuristic discussion of the parameters that each moment informs.

We begin with the moments that inform PhD attainment. We recall that, in the model, individuals may not obtain a PhD either because they cannot afford it (governed by the parameters μ and $\tilde{\theta}$) or because they prefer a production career (governed by dispersion parameter E).

[24] Note that we do not need to make assumptions on the cost of education κ to solve the model. However, estimating the costs of each policy is necessary to understand the budgetary costs of each policy and assess budget equivalence. In Online Appendix D.1, we explain in detail how educational costs are backed out.

M1 *Correlation between IQ and Parental Income*: In the model, there is a reduced-form correlation between individuals' talent and parental income, governed by the parameter μ. To inform this parameter, in the data we measure the correlation between IQ and father's income, obtaining a value of 0.175.

M2 *Ratio of Standard Deviation (SD) to Mean of Parental Income Distribution*: In the model, the distribution of parental income is governed by the parameter $\tilde{\theta}$. To inform this parameter, in the data, we compute the ratio of the standard deviation to the mean of the distribution of fathers' income and find a value of 0.663. We then compute and target the same ratio in our model.[25]

M3 *Mean Percentile IQ of PhDs*: In the model, we compute this moment as the average talent of researchers. In the data, the mean IQ percentile of PhD students prior to policy interventions in 2002 takes a value of 0.83. This moment is informative for the dispersion of preferences E, together with other determinants of average researchers' talent such as μ and $\tilde{\theta}$.

We now turn to the moments that inform the career choice between the research and the production sectors. In the model, this decision is primarily governed by the relative returns in the research sector as compared to the wage in the production sector, which depend on the following three parameters. First, the labor share in the output sector, β, influences the unskilled wage and intermediate goods producers' return. Second, the R&D efficiency ϕ affects the relative return to production versus research and the growth rate. Third, the shape parameter of the talent distribution, θ, influences the dispersion of returns in the research sector. These parameters are primarily informed by the following three moments.

M4 *Skill Premium of PhDs*: In the model, we compute this moment as the ratio of the average profits of researchers to the wage of production workers. This primarily informs the human capital share in idea production η and the R&D efficiency ϕ. In the data, we measure the skill premium of PhDs as the ratio of the average income of PhD graduates to the average income of individuals without a PhD and obtain a value of 1.747.

M5 *Ratio of Standard Deviation (SD) to Mean of PhDs' Income*: In the model, we compute this moment as the ratio of the standard deviation to the average profits of researchers. This moment primarily informs the talent shape parameter θ. In the data, we measure this moment as the ratio of the standard deviation of the income of PhD graduates relative to the average of their income during their peak income year, and we obtain a value of 1.44.[26]

M6 *Profits to Wages Ratio*: In the model, we compute this moment as the ratio of the total intermediate goods profits to the total wages paid out to production workers. This primarily informs the labor share in production β. In the data, it is measured as the ratio of profits of production firms[27] to total wages, obtaining an estimate of 0.073.

Finally, we turn to the moment that informs innovation and the growth rate of the economy.

[25] We restrict to the sample of individuals in the labor market when their children are of college graduation age (e.g., 21-22 years old). We test robustness to this measure in Online Appendix E.

[26] The peak income year captures a "mature" inventor to avoid life-cycle income dynamics. We test variations on this in Online Appendix E.

[27] Our data on firms includes firms with employees as well as self-employed individuals with no employees. We restrict our measure of profits to non-innovating firms with at least one employee.

M7 *Growth Rate of the Economy*: In the model, the aggregate growth rate of the economy is determined by the frequency of innovations and the composition of the research pool. Alongside other moments, this informs the R&D efficiency ϕ and talent share in innovation, η. We target a growth rate of 1%.

Table 1 summarizes the values of these moments in the data and the corresponding model-generated values. As can be seen, our model is generating a close match to the data.

