The Lost Marie Curies and Foregone Economic Growth

Jean-Félix Brouillette*

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Abstract

Women made up only 14% of U.S. inventors in 2023. Assuming no intrinsic gender differences in inventive potential, the scarcity of women in research reveals that the U.S. is missing out on some of its brightest minds. How costly is this talent misallocation for aggregate productivity? I develop a model of semi-endogenous growth in which individuals with heterogeneous talent choose between research and production careers. However, several barriers deter women from pursuing their comparative advantage. Lifting those barriers would increase U.S. income per person by 14.2% in the long run, compared with just 1.5% from a 30% R&D subsidy alone.

*HEC Montréal. E-mail: jean-felix.brouillette@hec.ca. I am grateful to Pete Klenow, Chad Jones, Chris Tonetti, three anonymous referees, and Ayşegül Şahin (the editor) for their helpful comments. This project was supported by the B.F. Haley and E.S. Shaw Fellowship for Economics at SIEPR, Stanford and the "Unlocking Our Potential" dissertation program at the Federal Reserve Board of San Francisco.

1 Introduction

Economic growth is the product of a handful of people discovering infinitely usable ideas that raise everyone's living standards. With this crucial role, the hope is that our brightest and most creative minds engage in the process of innovation. But is that really the case? In 1976, 3% of inventors in the U.S. were women, and by 2023, that fraction had only inched up to 14%. Under the natural assumption that there are no *innate* gender differences in inventive ability, the vast underrepresentation of women in research reveals that the U.S. is missing out on some of its most talented inventors. This observation raises an important question: How costly is the resulting misallocation of inventive talent for aggregate productivity and welfare?

To tackle this question, I interpret micro-level data on the universe of U.S. inventors and researchers through the lens of an overlapping generations general equilibrium model of semi-endogenous growth. This framework complements the prior work of Einiö, Feng and Jaravel (2022), who approach the question in a setting of endogenous (rather than semi-endogenous) growth. In my model, there are two occupations: researchers who discover new products and workers who produce existing ones. Individuals in this economy are heterogeneous in their *innate* talent for research and must make three key decisions: (1) whether to pursue a STEM education, (2) whether to work in research or production, and (3) whether to have children. However, different barriers may deter or prevent women from pursuing their comparative advantage in research.

While numerous factors contribute to women's underrepresentation in research, this paper does not seek to comprehensively explain *why* there are so few women inventors. Rather, it addresses a complementary but distinct question: *how costly* is it to miss out on half of our brightest minds? To answer this question, I focus on three particular barriers to female innovation highlighted in the literature that operate through different mechanisms and thus have distinct implications for aggregate productivity.

First, women can be denied due compensation for their inventions, which is modeled as a tax on their earnings as in Hsieh, Hurst, Jones and Klenow (2019).[1] To illustrate this distortion, consider the case of Gerty Cori, the first American woman to win a Nobel Prize in science. Two years after discovering the Nobel Prize-winning Cori cycle with her husband Carl Cori, the only employment she could find was that of a research associate at Washington University, receiving a tenth of her husband's salary. While Carl was extended an invitation to chair the university's pharmacology department, Gerty would have to wait another 16 years to be promoted to a full professorship (American Chemical Society,

[1] This "tax" is intended to broadly capture the many forms of professional barriers that disproportionately affect women (Becker, 1957; Phelps, 1972; Arrow, 1973).

2004a,b).[2] Her unfortunate experiences echo the many forms of workplace discrimination that women confront throughout their careers in research. These include, for example, the denial of promotions, an asymmetrical sharing of the rents from intellectual property, or biases that discredit women's scientific contributions.[3]

Second, women can face a "child penalty" that disproportionately hinders their career progress in research. I model this penalty as extra time off work for mothers, reflecting the well-documented reality that childcare and housework is still unequally shouldered by mothers. Moreover, I allow for the possibility that research is a "greedy job" in the sense of Goldin (2021)–one where working long, inflexible hours commands a premium–which can further magnify the costs of motherhood. Historical evidence corroborates this view: Kim and Moser (2021) document that mothers in mid-20th-century American science experienced a marked decline in research output for several years after the birth of a child. As a result, many mothers were forced out of the research pipeline before achieving tenure or establishing themselves as senior researchers. Illustratively, upon giving birth to her only child, Gerty Cori reportedly worked until she was admitted to the maternity hospital and returned to her laboratory just three days later (Encyclopedia.com, n.d.).

Lastly, women may simply not be as frequently "exposed" to inventive careers and opportunities during their formative years as their male counterparts, *regardless* of their talent. Receiving exposure to innovation is modeled as a binary random variable that determines whether someone can choose to invent or not. This distortion is intended to capture one of the key findings from Bell, Chetty, Jaravel, Petkova and Van Reenen (2018), which is that girls who grow up surrounded by more women who patent in a specific field are more likely to go on to patent in the same field. Hence, a lack of relevant role models could prevent girls from forming aspirations and/or having enough information to pursue research. Gerty Cori was no exception to this pattern. Her father Otto Radnitz was a chemist turned manager of beet-sugar refineries after successfully devising a sugar refining process. Perhaps not surprisingly, Gerty Cori would years later win her Nobel Prize for describing the fate of sugar in the human body.

The magnitude of those barriers is inferred from three corresponding moments: (1) the research productivity gender gap, (2) the gender gap in hours worked between researchers with and without children, and (3) the overall underrepresentation of women in research. First, the labor market distortion induces positive selection where only the most talented women opt for a research career despite being compensated below their marginal product.

[2]Despite all of their work being collaborative, Carl Cori was also the sole recipient of the Albert Lasker Award for Basic Medical Research and the American Chemical Society's Willard Gibbs Medal.

[3]See for instance Kline, Petkova, Williams and Zidar (2019); Ewens and Townsend (2020); Hannon (2021); Pairolero, Toole, DeGrazia, Teodorescu and Pappas (2022); Morazzoni and Sy (2022); Jensen, Kovács and Sorenson (2018); Hofstra, Kulkarni, Galvez, He, Jurafsky and McFarland (2020); Hochberg, Kakhbod, Li and Sachdeva (2023); Ross, Glennon, Murciano-Goroff, Berkes, Weinberg and Lane (2022).

Hence, under this distortion, women should exhibit higher research productivity than their male counterparts on average. The child penalty distortion directly reduces the hours worked of mothers in research. Finally, the exposure distortion is identified as the residual explaining the remaining underrepresentation of women in research. However, it is still an informative residual as it suggests that the gender gap in research is not due to distortions that operate through selection or family considerations.

These moments are measured from two data sources. The first is PatentsView, which contains information on all patents granted by the U.S. Patent & Trademark Office (USPTO) since 1976. PatentsView uses a series of disambiguation algorithms to uniquely identify inventors over time and, most importantly, predict their gender from their first name. Research productivity is measured as the average number of patents granted to an inventor per year over their career, where patents are weighted by different measures of their "quality".[4] The second data source is the U.S. Census Bureau's Decennial Census and American Community Survey (ACS), which provide demographic and occupational information on the U.S. population. To identify researchers in this data, occupations are classified into research using the mapping proposed by Ekerdt and Wu (2024).

Across these data sources, I find that female researchers exhibit only marginally higher productivity than their male counterparts, implying that barriers that operate through selection may not be the most prominent drivers of the research gender gap. Additionally, I document that mothers in research work approximately 5% fewer hours compared to women without children, whereas fathers tend to work slightly more than childless male researchers. Despite this clear gendered child penalty, the magnitude of the gap in working hours alone is too narrow to fully explain the extensive underrepresentation of women in research. Consequently, the analysis suggests that limited exposure to inventive careers during formative years emerges as the most significant barrier hindering women's participation in research.

Taking the theory to the data, I find that lifting all barriers to female inventorship would increase U.S. income per person by 14.2% in the long run. To get a sense of magnitudes, if we were to implement a uniform R&D subsidy of 30% in the model (absent any distortions), long-run income per capita would only increase by 1.5%, which shows that the potential productivity gains from research talent reallocation are considerable. Moreover, I show that these large gains mostly come from having *better* rather than *more* inventors. This is no surprise given that they are almost entirely achieved by raising exposure to innovation for aspiring female researchers, thus unlocking an entirely untapped pool of inventive talent. From a welfare perspective, closing the research gender gap would be equivalent

[4] As described in Section 2, we consider different definitions of patent quality, including its stock market valuation (Kogan, Papanikolaou, Seru and Stoffman, 2017), forward citations, and "importance" (Kelly, Papanikolaou, Seru and Taddy, 2021).

to permanently raising everyone's consumption by 7.2%. This figure comes shy of the long-run increase in income per capita due to slow transition dynamics.

Of this improvement in welfare, 95% results from higher mean consumption while the remainder comes from lower consumption inequality and utility from children. However, this is not to say that those gains are evenly shared. Carrying out the consumption-equivalent welfare calculation separately for different demographic groups shows that future generations would experience an 8.6% permanent increase in consumption, as opposed to a more modest 1% increase for current cohorts. Zooming in on the current generation of inventors, women would see their consumption rise by 1.3% while men would instead suffer a 1.7% *decrease* therein.

The rest of the paper is outlined as follows. In the remainder of this section, we discuss the relevant literature. Section 2 presents the data and motivating facts. Section 3 presents the theoretical framework. Section 4 discusses the model's calibration. Section 5 presents the results on the macroeconomic implications of barriers to female innovation. Section 6 proceeds with various theoretical extensions and Section 7 concludes.