Table 1: Moments

Moment	**Data**	**Model**
Correlation between IQ and parental income	0.175	0.175
Ratio of SD to mean of parental income	0.663	0.663
Mean percentile IQ of PhDs	0.830	0.830
Skill premium of PhDs	1.747	1.747
Ratio of SD to mean of PhD income	1.442	1.442
Profits to wages ratio	0.073	0.073
Growth rate (percentage points)	1.000	1.000

Table 2: Parameter Values

Parameter	**Description**	**Value**
	— Panel A. External Calibration —	
ρ	Discount rate	0.030
r	Interest rate	0.030
	— Panel B. Internal Calibration —	
N	PhD share of the labor force	0.010
δ	Death rate	0.025
β	Labor elasticity in final good	0.926
η	Inventor share in idea production	0.718
θ	Talent Pareto shape	2.217
ϕ	R&D efficiency	0.250
E	Preference shock parameter	8.311
μ	Fraction assortative match IQ - parental income	0.175
$\tilde{\theta}$	Parent income Pareto shape	2.810

Notes: All parameters are estimated jointly.

The resulting parameter values are reported in Table 2. Here, we discuss key parameters of interest. The human capital share of idea production η indicates that the researcher's own talent accounts for about 70% in idea output, with the remaining being attributed to capital such as lab equipment, data, and factories. This is consistent with survey data on R&D expenses for labor versus other inputs in Denmark. Other interesting parameters worth discussing are μ and $\tilde{\theta}$. These parameters suggest that around 1/3rd of the potential PhD population ($\tilde{\mu}$) can afford to pursue a PhD. We would like to reemphasize that the cost of schooling is broader than tuition cost, in that it includes living expenses and the opportunity cost of foregone income that might be required by individuals to support their families.

Figure 9: The allocation of talent in the economy

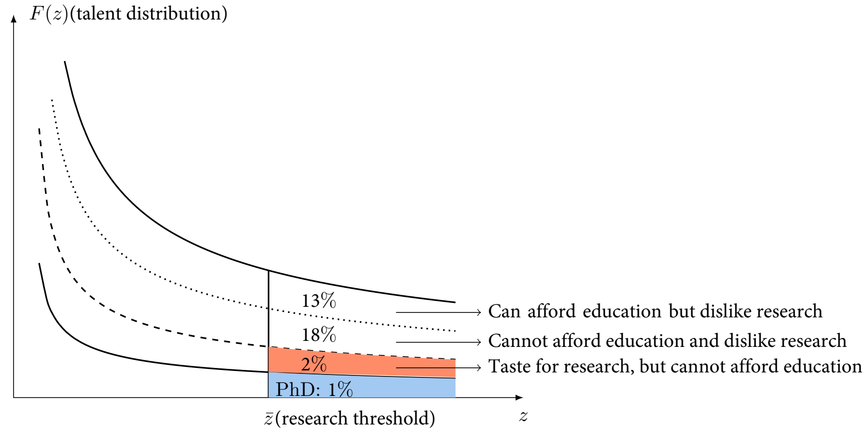


Figure 9 indicates the distribution of individuals above the talent threshold in the economy. Our model predicts that the fraction of people who are talented and able to afford education but dislike research is 13% of the population. More interestingly, the pool of people who are talented and willing to do research but are not able to afford education is about twice as large as the current pool of researchers (2% versus 1%). This group is misallocated in society.[28] We revisit this point in the policy counterfactuals in Section 5. Before turning to policy counterfactuals, we observe how the model hits non-targeted moments in the data.

4.2 Non-Targeted Moments

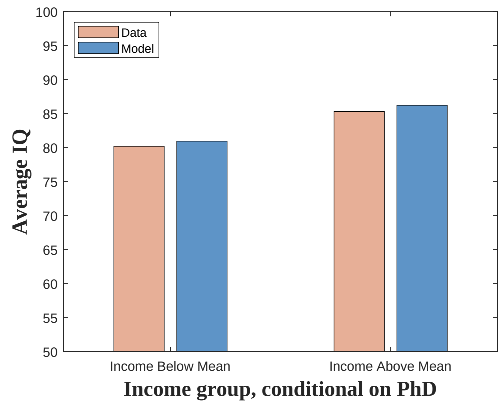
In order to assess the out-of-sample validity of the model, we explore how our model performs with non-targeted moments in the data. We perform two main out-of-sample matching exercises. First, we consider the relationship between parental income and IQ for individuals who obtain a PhD. To match the model, we only relied on the pairwise correlations between parental income, PhD, and IQ, but not the interaction of these three components. Second, we use our model to simulate the observed policy interventions in 2002 and compare the implied results for the talent of PhD enrollees to what we observe in the data.

Relationship between Paternal Income and IQ for PhDs

Figures 3 and 4 show that those who enroll in a PhD tend to have higher IQ and higher parental income. However, we have not discussed the relationship between IQ and parental income conditional on enrolling in a PhD. In this exercise, we use our simulated model to trace out the different IQs of the relatively wealthier and poorer individuals who enter a PhD program. The model implies that PhD enrollees with wealthier parents have higher talent. The result in the model comes from the fact that, on average, individuals with higher IQs have a higher preference shock, which proxies for greater opportunities outside the research sector. We find empirical support for this particular implication as shown in Figure 10.

[28] A social planner would always want to allocate individuals above the school cutoff who cannot afford education to research. We discuss the social planner's problem in greater detail in Online Appendix B.6.

Figure 10: IQ by Income Group, Data and Model Predicted



This figure illustrates model-simulated talent alongside the IQ from or data for two income groups of PhDs. We calculate the mean of parental resources for PhD enrollees, and we plot the average IQ for PhD students with parental resources below the mean and above the mean. Both in the model and in the data, average IQ increases in parental income conditional on being a PhD enrollee. We now turn to our second out-of-sample exercise.

Government Policy Intervention

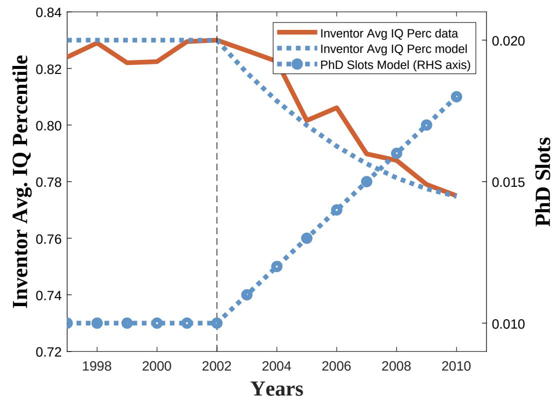
Here, we explore the responsiveness of PhD enrollee quality to a host of policy interventions. We did not directly use any Danish government policy interventions to calibrate the model, yet the major break in our sample provides an opportunity to test the power of our calibrated framework. Thus, we use the outcome of the policy interventions introduced in 2002 as an out-of-sample test of our model.

The Danish government introduced a number of education and innovation policies starting in 2002 with the goal of fostering innovation and technological progress. The "Innovation Danmark" database contains information on education and innovation programs, including the amount of funding and grants. We group the interventions into the three types of policies discussed in our model: R&D subsidies, subsidies to the cost of education, and increases in PhD slots. We estimate the expenditure for each type of policy from the data. Then, we feed the estimated policy rates into our model, and we compare the predicted outcome for the average IQ of PhD enrollees predicted by our model to the empirically observed outcome. The procedure to estimate policy rates from the data is outlined in Online Appendix D.2. We start from the initial calibrated steady state and solve for the transitional dynamics after the introduction of different policies. We assume that prior to the announcement of the program "Innovation Danmark" there is no expectation of a policy introduction but, once the policy is announced, all agents know the future paths: individuals understand the entire horizon of the policy and foresee the path of incomes.

Figure 11 displays the increase in PhD enrollees and the corresponding change in IQ after the policy intervention in both the data and model. Because we calibrate our model to the average IQ of PhDs before the policy intervention, both the data and the model predict the average IQ of enrollees at the 83rd percentile of the IQ distribution in 2002, prior to the introduction of these subsidies and slot expansion.

After 2002, in the model, the introduction of the policies and the expansion of slots then push average talent in opposite directions: subsidies to R&D and the cost of education lead to an increase in average

Figure 11: Policy Intervention and IQ of PhD enrollees: data vs. model.



IQ, while the expansion of PhD slots leads to a decline in average IQ. Nonetheless, the relative strength of these two forces predicted by our model overall matches the declining pattern in the average IQ of PhD enrollees observed in the data.

One point worth stressing is that the downward movement in IQ does not follow mechanically from the model. Due to the fact that Denmark combined policies for education, innovation, and enrollment slots, the quantitative and qualitative result depends on the mix of policies implemented. Both education and innovation policies increase the average IQ, while the increase in slots induces a decline in average IQ. Nonetheless, the quantitative fit between the out-of-sample model prediction and data is still very close, with both predicting a decline in IQ of 6 percentage points over 10 years.