Related Literature

This paper relates and contributes to two growing strands of literature. The first is a collection of studies on the macroeconomic consequences of talent misallocation. A prominent example is Hsieh et al. (2019) showing that convergence in the gender and racial composition of the U.S. labor market between 1960 and 2010 is responsible for as much as 40% of economic growth over that period. Hsieh and Moretti (2019) and Bryan and Morten (2019) study the allocation of talent across geographic locations and find that barriers to local migration can be a considerable drag on aggregate productivity. Lagakos and Waugh (2013) and Buera, Kaboski and Shin (2011) argue that selection on talent goes a long way in explaining the large productivity differences across countries. Morazzoni and Sy (2022) focus on entrepreneurs to document that financial frictions are particularly salient for women and that closing the gender gap in credit access could deliver sizable economic gains. Chiplunkar and Goldberg (2024) and Bento (2024) consider a larger set of barriers to female entrepreneurship and find similarly large productivity and welfare gains from eliminating gendered distortions.

Closer to this paper are studies that focus on the allocation of *inventive* talent. Celik (2023) argues that if inherited wealth is only weakly correlated with inventive ability, the overrepresentation of inventors from wealthy backgrounds is indicative of talent misallocation resulting from financial frictions. Akcigit, Pearce and Prato (2024) show that when aspiring inventors face financial barriers to human capital accumulation, education subsidies may be better suited than R&D tax credits in raising aggregate productivity.

Lehr (2023) argues that firms' monopsony power over inventors can lead to a substantial misallocation of R&D. Arkolakis, Lee and Peters (2020) and Prato (2024) show that lifting immigration restrictions between Europe and the United States can reallocate inventors to where they are most productive and propel knowledge diffusion.

Closest to our paper is Einiö et al. (2022) who first document that people from different social backgrounds and experiences produce innovations that are more tailored to their own needs. Unequal access to the innovation system can thus distort the direction of inventions, with potentially dire consequences for cost-of-living inequality and economic growth. To quantify the latter, the authors develop a two-sector endogenous growth model with heterogeneous consumer tastes and unequal access to innovation across different sociodemographic groups (including gender). Through the lens of this model, they find that barriers to female innovation are responsible for an 18.2% difference in the cost of living between women and men, and reduce the rate of economic growth by 1.4 percentage points.

In comparison to their analysis, I approach the question through the lens of a *semi-endogenous* growth model, which offers a different yet valuable perspective. I do so for two reasons. First, despite sustained population (and researcher) growth in most developed economies over the past decades, the growth rate of living standards has not trended upward.[5] In an overlapping generations setting where demographic and fertility margins are central, disciplining the model to this fact seems important. Second, the semi-endogenous growth framework I develop accommodates the established fact that "ideas are getting harder to find" at the microeconomic level both qualitatively and quantitatively (Bloom, Jones, Van Reenen and Webb, 2020), which most endogenous growth models cannot capture.[6] Crucially, this assumption implies that reallocating research talent cannot affect the long-run *growth rate* of living standards, although it can still affect its *level*. Hence, we find more modest effects of eliminating barriers to female innovation on productivity growth and welfare. Moreover, we extend their framework to further account for labor market discrimination and a child penalty for female researchers. Yet, our framework abstracts from the direction of innovation, which the authors show is an important margin in their counterfactual experiments. In that sense, our analysis and that of Einiö et al. (2022) provide complementary insights into the welfare consequences of unequal access to innovation by gender.

The second strand of literature to which this paper contributes is the extensive empirical

[5]This does not preclude the possibility that other forces have slowed economic growth over that same period, but such forces would need to have operated simultaneously across many advanced economies.

[6]A recent exception is Aghion, Bergeaud, Boppart and Brouillette (2025). However, there is still an active literature using both modelling approaches, which are equally useful in different contexts. Hence, the key contribution of this paper is to quantify the macroeconomic consequences of barriers to female innovation in a semi-endogenous growth environment.

evidence on gender-based barriers in research. Historically, Kim and Moser (2021) show that during the peak of the baby boom, mothers pursuing innovative careers were highly positively selected, patenting more than twice as frequently as their counterparts without children. More recent studies by Carrell, Page and West (2010) and Breda, Grenet, Monnet and Van Effenterre (2023) document that the findings of Bell et al. (2018) and Hoisl, Kongsted and Mariani (2023) on the importance of having access to relevant role models persist further down the pipeline. Indeed, they show that female students are more likely to enroll in science and mathematics classes and go on to graduate with a STEM degree when they are assigned to female professors or when they are exposed to STEM role models in the classroom. Yet, Hunt, Garant, Herman and Munroe (2013) find that only 7% of the gender gap in patenting can be explained by women's lower probability of holding a STEM degree.

Ross et al. (2022) provide evidence that women are 59% less likely to be credited with authorship on patents to which they contributed. When they do receive due credit, Jensen et al. (2018) find that their applications are more likely to be rejected, those rejections less likely to be appealed, and even for successful applications, women are granted a lower fraction of their claims, receive fewer citations and their patents are less likely to be maintained. This evidence is further supported by recent work from Hochberg et al. (2023) who use state-of-the-art tools from machine learning to estimate gender bias in patent citations.

My contribution to this literature is threefold. First, I focus on a large and salient source of talent misallocation: the underrepresentation of women among U.S. inventors. Women represent perhaps the largest pool of underutilized inventive talent, suggesting that there is ample scope to expand aggregate research effort. Second, I leverage detailed micro-level data on the universe of U.S. inventors and researchers to quantify different sources of barriers to female innovation. Instead of honing in on a particular friction in isolation, I let the data speak through the lens of a model that compares those barriers in common units. Finally, the rich yet tractable general equilibrium framework developed in this paper brings new insights to a largely empirical literature on female innovation. It plays the role of a laboratory through which one can study the aggregate and distributional implications of various counterfactuals when price adjustments and transitional dynamics can play a first-order role.

2 Motivating Facts

In this section, I present several empirical observations about researchers that will guide the theoretical framework proposed in Section 3. But first, who should be defined as a researcher? In practice, one is spoiled for choice from a plethora of definitions: scientists, engineers, entrepreneurs, GitHub developers, or even artificial intelligence algorithms. This choice is, however, far from obvious as it is notoriously difficult to track inventions and their origins. With this caveat in mind, I consider two definitions for which a vast amount of information is available: (1) patent grantees and (2) individuals employed in research occupations as classified by Ekerdt and Wu (2024).

2.1 Data Sources

The data I use comes from PatentsView and the U.S. Census Bureau's Decennial Census and ACS. The former contains information on all utility patents granted by the U.S. Patent & Trademark Office (USPTO) since 1976. PatentsView uses a series of algorithms to uniquely disambiguate inventors over time and, most importantly, predict their gender from their first name.[7] The sample I consider is restricted to inventors residing in the U.S. to whom gender is successfully attributed. With those restrictions, there remain about 1.7 million inventors to whom 3.7 million patents have been granted.

The Decennial Census and ACS provide a snapshot of the U.S. population capturing detailed demographic and occupational information. To identify researchers in this data source, I use the occupation classification developed by Ekerdt and Wu (2024). In particular, they define researchers as scientists or engineers whose primary work activity is research and development (R&D), based on data from the National Survey of College Graduates (NSCG). Then, they construct the classification by identifying specific occupation codes associated with R&D activities in the NSCG data and subsequently mapping these codes to corresponding Census occupations.

2.2 Empirical Evidence

The Underrepresentation of Women in Research

Figure 1(a) illustrates that women made up only 3% of inventors in 1976, with that share climbing to just 14% by 2023.[8] Although this represents a threefold increase over the past 40 years, the overall representation of women among U.S. inventors remains strikingly low. For context, Figure 1(b) compares these trends across other professions using data from the U.S. Decennial Census and ACS for employed individuals between the ages 25 and 45. In 1960, women accounted for 3% of lawyers and 6% of doctors; by 2023, these figures had risen to 49% and 46%, respectively–almost achieving parity. Meanwhile, the share of women among researchers started at 3% in 1960 and plateaued at about 27% around

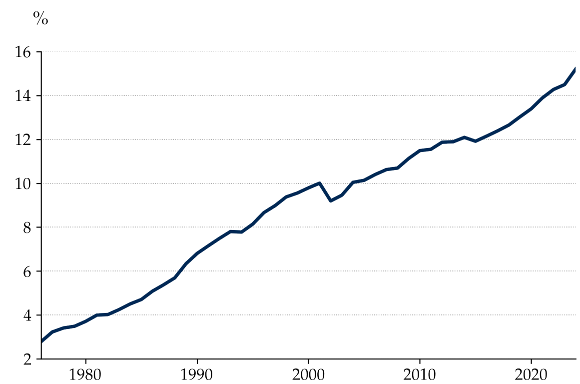
[7] For more information on the gender attribution algorithm used by PatentsView, see https://patentsview.org/gender-attribution.

[8] In this plot, and hereafter, years correspond to the date at which a patent is granted.

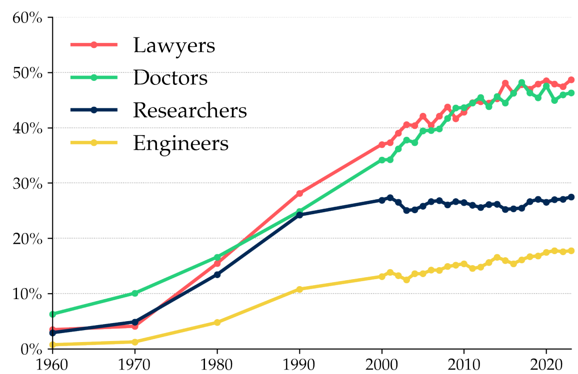
the turn of the century. In contrast, the engineering field showed even less progress, with women representing less than 1% in 1960 and only 18% by 2023.