On top of matching the decline in the average IQ of incoming students, we also are able to hit the patterns in patenting after the policy implementation, as we illustrate in Online Appendix C.4. We find that overall PhD innovation increases, in large part due to the increased class size. However, the average PhD has fewer innovations.

The two out-of-sample tests show that our model not only does well with the targeted moments but also is able to reproduce both specific facts in the data and the policy intervention that was implemented in 2002. We are now ready to study the implications of our model for education and innovation policies.

5 Policy Experiments

Our calibration enables us to study the impact of policies in the short and long run and speak to policy combinations that maximize growth. In this section, we use our model to perform a number of counterfactual policy exercises to quantify the strength of different policies in increasing the growth rate. We explore the quantitative impact of each policy individually and then introduce them simultaneously in order to evaluate their interaction and the optimal policy mix. We then discuss how the effectiveness of each policy depends on the underlying parameters of the economy.

Our results are organized as follows. Section 5.1 looks at the comparison of steady states under different subsidies and puts our new mechanisms into perspective by comparing our findings to the literature. We highlight the implications of educational and occupational decisions in our model and what this suggests for longstanding debates in the literature on R&D policies. Section 5.2 illustrates the complementarity of education and innovation policies – directing particular focus to the growth-maximizing policy mix for different budgets. Section 5.3 focuses on how the optimal policy depends on the inequality of parental income in the economy. Section 5.4 discusses the transitional dynamics with the introduction of each policy to illustrate the intertemporal tradeoffs and to describe what a policymaker should expect on the horizon of the impact.

5.1 Steady State Impact of Policies

We begin by describing the impact of our policies individually in steady state. We focus on revenue equivalent policies and their effects on the quality of PhDs, the total number of PhDs, and the overall growth rate. To generate policies that are revenue equivalent for the government, we impose policy rates that generate the same tax rate, as described in more detail in Online Appendix D.1.

There are three main policies of interest: R&D subsidies, educational subsidies, and expansion of educational slots. Each policy on its own increases innovation but through different channels. One important point to note is that an expansion in the number of PhD slots will increase the number of researchers, but induce a decline in their average talent, while R&D and educational subsidies, without expansion of the pool of researchers, increase the talent of the average researcher through different margins. The effects from R&D subsidies, educational subsidies, and educational slots expansion were illustrated in Figures 8a, 8b, and 8c in Section 3.2 respectively. Table 3 compares these three policies by showing the overall growth rate effect of a budget equivalent to a 10% R&D subsidy spent on R&D, education subsidies, and slot expansion, respectively.[29]

Table 3: Simulation of Alternative Policy Interventions (10% R&D Subsidy Equivalence)

	%ΔInnovation	Avg. PhD IQ percentile
Baseline	0%	83
R&D subsidy	6.4%	84
Educational subsidy	9.6%	87
University slots	3.8%	78

A number of important observations are in order. First, a 10% subsidy rate to R&D increases the baseline innovation by 6.4%. Note that unlike the standard growth models (Romer, 1990; Aghion and Howitt, 1992), this intervention keeps the number of researchers fixed (e.g., no scale effect), and the effect comes mostly through the quality composition of the inventor pool. The rest of the effect comes from the additional use of lab equipment for researchers with a given subsidy. The change in inventor talent happens due to an increase in the compensation of researchers as a result of the subsidized R&D. The return to being a researcher increases, pulling in individuals who can afford a career in research but, on the margin, would prefer working in production in the absence of the subsidy.

Second, when we use the same amount of resources to subsidize education, the impact on innovation is 50% larger (9.6% versus 6.4%) than the R&D subsidy. This is due to the fact that educational subsidies alleviate financial frictions by bringing in high-ability individuals who could not afford education into research. There is evidence in the literature that there are many talented individuals from poor family backgrounds who have the ability for a research career (Aghion et al., 2017; Akcigit et al., 2017; Bell et al., 2018), but their inability to enter the research sector could have large effects on innovation (Celik, 2023).

[29] This equals approximately 0.25% GDP in our framework and corresponds approximately to the amount spent on R&D subsidies and education subsidies in Denmark from 2000–2014. We use this as our baseline expenditure, but we present our results for a wider range of budgets in Online Appendix D.3 and we explore how changing the budget changes the optimal allocation in Section 5.2.

Third, when we use the same amount of resources to expand the PhD slots, we observe only a 3.8% increase in innovation. Given this subsidy level, an expansion in slots is about half as effective as an R&D subsidy. Note that, unlike standard models that often assume homogeneous skills of inventors, our framework with talent heterogeneity introduces a trade-off between the quantity and quality of researchers. When researcher supply is increased, schools lower the cutoff and the marginal additional researcher will be less talented than the existing inventors. This would create a non-linear relationship between policy and aggregate innovation response (as in Jaimovich and Rebelo, 2017). This finding also squares facts related to an increasing pool of researchers not creating a significant impact on aggregate innovation (Jones, 1995; Bloom et al., 2020).

Lastly, we want to relate the growth implications of these policies in our framework to existing models in the literature. Standard workhorse models of endogenous growth (such as Aghion and Howitt, 1992), assume that labor is homogeneous and can be allocated to both production and R&D, obtaining a very elastic margin of effective researchers. These models have been criticized for giving very high responses of growth to policy that are not observed empirically (e.g., Goolsbee, 1998; Romer, 2000; Wilson, 2009, among others).

In our model, there are two reasons why talented individuals may not enter a PhD: financial resources to access education and preferences. Each channel dampens the response of the growth rate to R&D subsidies compared to standard models. For instance, if all high-talent individuals cannot afford education, R&D subsidies have minimal effects because these individuals do not have the ability to respond to the increased wage in the research sector. Similarly, in models in the literature where the supply of researchers is inelastic and there is a fixed endowment of researchers, R&D subsidies only increase the wage of researchers and have no effect on the growth rate (Goolsbee, 1998; Romer, 2000).

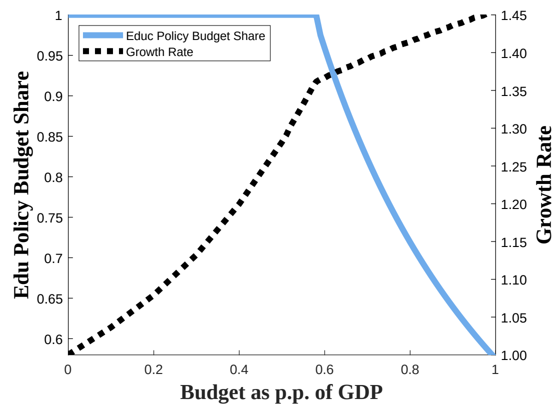
The response of the growth rate to R&D subsidies in our model is modulated by the importance of lab equipment in idea production, as the subsidy induces researchers to spend more on lab equipment. For instance, setting the coefficient of lab equipment to zero in our model (and thus $\eta = 1$) would reduce the change in growth rate in response to a 10% R&D subsidy to only 3.9% (as opposed to 6.4% in our benchmark model with lab equipment). We next turn to a discussion of the complementarities of innovation and education policies when introduced jointly.

5.2 Policy Complementarities and Growth-Maximizing Policy Mix

Motivated by the different margins that each policy hits, we now investigate how these policies interact. First, we consider the growth-maximizing mix of R&D and education subsidies for the existing level of slots, $N = 0.01$. More specifically, the solid blue line in Figure 12 plots the optimal share of education subsidy (with the remaining share going to R&D policy) for any given budget. In the same graph, the dotted black line plots the resulting growth rate.

The results show a pecking order of the two policies. The policymaker prioritizes education subsidies by allocating 100% of the policy budget to education when the budget is low ($\leq$ 0.6% of GDP). This is due to the fact that the policymaker first finds it most effective to sort talented but poor individuals into higher education to strengthen the talent pool, because the education subsidy is more cost-effective than the R&D subsidy. To see that, note that for R&D policy to be effective, it must induce individuals with high-valued outside options to switch to research. Given that the subsidy is proportional to researchers' profits, it becomes increasingly more expensive for highly talented individuals. On the other hand, the

Figure 12: Growth Maximizing Policy Mix



education subsidy is proportional to the cost of education and so it is equally expensive for all individuals.

Only when all individuals seeking a PhD are fully subsidized, it is then optimal to devote part of the budget left over to R&D subsidies. This happens when the level of budget is larger than 0.6% of GDP, at which point the policymaker introduces a mix between education and R&D policies. For instance, when the government allocates 1% of GDP to maximize innovation, it is optimal to split it with 42% going to R&D and 58% going to education subsidies.