Figure 1: Representation of Women in Different Occupations

(a) Inventors



(b) Other occupations



Note: The share of women among U.S. inventors has been slowly but steadily increasing from 3% in 1976 to 14% in 2023. This path resonates with the experience of women engineers in those same years (and that of researchers to some degree) but is in sharp contrast with the much faster convergence that occurred in the legal and medical professional spheres. Author's calculation using data from PatentsView and the U.S. Decennial Census and ACS.

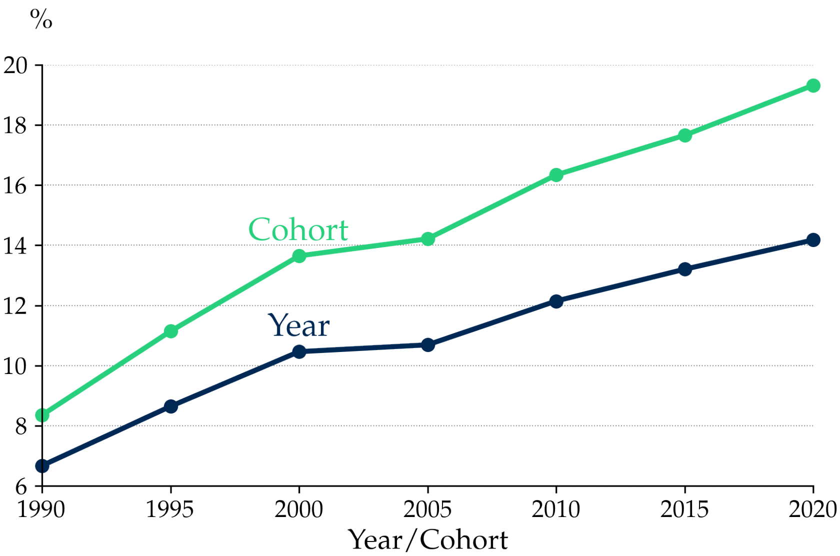
Figure 2 plots the fraction of women among patent grantees, but by cohort instead of year.[9] Here, an inventor's cohort is defined as the year of first appearance in the data, and since the PatentsView data starts in 1976, cohort inference is restricted to inventors who first appear after 1986. This figure shows that convergence is slowly but clearly underway as new cohorts composed of more women gradually replace previous ones.

However, as evident in Figure 3, there is a nontrivial degree of heterogeneity in the gender composition of different technological fields.[10] In that figure, technological fields are divided in two groups, as shown in panels 3(a) and 3(b): fields where women have been relatively more and less represented over our sample period. To highlight the two most contrasting examples, between the 1990 and 2020 cohorts, the female share of inventors went from 13% to almost 30% in the field of chemistry and metallurgy, and from less than 5% to about 10% in the field of fixed constructions and mechanical engineering. Despite women's lower representation in these fields, they accounted for about 53% of total patents granted in 2023.

[9]Cohorts are grouped in 5-year periods indexed by their ending year.

[10]Those broad fields are defined according to the single digit classes of the Cooperative Patent Classification (CPC) system, with the exception that the "textiles and paper" and "fixed constructions" classes are respectively grouped with the "human necessities" and "mechanical engineering" ones.[11] In particular, an inventor's field is here defined as the modal CPC class across all patents they have been granted over their career.

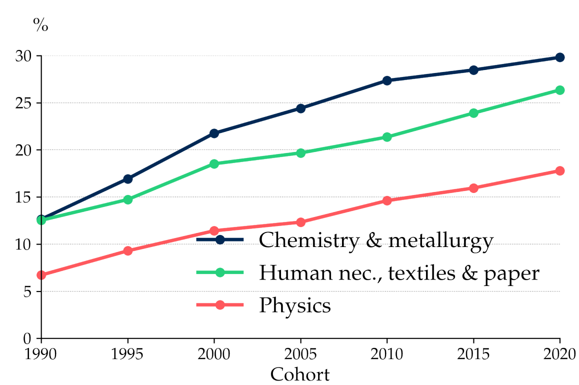
Figure 2: Female Share of Inventors by Cohort



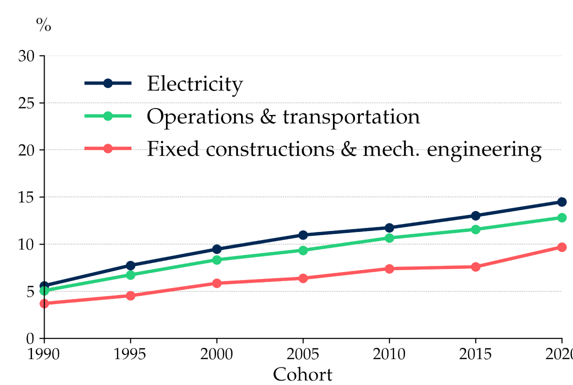
Note: The fraction of women in the 1990 cohort of U.S. inventors was 7.5% and now stands at 17.6% among the 2020 cohort. Cohorts are grouped in 5-year periods indexed by their ending year. Author's calculation using data from PatentsView.

Figure 3: Female Share of Inventors by Technological Field

(a) Higher Representation



(b) Lower Representation



Note: Between the 1990 and 2020 cohorts, the female share of inventors in the field of chemistry and metallurgy has grown from 13% to 28%. In contrast, it went from 5% to 10% in the field of fixed constructions and mechanical engineering. Author's calculation using data from PatentsView.

The Research Productivity Gender Gap

A notable feature of the PatentsView data is its state-of-the-art disambiguation procedure. It allows us to uniquely identify inventors across multiple patent issues to measure the number of patents granted to each of them in every year. However, simple patent counts might only deliver a partial depiction of individual research productivity (Griliches, 1990). Then, which proxy of a patent's quality should we consider? A familiar candidate is the number of citations received by a patent. However, one might question using citations as the metric of a patent's quality in the context of a study focused on gender. After all, citations are deliberately chosen by applicants and examiners who are not insusceptible to their own gender biases.

A plausible instance of such biases is documented by Jensen et al. (2018) looking at U.S. patents by lone inventors. They show that among inventors with relatively common forenames (where gender is easily inferred), women are cited 30% *less* frequently than men. Conversely, among inventors with rare first names, this pattern is completely reversed, with women being cited 20% *more* frequently than men.[12] Moreover, citations are not the only margin on which women might be denied credit for their scientific contributions. Indeed, Ross et al. (2022) show that women are 59 percent less likely to be attributed authorship on patents to which they contributed. This suggests that the PatentsView data might be missing a nontrivial fraction of the female researcher population.

To better gauge the quality of each patent, I additionally use two alternative measures; their stock market valuation (Kogan et al., 2017) and their "importance" (Kelly et al., 2021). The former is inferred from stock market reactions to a patent's grant announcement. It offers an economically sound perspective on the valuation of innovations, bridging scientific significance with market relevance. Critically, by grounding comparisons in stock market valuations rather than subjective interpretations, it offers a safeguard against potential biases and thus yields a more impartial evaluation of a patent's worth.

The latter reflects the idea that an important patent is both novel relative to previous patents and influential in subsequent ones, as measured from textual similarity between patent pairs. This definition can also be measured with backward and forward citations, but the critical advantage of textual similarities is its robustness to the gender biases documented above. In fact, if an inventor sought to use an existing idea without crediting its originator on the basis of their gender, one can imagine that it would be much easier to omit a citation than to carefully pick paraphrases in a highly technical language.

For all three patent quality metrics, I adjust for systematic quality differences across fields using 3-digit CPC class fixed effects and account for the individual contribution of an inventor by controlling for co-inventorship team size. Next, I aggregate quality-weighted patents at the level of inventors. To do so, I first sum all quality-weighted patents for each

[12]These estimates not only condition on technological fields but also on forename frequency to control for any association between the rarity of an inventor's name and citations received. However, a caveat of this exercise is that it could, in principle, reflect differential gender selection into inventorship for domestic and foreign applicants.

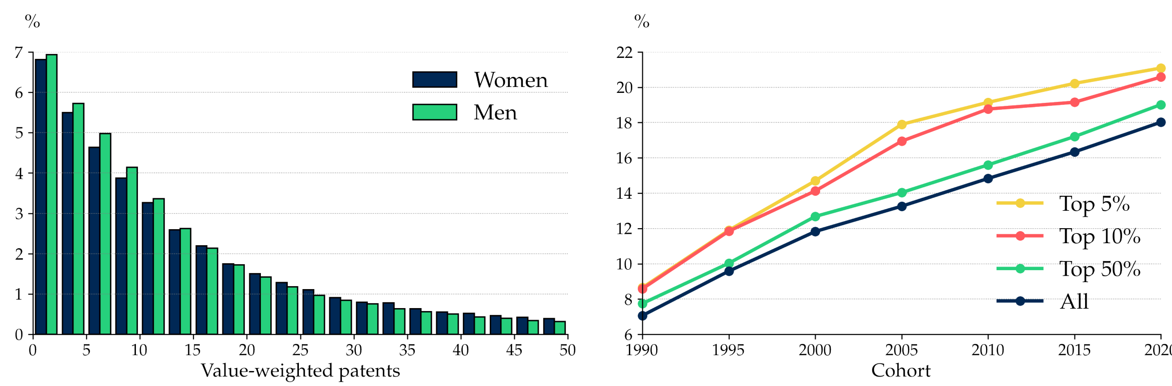
inventor in each year, conditioning on differences in patenting rates across 3-digit CPC classes. This delivers a measure of annual inventive output for each inventor in our sample and for all years in which they appear in the data. Then, to condense those multi-year observations to a single number, I first purge them from experience fixed effects (where experience = year − cohort).[13] Finally, I take the average across years for each inventor to obtain the key empirical counterpart to individual research productivity.