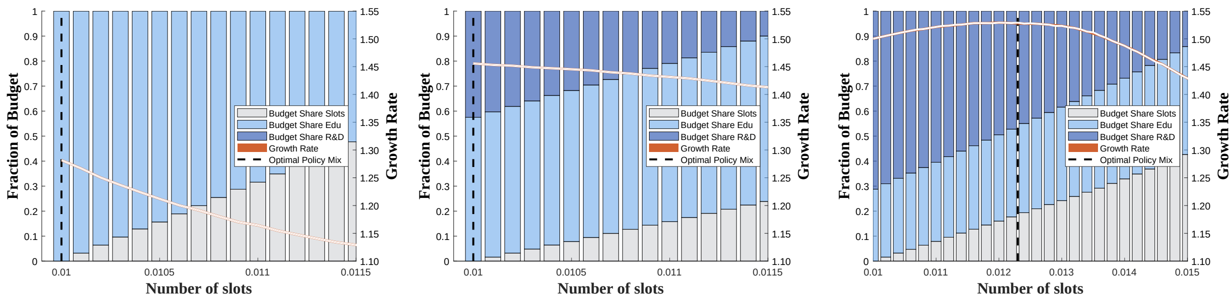
We now investigate what the growth-maximizing policy mix would be if the government could also expand the number of slots available in universities. Figure 13 shows the maximum growth rate attainable at different levels of slots for budgets of 0.5, 1, and 2% of GDP. The x-axis shows the number of slots available, N. The vertical bars display the share of budget spending going to each policy for each level of slots. In particular, the bars represent (i) R&D subsidy (dark blue bars), (ii) subsidizing the cost of education (light blue bars), and (iii) slot creation (grey bars). The grey bars compute the share of the budget going to slots creation corresponding to the level of slots given on the x-axis. The other bars show the optimal allocation of the remaining budget between R&D subsidies and education subsidies at the given slots level. The solid red curve displays the growth rate at each level of slots for the aforementioned policy mix.

Panels (A), (B), and (C) of Figure 13 display the growth-maximizing mix given 0.5% of GDP, 1% of GDP, and 2% of GDP respectively. The black dashed line indicates that in both cases the optimal policy mix does not involve any spending on additional PhD slots. In particular, the optimal policy mix at a budget of 0.5% of GDP consists in spending the entire budget on education subsidies, whereas at a budget of 1% of GDP, it allocates 42% of resources to R&D subsidies and 58% to education subsidies, consistent with the results in Figure 12.

For larger budgets, it is optimal to use a mix of all policy tools available, including adding PhD slots, which target complementary margins of talent allocation. Figure 13c indicates that the growth-maximizing mix given 2% of GDP, indicated by the black dashed line, corresponds to roughly spending 46% on subsidizing R&D, 35% of the budget on subsidizing the cost of education, and 19% of the budget on the creation of new slots. The increase in slots expands the size of the talent pool in the economy, while R&D and education subsidies sort talented individuals who either had better options in the production sector or could not afford higher education into the research sector.

To summarize our results on the growth-maximizing policy mix, if the government has limited re-

Figure 13: Growth Maximizing Policy Mix



(a) Budget = 0.5 pp GDP (b) Budget = 1 pp GDP (c) Budget = 2 pp GDP

This figure compares the change in patenting per PhD cohort after the 2002 increase in PhD enrollment in the data (red dashed lines) and to the change in innovation predicted by the model (blue solid lines). Figure (A) displays the total PhD innovation per cohort. Figure (B) shows the average innovation per student in the enrolling PhD class .

sources (less than 0.6% of GDP in our calibration), our framework suggests that it should allocate all of its resources towards educational subsidies only, to improve the talent pool by enabling access to education for talented individuals from poor families. For intermediate budget levels between 0.6% and 1.2% of GDP, the government should mix only R&D and educational subsidies. With a larger budget, the government should mix subsidies to education, subsidies to R&D, and an expansion in the supply of education slots.

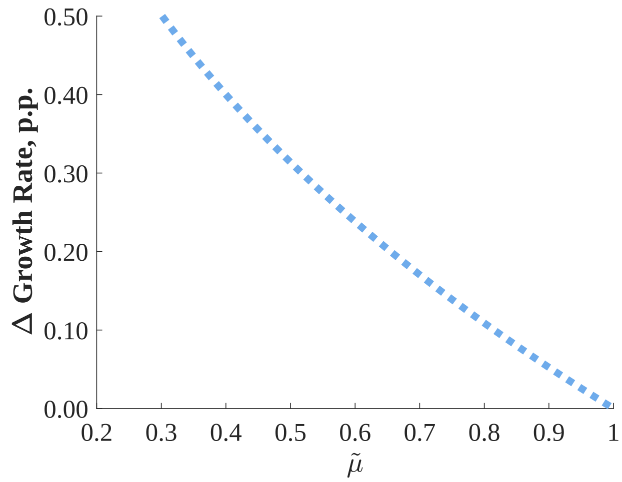
5.3 Inequality and Education Policy

In this section, we use our quantitative model to explore the link between the distribution of parental income and the impact of education policy. In our model, we assume that the economy has enough resources so that all potential students could afford education if parental resources were evenly distributed. Yet, the extent of inequality reduces the fraction of people who can afford education, generating a potential source of misallocation. The measure linking inequality to access to education is given by $\tilde{\mu}$ as defined Equation (1): as $\tilde{\mu}$ tends to 1, the fraction of individuals who cannot afford education tends to 0.

Figure 14 analyzes the effectiveness of education policy depending on the access to financial resources in the economy. The x-axis represents the fraction of individuals who can afford education, $\tilde{\mu}$. We then compute the growth rate in response to a 0.5% of GDP subsidy to the cost of education, ignoring taxes used to finance expenditure. On the y-axis, we plot the difference between the growth rate with the subsidy and the baseline growth rate of the economy without subsidy. The figure shows that as the fraction of individuals who can afford education increases, the effectiveness of subsidizing the cost of education declines. This is because the subsidy to the cost of education targets talented individuals who would like to obtain higher education but cannot afford it.

The overall takeaway from this result is that, as society becomes more unequal and more families cannot afford education, government intervention to subsidize education becomes more desirable to develop the innovative capacity of the economy.

Figure 14: Effectiveness of Education Policy at Different Levels of Education Access



5.4 Transitional Dynamics

We next turn to the dynamic evolution of the economy in response to each policy. A key component of the dynamics is that human capital takes significantly longer than physical capital to affect aggregate innovation and will thus induce longer delays in the transmission of policies.[30] We start from the initial calibrated steady state and solve for the transitional dynamics after the introduction of different policies. We assume prior to the announcement of the program "Innovation Danmark" there is no expectation of a policy introduction but, once the policy is announced, all agents know the future paths. Individuals understand the entire horizon of the policy and foresee the path of wages and profits.

Figure 15: Transitional dynamics response to 0.5% GDP

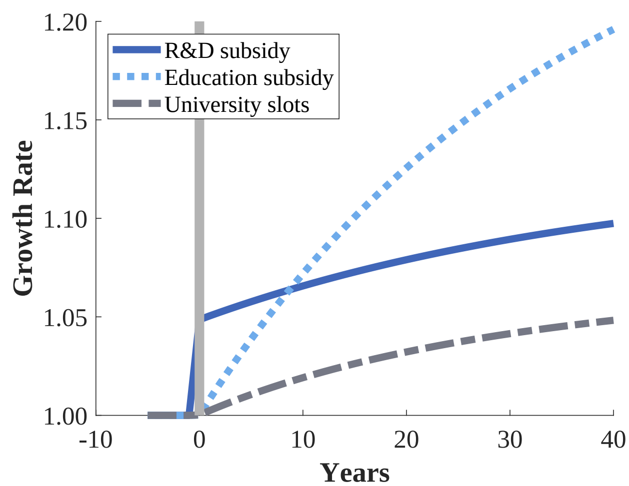


Figure 15 illustrates the dynamic evolution of the economy in response to each of the three policies

[30]This occurs through two channels. First, due to the cohort structure of the human capital life cycle. Second, Akcigit et al. (2020) explicitly model time to build human capital in innovation.

discussed in this paper, education subsidies, R&D subsidies, and the expansion of educational slots.[31] In particular, we perform and compare three counterfactuals. At time 0, we introduce three distinct budget equivalent policies using 0.5% of GDP into the economy that will remain in place permanently. This budget corresponds to a 20% R&D subsidy rate, which is approximately the rate of R&D support in OECD countries. We compare these policies over the following 40-year period to observe the corresponding evolution of the growth rate. The solid dark blue line corresponds to an R&D subsidy, the dotted light blue line corresponds to an educational subsidy, and the dashed grey line corresponds to an expansion in PhD slots.