Panel 4(a) presents a histogram of our research productivity measure by gender, revealing a striking similarity in the distribution of research output between male and female inventors (using patents' stock market valuation). Complementing this, Panel 4(b) displays the female share among top inventors by cohort across various productivity quantiles. Although women are slightly overrepresented among the upper echelons, the discrepancies in representation across productivity tiers are small.

Figure 4: Distribution of Individual Inventive Productivity by Gender

(a) Histogram

(b) Female Share of Top Inventors



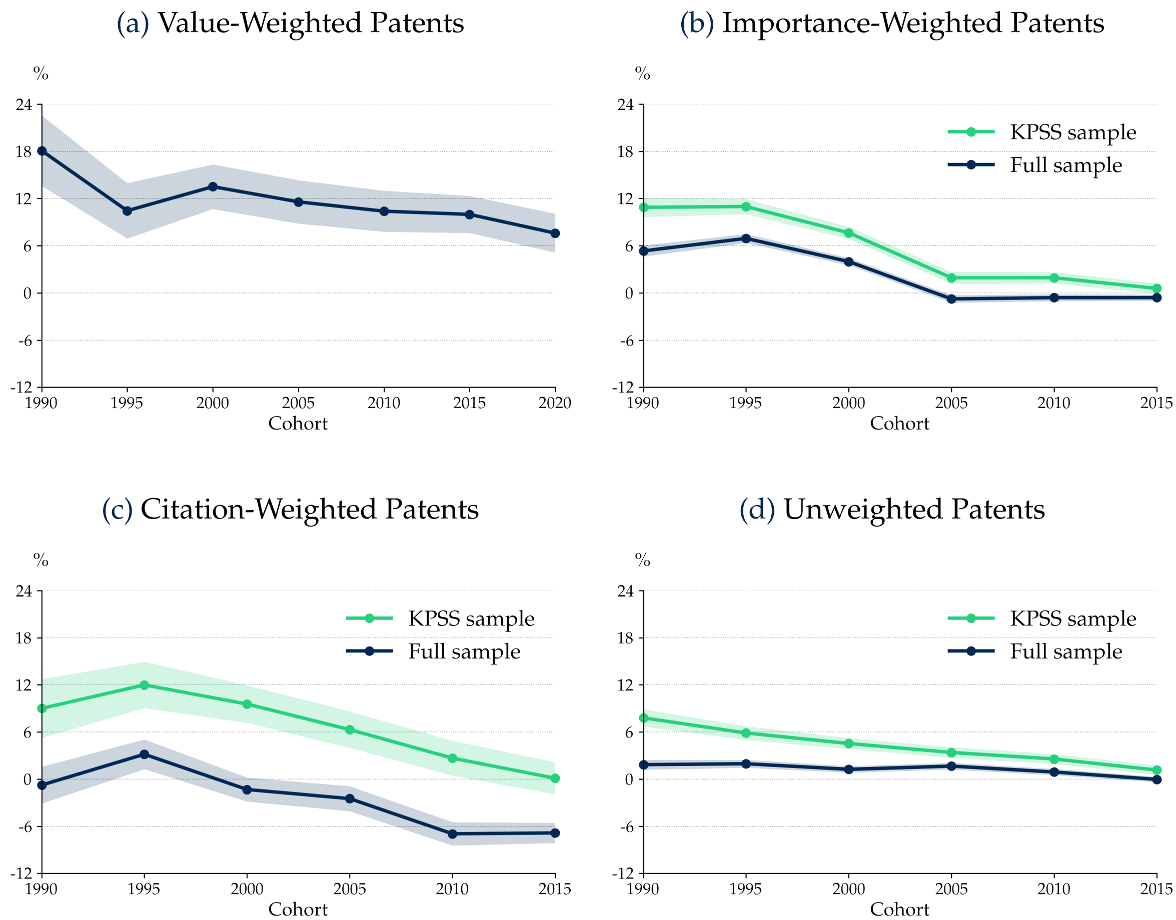
Note: As evident in these panels, women are only slightly overrepresented among top inventors. Author's calculation using data from PatentsView.

Figure 5 illustrates that female inventors are slightly more productive than their male counterparts. Specifically, the figure shows the gender gap in inventive output—where a positive value indicates a productivity advantage for women—after controlling for technological fields. In Panel 5(a), patents are weighted by their stock market valuation, in Panel 5(b), they are weighted by their assessed "importance", in Panel 5(c) they are weighted by their forward citations, and in Panel 5(d) they are simply unweighted. In almost all cases, women prove to be at least as productive as men, if not more so. Interestingly, Panel 5(b) compares the entire sample (KPST sample) with the subset of inventors at publicly listed firms (KPSS sample), revealing a modest positive selection for women in that group.

One may wonder whether Figure 5 hides heterogeneity across different technological

[13]This is consistent with the model being silent on the life-cycle of inventive productivity.

Figure 5: Inventive Productivity Gender Gap



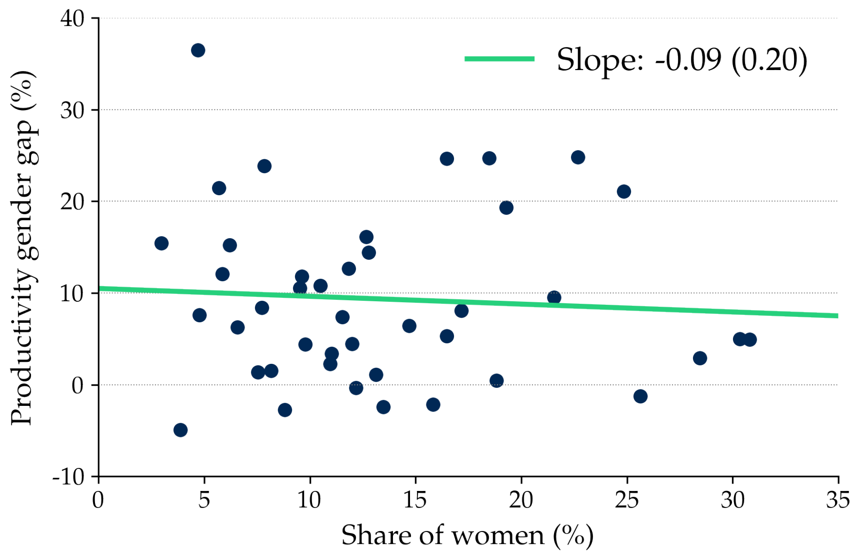
Note: Female inventors exhibit slightly higher productivity relative to their male colleagues. The shaded area corresponds to the 95% confidence interval around the estimates. Author's calculation using data from PatentsView.

fields. To explore this, Figure 6 plots the inventive productivity gender gap (using patents' stock market valuation) against the share of female inventors across various technological fields and cohorts. The figure reveals no significant relationship between women's underrepresentation in certain fields and their productivity relative to male colleagues. This finding implies that selection-based barriers may not be the primary factor driving the observed differences in representation across fields.

Research Careers and Family

A substantial body of evidence documents that parenthood imposes a steeper professional cost for women than men. Research by Bertrand, Goldin and Katz (2010), Angelov, Johans-

Figure 6: Inventive Productivity Gender Gap and Underrepresentation



Note: The slope of the relationship between the two variables is -0.09, with a standard error of 0.2. Author's calculation using data from PatentsView.

son and Lindahl (2016), Kleven, Landais and Søgaard (2019), Andresen and Nix (2022), and Cortés and Pan (2023) highlight a pronounced "child penalty", demonstrating that the career costs associated with childbearing and subsequent caregiving responsibilities disproportionately hinder women's advancement and long-term earnings. Collectively, these studies underscore how the burden of balancing work and family responsibilities is significantly heavier for women across a wide range of occupations and settings.

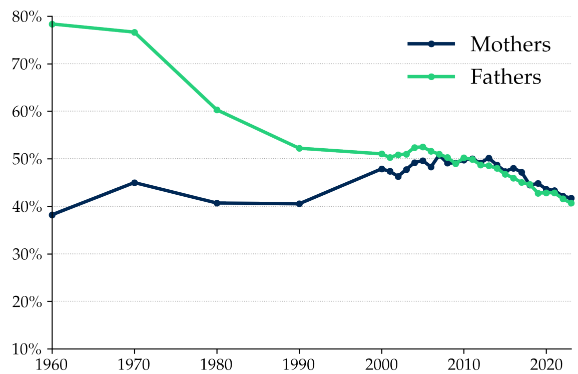
Complementing these findings, Goldin (2021)'s work reveals that "greedy jobs" that demand long, inflexible hours exacerbate the costs associated with motherhood. In such occupations, extended working hours are rewarded at a premium, making it suboptimal for couples to evenly distribute their labor supply, which in practice often leads women to curtail their hours worked to accommodate family responsibilities.

How do research careers fare in this context? The answer is not straightforward. On one hand, Goldin (2014) documents that science and technology careers tend to offer more flexibility than those in business and law. On the other hand, Kim and Moser (2021) found that in mid-20th-century research fields, the struggle to sustain high productivity while managing family duties was particularly pronounced for female scientists.

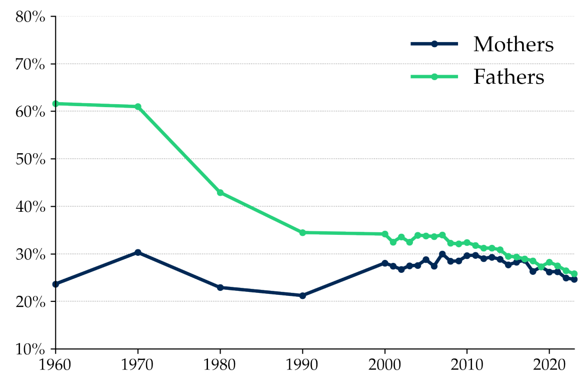
Figure 7(a) illustrates that in 1960, about 40% of female researchers between the ages of 25 and 45 were mothers, compared to nearly 80% of their male counterparts being fathers. Over time, however, this gap has narrowed considerably, with both figures converging to roughly 40% by 2023. Additionally, Panel 7(b) shows that this trend holds even among parents with more than one child. These findings suggest that research careers–once seen as particularly challenging for women balancing work and family–have become more accommodating over time.

Figure 7: Share of Parents among Researchers

(a) One Child or More



(b) More than One Child



Note: Panel 7(a) shows that the share of mothers and fathers among researchers has been converging over the past 60 years. Author's calculation using data from the U.S. Decennial Census and ACS.

How do these family dynamics translate into labor supply decisions? Figure 8(a) shows that the average number of hours worked per week by researchers with children does not differ substantially from that of their childless peers. However, there are nontrivial differences across gender. Mothers work fewer hours compared to women without children, whereas fathers work more. Notably, these gaps have narrowed considerably over time. In contrast, Panel 8(b) reveals that among non-researchers, gender convergence in labor supply has been much less pronounced–a finding consistent with Goldin (2014), which suggests that research careers may offer greater flexibility than other occupations.

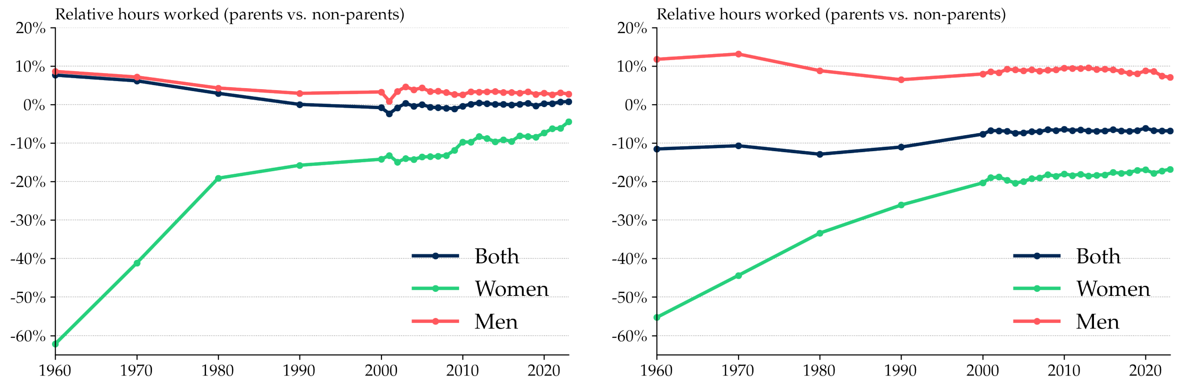
In summary, although balancing family and research once posed significant challenges for female scientists, these obstacles appear less acute today. While gender differences in labor supply persist–with mothers working fewer hours and fathers slightly more–the overall similarity between parent and non-parent researchers (both in terms of fertility and labor supply) suggests that family responsibilities may no longer be the primary driver behind women's underrepresentation in research relative to other occupations.

The Gender Gap in STEM

STEM credentials are pivotal in research careers–approximately 70% of researchers hold a STEM degree, according to U.S. Decennial Census and ACS data. Yet, despite significant strides toward educational gender equality, women remain markedly underrepresented in

Figure 8: Hours Worked by Parental Status and Occupation

(a) Researchers (b) Non-researchers

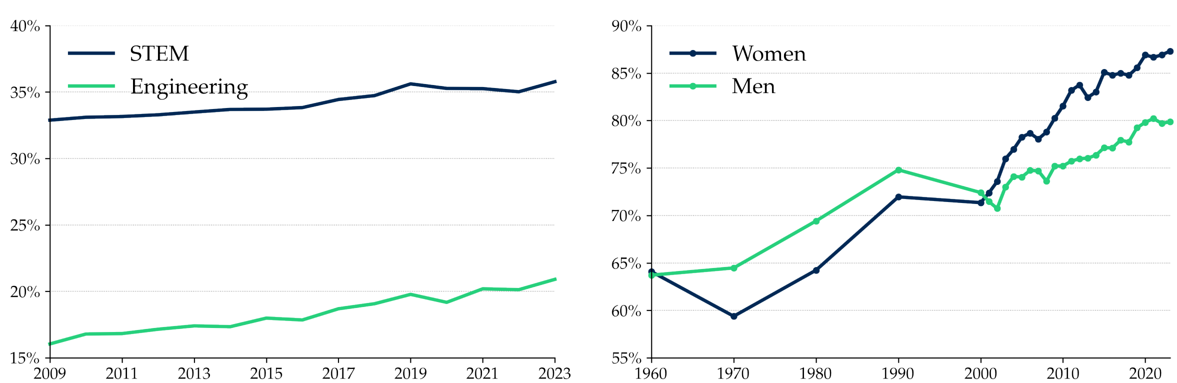


Note: While the average hours worked by researchers do not seem to differ substantially based on parental status, a closer look reveals notable gender differences. Author's calculation using data from the U.S. Decennial Census and ACS.

STEM fields. As shown in Figure 9(a), women account for only about 35% of employed STEM graduates aged 25 to 45, and the disparity is even more pronounced in engineering, where just over 20% of degree holders of the same age are female.

Figure 9: Education and Research Careers

(a) Female Share of STEM Graduates (b) Share of Researchers with College Degrees



Note: To this day, women remain vastly underrepresented among employed STEM and engineering college graduates. Yet, since the early 2000s, the fraction of college graduates among female researchers has surpassed that of their male colleagues. Author's calculation using data from the U.S. Decennial Census and ACS.

Interestingly, this underrepresentation in STEM alone does not fully account for the gender gap observed in patenting. Using the 2003 wave of the NSCG–which recorded whether respondents had been granted a patent in the preceding five years–Hunt et al.

(2013) found that a mere 7% of the patenting gender gap could be explained by women's lower propensity to hold a STEM degree. Instead, a substantial 78% of the gap stemmed from differences in patenting behavior among STEM graduates. Moreover, as Figure 9(b) shows, female researchers have been more likely than their male counterparts to hold a college degree since the early 2000s, suggesting that the disparity is not simply a reflection of educational attainment.

Taken together, these findings imply that the hurdles for women pursuing research careers are set in motion early on–well before entering the workforce. Although roughly 35% of STEM graduates are women, only about 27% of researchers are female (Figure 1(b)). This indicates that women are already underrepresented at the education stage, and a nontrivial share of potential female researchers are lost during the transition from earning a STEM degree to embarking on a research career.

3 Theoretical Framework

In this section, I develop a model of endogenous economic growth à la Romer (1990) and Jones (1995) guided by the facts presented in the previous section. This model combines several ingredients: semi-endogenous growth through an expanding measure of products, an overlapping generations structure, inventive talent heterogeneity, education, occupation, and fertility choices, and, most importantly, gendered barriers to innovation.

The exposition of the theoretical framework proceeds as follows. In Section 3.1, I present the economic environment without any distortion. Section 3.2 describes the agents' decision problems and introduces the gendered barriers to innovation. Finally, Section 3.3 defines the equilibrium allocation and characterizes the aggregation of individual decisions.

3.1 Economic Environment

Population and Preferences. The economy is populated by a measure N_t of working individuals indexed by i and their gender $g \in \{\text{women}, \text{men}\}$.[14] In the spirit of Yaari (1965) and Blanchard (1985), the working population features overlapping generations denoted by k in which individuals retire at rate d. New individuals enter employment at rate b to form the most recent cohort such that the working population evolves as:

$$\dot{N}_t = n \cdot N_t \quad \text{where} \quad n = b - d > 0. \tag{1}$$

[14] The population is composed of as many women and men.

Each individual has logarithmic preferences over a consumption basket c_{it} and preferences over children. The lifetime utility of individual i is defined as:

$$U_i = \int_k^{\infty} e^{-(\rho+d)(t-k)}[\ln(c_{it}) + \mathbb{1}_{\{i\in\mathcal{C}_t\}} \ln(x_i)]\mathrm{d}t \tag{2}$$

where $\rho > 0$ is the pure rate of time preference, d reflects discounting from the stochastic retirement rate and the second additive term captures the flow utility from having children. In particular, $\mathcal{C}_t$ denotes the set of parents and x_i is an individual-specific preference shock for having children drawn from a Pareto distribution with shape parameter $\beta > 1$:

$$F(x) = 1 - x^{-\beta}. \tag{3}$$

The consumption basket is a Dixit and Stiglitz (1977) aggregator of differentiated products indexed by $j \in \mathcal{J}_t$:

$$c_{it} = \left(\int_{j\in\mathcal{J}_t} c_{jit}^{\frac{\sigma-1}{\sigma}} \mathrm{d}j\right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where c_{jit} is the quantity of product j consumed by individual i at time t, $M_t \equiv |\mathcal{J}_t|$ is the measure of existing products, and $\sigma > 1$ is the elasticity of substitution between those products.

Education, Occupation, and Fertility. Individuals make three sequential decisions about their education, occupation, and fertility.[15] They first choose whether to enroll in a STEM education program, which is a prerequisite for a research career. Then, they decide whether to work in research or production. Finally, they decide whether to have children, which reduces the amount of time available for work.