We highlight the following findings. First, it takes time for each policy to show its full impact. All education policies take more than ten years to get halfway to the new steady state. Second, the policies that look more effective in the short run are different from the policies that look effective in the medium to long run. For instance, R&D subsidies generate the strongest immediate growth effects through increased use of lab equipment, while educational subsidies take some time to bring in new talent and surpass R&D in 9 years. Educational subsidies take the longest to transmit to the growth rate, but gradually become the most effective policy tool in the long run by increasing the quality of researchers. The new cohorts with higher talent eventually replace older cohorts with lower talent and then transmit their skill to aggregate innovation.

An important takeaway from these transitional dynamics is that it takes time to build a high-quality talent pool. For instance, it takes educational subsidies over ten years to reach the halfway point to the new steady state. Hence, empirical innovation policy evaluations based on data with short time spans could potentially lead to wrong conclusions about their effectiveness if the lagged nature of these policies is not taken into account.

6 Conclusion

This paper puts the development of scarce talent and career choice at the center of an endogenous growth framework and uses this framework to understand the effects of education policies, innovation policies, and their interaction. Individuals decide their career path as a function of their talent, preferences, and family financial background. These choices eventually transmit to aggregate innovation as talent builds into human capital and contributes to idea production. We discipline these micro-level decisions and outcomes with rich micro-level datasets from Denmark. Our estimated model not only matches a host of facts in the data, but replicates the response of the talent pool to policy interventions in the 2000s. We then use this framework to study policy counterfactuals of education and innovation policies. The framework delivers several important messages for understanding and designing optimal policies.

We highlight four main findings. First, we find that the introduction of a subsidy to innovation is less effective than in standard models, squaring the empirical evidence with the theory, due to a host of forces, such as talent heterogeneity, preferences, the elasticity of education supply, and the distribution of financial resources. However, the impact of R&D subsidies can be strengthened when combined with higher education policy that sorts talented but credit-constrained individuals into research. Second, education and innovation policies are tapping into a different part of the talent distribution depending on the types

[31] We solve the transition dynamics numerically by guessing a vector of cutoffs $\{\bar{z}(t)\}_t$ along the transition and verifying whether the implied wages and profits are consistent with individuals' decisions. The algorithm we use to numerically solve for the equilibrium of the economy along the transition is discussed in Online Appendix D.4.

of frictions individuals face. Third, R&D and education policies impact innovation at different horizons, which makes the optimal policy design a function of the time horizon of the policymaker. Finally, the optimal policy will depend on the amount of parental income inequality in society. In highly unequal societies, education policy is likely to be significantly more effective than R&D policy because education policy targets talented individuals who cannot afford education. In societies with a more even distribution of financial resources, R&D subsidies are more likely to be effective because, while the inability to afford higher education will be limited, R&D subsidies can increase the available capital for researchers and induce those who would have otherwise not worked in research to enter the research sector.

We conclude with a discussion of some interesting extensions for the individual-based endogenous growth agenda put forward in this paper. First, policies to expose talented youth to education can be broadened to think about access to information about career opportunities (e.g., Hoxby and Turner, 2015), and this study could provide a framework to analyze these other margins of educational exposure. Second, the financial risk in innovative careers could play an important role in the allocation of talent and, thus, preferences not just over careers but over risk will also be important to understand the choice of innovative careers. Third, in light of the increasing inequality observed around the world, it would be interesting to apply the current framework to societies with more extreme income inequality relative to Denmark. Fourth, our results highlight that domestic talent is scarce and induces a country to run into diminishing returns when relying only on a domestic talent pool. One way to ameliorate this problem could be to tap into international talent, drawing implications for immigration policy. These are very fruitful extensions that await further research.

7 Data Availability and Provenance Statement

The data underlying this article were provided by the Danish Statistical Office (DST) by permission. The raw data can be accessed with an application to DST (see Statistics Danmark). Some intermediate and final data outputs are available directly in the article and in the replication files, together with the code underlying this research, available on Zenodo at https://doi.org/10.5281/zenodo.10456771.

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