Beyond being a prerequisite for a research career, a STEM education also reveals information about one's *innate* inventive talent. That is, each individual is born with some inventive talent $z_i = z_i^s \cdot z_i^n$ composed of two multiplicative components: a signal z_i^s observed at birth and a noise shock z_i^n revealed only if the individual goes into STEM. The signal is drawn from a Pareto distribution with shape parameter $\theta_s > 1$:

$$G_s(z^s) = 1 - \left(\frac{1}{z^s}\right)^{\theta_s} \tag{5}$$

whereas the shock is drawn from another Pareto distribution with shape parameter $\theta_n > \theta_s$:

$$G_n(z^n) = 1 - \left(\frac{\vartheta_n}{z^n}\right)^{\theta_n} \quad \text{with} \quad \vartheta_n = \frac{\theta_n - 1}{\theta_n}. \tag{6}$$

[15] All of those decisions are irreversible.

where ϑ_n is the distribution's scale parameter, which is chosen such that the shock has a unit mean and acts as a mean-preserving spread to the signal. Therefore, some individuals may be born with a high signal and choose to enroll in STEM just to realize that they have a low talent noise shock and ultimately decide to work in production. The cost of a STEM education is equal to a fraction $\epsilon \in (0,1)$ of a person's expected future earnings.

Before making their occupation choice, each person takes into account that they are endowed with one unit of time, which can be allocated to either work or child-rearing. If a person chooses to have children, they must spend a share $1-\alpha \in (0,1)$ of their time raising them and their remaining time is spent working. Individual labor supply ℓ_i^P in production is given by:

$$\ell_i^P = \begin{cases} \alpha & \text{if } i \in \mathcal{C}_t, \\ 1 & \text{if } i \notin \mathcal{C}_t. \end{cases} \tag{7}$$

That is, workers who have children are less productive than those who don't. Similarly, individual labor supply ℓ_i^R in research is given by:

$$\ell_i^R = \begin{cases} z_i \cdot \alpha^{1+\delta} & \text{if } i \in \mathcal{C}_t, \\ z_i & \text{if } i \notin \mathcal{C}_t. \end{cases} \tag{8}$$

Here, $\delta > 0$ is a parameter that determines the additional return to hours worked in research relative to production. This captures the idea that research may be what Goldin (2021) refers to as "greedy work" where working long hours is compensated at a premium.

Production and Research Technology. Each product is manufactured by a single firm using production labor l_{jt} according to a linear technology:

$$y_{jt} = l_{jt}. \tag{9}$$

However, before it can be brought to market, a variety must first be discovered. This role is played by the research sector, which combines research labor R_t with the existing stock of "ideas" M_t to develop products that are entirely new to society:

$$\dot{M}_t = M_t^{\phi} R_t. \tag{10}$$

As discussed in Jones (1995), $\phi < 1$ measures the strength of knowledge spillovers. If ϕ is positive, the discoveries of yesterday make inventors more productive today. Otherwise, it becomes harder and harder to find new ideas (Bloom et al., 2020).

Resource Constraints. The resource constraint for research labor is:

$$R_t \leq \int_{i \in \mathcal{R}_t} \ell_i^R \mathrm{d}i \tag{11}$$

where $\mathcal{R}_t$ is the set of researchers and the resource constraint for production labor is:

$$L_t \equiv \int_0^{M_t} l_{jt} \mathrm{d}j \leq \int_{i \in \mathcal{P}_t} \ell_i^P \mathrm{d}i \tag{12}$$

where $\mathcal{P}_t$ is the set of production workers. Finally, the resource constraints for products are:

$$\int_0^{N_t} c_{jit} \mathrm{d}i \leq y_{jt}, \quad \forall j \in [0, M_t]. \tag{13}$$

3.2 Decision Problems

In the following sections, I describe the decision problems faced by the agents that populate the economy and introduce the distortions in the individual's problem.

The Individual's Problem

The problem of an individual has four stages: (1) they decide whether to enroll in STEM, (2) they choose between a career in research or production, (3) they decide whether to have children, and (4) they make consumption and saving decisions to maximize lifetime utility. These stages are presented below in reverse chronological order, following the logic of backward induction. Importantly, these decisions are influenced by three distortions, each of which varies by gender.

Introducing the Gendered Barriers to Research. The first is a labor market distortion, which operates as a tax of τ_{gt}^L percent on the labor earnings of researchers of gender g at time t. The second is a "child penalty" distortion through which the labor supply of a parent researcher from the same demographic group is reduced by τ_{gt}^C percent. Finally, the third is an "exposure" distortion by which some individuals may never encounter the opportunity to enroll in a STEM program and become researchers, irrespective of their talent. That is, only those who were exposed to innovation can opt for it as an educational and career path. As in Bell, Chetty, Jaravel, Petkova and Van Reenen (2019), this distortion is modeled as a Bernoulli random variable this exposure is modeled as a Bernoulli random variable e_i with mean parameter $1 - \tau_{gt}^E \in [0, 1]$.

It is important to note that the model does not incorporate any gendered barriers to completing a STEM education. Two key reasons justify this assumption. First, research by Carrell et al. (2010) and Breda et al. (2023) shows that exposure to role models is a crucial factor influencing girls' decisions to pursue STEM. Second, if a higher cost of STEM education were the primary barrier for women, the model would imply that only the most talented women would opt for a research career, thereby suggesting that women would, on average, be more productive as inventors–a prediction that empirical data does not support, as described in section 2. However, the model can still rationalize the underrepresentation of women in STEM programs by attributing it to an insufficient exposure to relevant STEM role models.

The Consumption-Saving Problem. The last stage of an individual's decision problem is to choose how much of each product to consume over time to maximize lifetime utility:

$$U_i = \max_{\{\{c_{jit}\}_{j=0}^{M_t}\}_{t=k}^{\infty}} \int_k^{\infty} e^{-(\rho+d)(t-k)}[\ln(c_{it}) + \mathbb{1}_{\{i\in\mathcal{C}_t\}}\ln(x_i)]\mathrm{d}t$$

subject to equation (4) and the flow budget constraint:

$$\dot{a}_{it} = r_t a_{it} + (1 - \mathbb{1}_{\{i\in\mathcal{R}_t\}}\tau^L_{gt})w^o_t \ell^o_i - c_{it}.$$

Here, a_{it} is financial wealth, r_t is the return on this wealth, and w^o_t is the wage paid in occupation o. This simple problem structure delivers the usual individual demand functions:

$$c_{jit} = c_{it}/p^{\sigma}_{jt}, \quad \forall j \in [0, M_t]$$

and total individual consumption is optimally chosen to be proportional to total wealth (financial and human):

$$c_{it} = (\rho + d)[a_{it} + (1 - \mathbb{1}_{\{i\in\mathcal{R}_t\}}\tau^L_{gt})\omega^o_t \ell^o_i]$$

where ω^o_t denotes the present value the stream of future wages in occupation $o \in \{R, P\}$:

$$\omega^o_t \equiv \int_t^{\infty} e^{-\int_t^{t'} r_{t''}\mathrm{d}t''} w^o_{t'}\mathrm{d}t'.$$

Finally, individual consumption also satisfies the usual Euler equation:

$$\frac{\dot{c}_{it}}{c_{it}} = r_t - \rho - d.$$

For tractability, we make several simplifying assumptions. First, we assume that new cohorts receive no inheritance, accumulate savings, and then eventually retire to consume their remaining financial wealth in retirement. Second, when choosing their occupation, individuals expect current distortions to prevail for the rest of their career. Therefore, individuals start their career with financial wealth:

$$a_{ik} = -\mathbb{1}_{\{i \in \mathcal{S}_t\}} \epsilon (1 - \mathbb{1}_{\{i \in \mathcal{R}_t\}} \tau_{gk}^L) \omega_k^o \ell_i^o.$$

That is, those who enroll in a STEM program start their career with a some student debt, which is proportional to their expected future earnings.

The Fertility Choice Problem. Individuals choose whether to have children by weighing their personal preference for parenthood against the opportunity cost in terms of reduced labor supply. Consequently, they will become parents only if their expected lifetime utility from having children exceeds that of remaining childless. In Appendix A.1, I show that an individual will opt into parenthood if and only if their realized preference shock for children exceeds a gender- and occupation-specific threshold $\underline{x}_{gk}^o$:

$$\underline{x}_{gk}^o \equiv \begin{cases} 1/[(1 - \tau_{gk}^C)\alpha]^{1+\delta} & \text{if } o = R, \\ 1/\alpha & \text{if } o = P. \end{cases}$$

Therefore, the child penalty distortion raises the threshold preference shock above which parenthood is chosen, reflecting the heightened costs of balancing a career with family responsibilities. Moreover, the "greedy work" parameter δ magnifies the opportunity cost of having children in research relative to production.

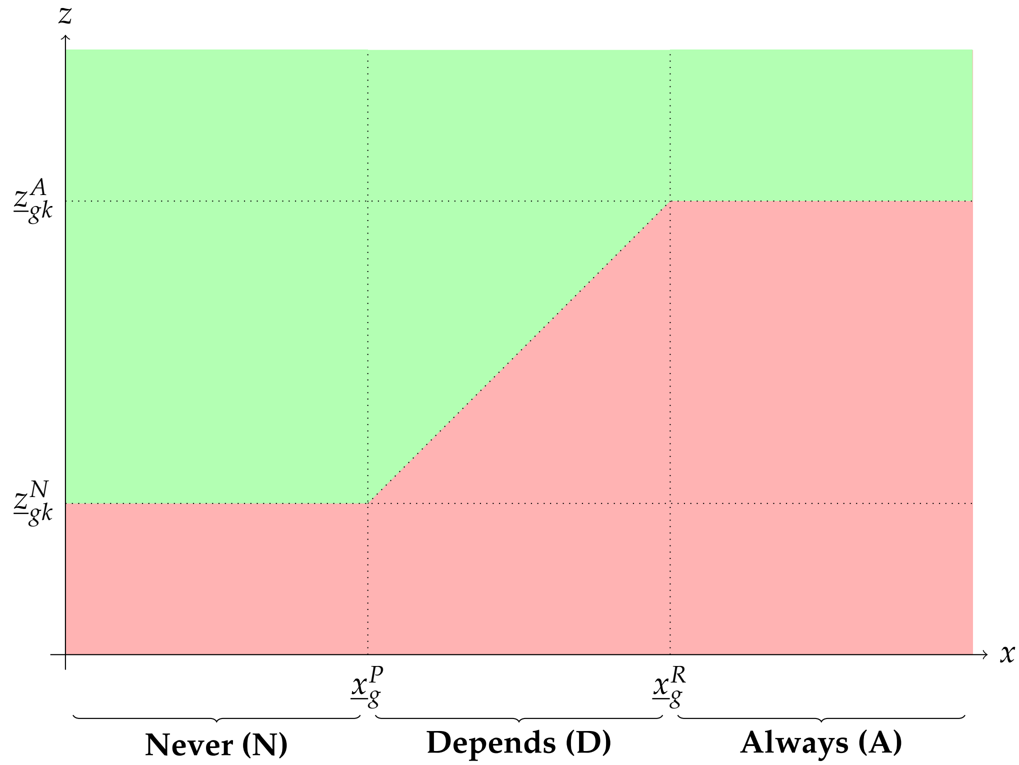
The Occupation Choice Problem. Conditional on their education choice and having received exposure to innovation, a person must decide whether to work in research or in production. This person will choose to work in research if and only if the expected lifetime utility from doing so exceeds that of working in production.

The occupation choice is summarized in Figure 10 and detailed in Appendix A.1. The figure divides the (x, z)-plane–where x is preference for children and z is inventive talent–into regions that separate occupation decisions. In the green regions, individuals choose work in research, while in the red regions, they opt for a production career.

Among individuals whose preference for children is sufficiently low that they would *never* (N) have children regardless of their occupation $(x_i < \underline{x}_{gk}^P)$, only those with talent exceeding the threshold $\underline{z}_{gk}^N$ will opt for a research career:

$$\underline{z}_{gk}^N \equiv \frac{1}{1 - \tau_{gk}^L} \cdot \frac{\omega_k^P}{\omega_k^R}.$$

Figure 10: The Occupation Choice



This threshold increases with the labor-market distortion because it reduces the return to research differentially by gender, thus making this choice less attractive. Likewise, a lower relative wage in research also "raises the bar" for pursuing this career, but it does so uniformly across genders.

For someone who would instead *always* (A) decide to have children regardless of their occupation $(x_i > \underline{x}_{gk}^{R})$, the talent threshold for pursuing research is higher:

$$\underline{z}_{gk}^{A} \equiv \frac{1}{(1-\tau_{gk}^{C})^{1+\delta}\alpha^{\delta}} \cdot \underline{z}_{gk}^{N} > \underline{z}_{gk}^{N}.$$

Indeed, having children is particularly costly in research careers since there is a premium on working long hours. Hence, only the most talented would-be parents find it worth their while to choose this option. In addition, the talent signal threshold is increasing in the child penalty distortion, which amplifies the opportunity cost of childbearing in research differentially by gender.

Finally, for individuals whose fertility decision *depends* (D) on their occupation choice $(\underline{x}_{gk}^{P} < x_i < \underline{x}_{gk}^{R})$, meaning they would only have children if they worked in production, the talent threshold is increasing in their preference shock for children and contained between the previous two thresholds:

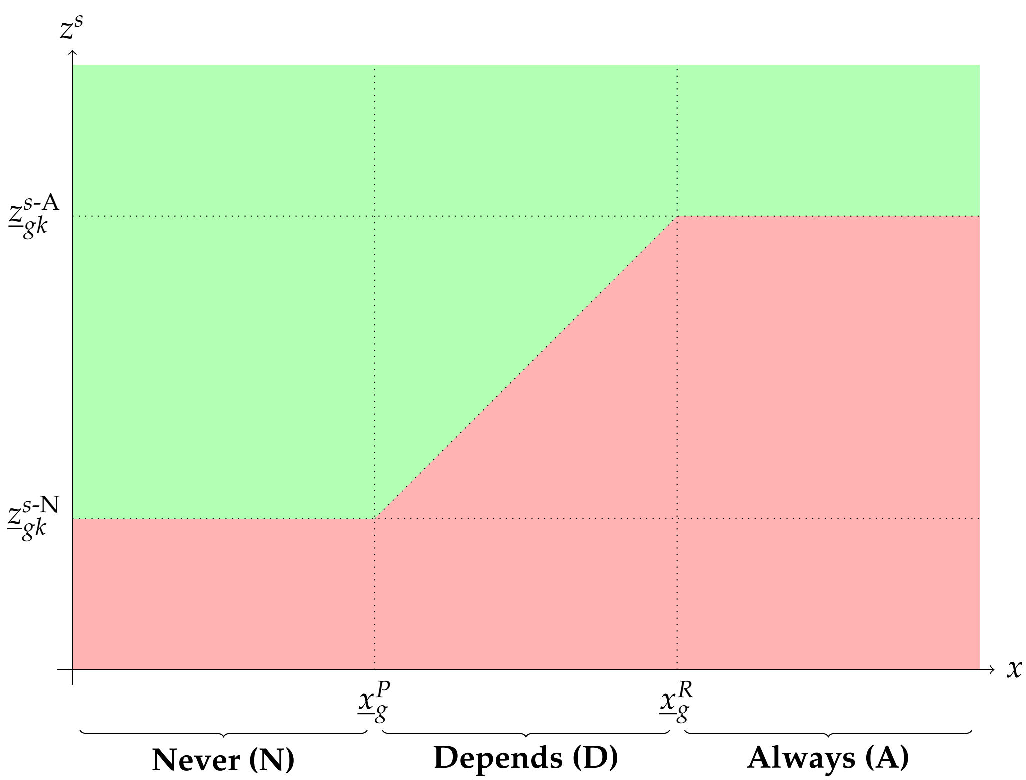
$$\underline{z}_{gk}^{D}(x) \equiv \alpha x \cdot \underline{z}_{gk}^{N} \in (\underline{z}_{gk}^{N}, \underline{z}_{gk}^{A}].$$

This threshold increases with an individual's preference for children, meaning that those who have a strong desire to have children must possess a higher level of talent to justify pursuing a research career without having children.

The Education Choice Problem. A person will choose to pursue a STEM degree if and only if the expected lifetime utility from doing so is higher than otherwise. There are two important considerations that determine this choice. First, individuals recognize that even after receiving their degree, they retain the option to work in production. Second, they make this education choice behind the veil of ignorance regarding their talent noise shock.

The decision to enroll in STEM is summarized in Figure 11, which is very similar to that of the occupation choice problem. The figure divides the (x, z^s)-plane–where z^s is now the talent *signal*–into regions that determine optimal education choices. In the green regions, individuals choose a STEM education, while in the red regions, they do not.

Figure 11: The Education Choice



As in the occupation choice problem, the education choice problem is divided into the same three fertility regions. Moreover, the thresholds on talent signals are proportional to those derived in the occupation choice problem, so the underlying intuition carries over. The constant of proportionality is given by:

$$\eta \ln\left(\frac{1}{1-\epsilon}\right)^{1/\theta_n} \quad \text{where} \quad \eta \equiv \frac{\theta_n^{1/\theta_n}}{\vartheta_n}.$$

Because this constant increases with the education cost parameter ϵ, only the most talented individuals will choose to enroll in a STEM program. Moreover, the elasticity of the talent signal threshold with respect to this cost is decreasing in the shape parameter θ_n of the talent noise shock distribution. Indeed, for lower values of this parameter, the noise shock is more dispersed, which makes the signal less informative, and the returns to a STEM education less predictable. In such an uncertain environment, only those who receive a sufficiently high signal will choose to enroll in a STEM program, thereby intensifying the positive selection effect of the education cost.

The Firm's Problem

To hold a claim on a product's perpetual profits, a firm must first purchase its patent from the research sector through free-entry. Once that firm holds a patent, it engages in monopolistic competition on the market for intermediate inputs and perfect competition in the production labor market. That is, it chooses a price as well as production labor to maximize profits π_{jt} while taking as given the demand for its product and the wage paid to workers w_t^P:

$$\pi_{jt} = \max_{p_{jt}, l_{jt}} \{p_{jt} y_{jt} - w_t^P l_{jt}\}.$$

Firms thus set their price to a constant markup μ above marginal cost:

$$p_{jt} = \mu \cdot w_t^P \quad \text{where} \quad \mu \equiv \frac{\sigma}{\sigma - 1}$$

which implies that profits are perfectly symmetric across firms:

$$\pi_{jt} = \frac{C_t}{\sigma M_t}, \quad \forall j \in [0, M_t].$$

The Research Sector's Problem

Similarly, the research sector is assumed to be monopolistically competitive in the market for patents and perfectly competitive in the research labor market. Hence, it chooses a patent price q_t as well as research labor to maximize profits, while taking as given the wage

w_t^R paid to researchers and the measure of products:

$$\max_{q_t, R_t} \{q_t M_t^{\phi} R_t - w_t^R R_t\}.$$

This delivers the following equilibrium condition:

$$q_t M_t^{\phi} = w_t^R.$$

With free-entry among patent buyers, the research sector sets the price of a patent to extract all possible rents from the commercialization of an invention, which corresponds to the present value of a firm's stream of future profits:

$$q_t = \int_t^{\infty} e^{-\int_t^{t'} r_{t''} \mathrm{d}t''} \pi_{t'} \mathrm{d}t'.$$

3.3 Equilibrium Allocation

Now that all the decision problems have been described, we can define the concept of an equilibrium allocation. Given distortions, an equilibrium consists of time paths for allocations and prices such that for all t:

1. $\{\{\{c_{jit}\}_{j=0}^{M_t}\}_{i=0}^{N_t}\}_{t>0}$ and the education, occupation, and fertility decisions solve the individual's problem.
2. $\{\{p_{jt}, l_{jt}^P\}_{j=0}^{M_t}\}_{t>0}$ solve the firm's problem.
3. $\{q_t, R_t\}_t$ solve the research sector's problem.
4. $\{\{p_{jt}\}_{j=0}^{M_t}\}_{t>0}$ clear the product markets.
5. $\{w_t^P, w_t^R\}_{t>0}$ clear the production and research labor markets.
6. $\{r_t\}_{t>0}$ clears the asset market: $\int_0^{N_t} a_{it} \mathrm{d}i = q_t M_t$.

3.4 Aggregation

Having established how individuals choose between research and production, we now examine the implications of these choices at the aggregate level. In Appendix A.4, we show that per-capita consumption satisfies:

$$c_t = M_t^{\frac{1}{\sigma-1}} \cdot \frac{L_t}{N_t}.$$

Therefore, living standards depend on (1) the measure of products M_t due to a "taste for variety" modulated by the elasticity of substitution across products σ and (2) the aggregate production labor supply per person. The law of motion for the former is given by:

$$\dot{M}_t = M_t^{\phi} R_t.$$

As in all semi-endogenous growth models, along a balanced growth path (BGP), the growth rate of per-capita consumption is constant and given by:

$$g \equiv \frac{\dot{c}_t}{c_t} = \frac{n}{(\sigma - 1)(1 - \phi)}.$$

Importantly, this assumption implies that reallocating research talent cannot affect the long-run *growth rate* of living standards. However, it can still affect its *level*. Indeed, even though ideas become harder to find over time, the cumulative stock of ideas matters for the level of living standards. Achieving a more efficient allocation of research talent generates more ideas cumulatively, shifting the entire technological trajectory upward. In contrast, a less efficient allocation might eventually achieve a similar growth rate, but the cumulative stock of ideas–and, therefore, GDP–would remain permanently lower. Indeed, on a BGP, per-capita consumption is proportional to

$$c_t \propto R_t^{\gamma} \cdot \frac{L_t}{N_t} \quad \text{where} \quad \gamma \equiv \frac{1}{(\sigma - 1)(1 - \phi)}.$$

Here, γ measures the overall degree of increasing returns to scale. To put this into perspective, if we were to double the quantity or quality of researchers, consumption per person would approximately increase by a factor of 2^{γ}.[16] However, reallocating more people to research can be counterproductive if there are not enough production workers to manufacture their new ideas. In contrast, improving the allocation of research talent unambiguously raises the average quality of researchers and, therefore, long-run living standards.

The Extensive Margin (Quantity)

The fraction of researchers among individuals of gender g and cohort k who would *never* have children is denoted by I_{gk}^N and given by:

$$I_{gk}^N \equiv \underbrace{(1 - \tau_{gk}^E)}_{\text{Exposure dist.}} \cdot \underbrace{(1 - \tau_{gk}^L)^{\theta_s}}_{\text{Labor market dist.}} \cdot \underbrace{(\omega_k^R / \omega_k^P)^{\theta_s}}_{\text{Wages}} \cdot \mathcal{I}$$

[16]This approximation holds when the fraction of researchers is relatively small.

where $\mathcal{I}$ (defined in Appendix A.4) is a constant that only depends on parameters. This expression shows that high relative wages in research attract more people regardless of their gender, whereas distortions are responsible for gender differences in occupation choices. Indeed, larger exposure and labor market distortions reduce the pool of potential researchers by making research careers either less accessible or attractive, respectively.[17]

Among those who would *always* have children, that fraction is given by:

$$I^A_{gk} \equiv \underbrace{[(1-\tau^C_{gk})^{1+\delta}\alpha^{\delta}]^{\theta_s}}_{\text{Child penalty dist.}} \cdot I^N_{gk}.$$

This proportion is lower than that of individuals who never have children. The limited time available for work and associated child penalty distortion reduce the attractiveness of research careers for parents. This disincentive is especially pronounced for larger values of the "greedy work" parameter δ, which reflects a higher opportunity costs of not working. Hence, only the most talented parents are willing to pursue research careers, resulting in a smaller pool of parent researchers.

Finally, the share of researchers among those whose fertility decision *depends* on their occupation choice is given by:

$$I^D_{gk} \equiv \underbrace{\frac{\beta}{\beta+\theta_s} \cdot \frac{1-[(1-\tau^C_{gk})^{1+\delta}\alpha^{\delta}]^{\beta+\theta_s}}{1-[(1-\tau^C_{gk})^{1+\delta}\alpha^{\delta}]^{\beta}}}_{\text{Child penalty dist.}} \cdot I^N_{gk},$$

which lies between the shares of individuals who never and always have children. The reason is that these individuals have a relatively high preference for children, but not high enough to balance family responsibilities with a research career. Consequently, only the few with relatively high inventive talent in this group are willing to forego having children to pursue their research aspirations.

The Intensive Margin (Quality)

Since career choices follow a cutoff rule on talent, distortions may not only affect the *quantity* of inventors but also the *quality* of the resulting pool. Taking the product of talent and hours worked, and integrating over the resulting distribution delivers an expression for average research labor supply by cohort k and gender g. For individuals who would

[17]The fraction of researchers depends on the relative labor market distortion and relative future wage with elasticity θ_s. In fact, for large values of θ_s, the distribution of talent is tightly compressed around the selection threshold such that small changes in this cutoff induce large flows across occupations.

never have children, this average is denoted by Z^N_{gk} and given by:

$$Z^N_{gk} \equiv \frac{\omega^P_k}{(1-\tau^L_{gk})\omega^R_k} \cdot \mathcal{Z}$$

where $\mathcal{Z}$ (defined also in Appendix A.4) is a constant that only depends on parameters. The average quality of inventors in that group is inversely proportional to the "keep rate" of the earnings tax. This reflects the selection mechanism. That is, if female inventors were only paid a fraction of their marginal product, only the very best would earn enough to prefer a career in research over one in production.

Among those who would have children regardless of their occupation, the average research labor supply is proportional to:

$$Z^A_{gk} \equiv \alpha \cdot Z^N_{gk}.$$

This average is strictly lower than that of non-parents. On one hand, the child penalty in research directly reduces a parent's labor supply. On the other, it excludes marginally talented parents from research thereby raising average talent among those who remain through positive selection. These two effects exactly offset each other. Nonetheless, parents who opt for research are more *productive* than non-parents in that they supply more research labor *per hour*. This result is consistent with the evidence in Kim and Moser (2021), who document that mothers in research are highly positively selected—even though their overall productivity declines after having children.

Finally, consider those who might have children if they were not in research. For them, the average research labor supply is proportional to:

$$Z^D_{gk} \equiv \frac{\beta}{\beta-1} \cdot \frac{1-[(1-\tau^C_{gk})^{1+\delta}\alpha^\delta]^{\beta-1}}{1-[(1-\tau^C_{gk})^{1+\delta}\alpha^\delta]^{\beta}} \cdot Z^N_{gk}.$$

In this group, the average is strictly higher than for those who never have children. Indeed, only the most talented individuals who have a strong preference for children are willing to sacrifice family life for a research career.

4 Quantification

Let us now discuss how sensible empirical counterparts to the model's predictions can be used to quantitatively discipline the model's key driving forces and help us shed light on the barriers faced by female researchers.

4.1 Model Calibration

Our model features 11 parameters to be determined. The pure rate of time preference ρ is set to a standard value of 0.02. Turning to the demographic parameters, the retirement rate d is set to $1/30$ to match an expected work-life of 30 years (reflecting the prime-age interval of 25 to 54 years old), and the cohort arrival rate b is correspondingly chosen to deliver a population growth rate of 1%. The shape parameter β of the fertility preference shock distribution is calibrated to 12.96 to match the fraction of U.S. workers who have children of 39% in 2024 (U.S. Census Bureau, 2024) and the STEM education cost parameter ϵ is set to 0.01 to match the fraction of researchers in the U.S. of 0.9% in 2020.[18]

Turning to the labor supply parameters, the fraction of time spent working by parents α is set to 0.93 to match the empirical gap in hours worked between parents and non-parents in the U.S. Census and ACS. As shown in Figure B.1, parents typically work 7% fewer hours per week than non-parents. The "greedy work" parameter δ is estimated to match the relative elasticity of hourly earnings with respect to hours worked for researchers in the U.S. Census and ACS. Specifically, I estimate the following equation:

$$\ln(w_{it}) = \alpha + \beta \cdot \ln(h_{it}) + \delta \cdot \ln(h_{it}) \cdot \mathbb{1}_{\{\text{researcher}\}} + \mathbf{x}_{it}\boldsymbol{\gamma} + \epsilon_{it} \tag{14}$$

where w_{it} is the hourly wage, h_{it} is hours worked per week, $\mathbf{x}_{it}$ is a vector of controls, and ϵ_{it} is an error term.[19] I find a statistically significant estimate of 0.004 for δ, implying that research is a modestly greedy job, consistent with the evidence in Goldin (2021).[20]

In Appendix A.4, we show that the right tail of individual research labor supply behaves as a power law with tail exponent θ_s. Hence, one can estimate θ_s from the empirical tail exponent of the earnings distribution among researchers. Bell et al. (2019) link patent records to tax records from 1999 to 2012 and estimate a tail exponent of 1.26.[21] The shape parameter of the talent noise distribution θ_n is calibrated to 2.81 to match the 65% share of STEM graduates who do not end up pursuing a research career, as calculated from the U.S. Census and ACS in 2023.

Finally, the knowledge externality parameter ϕ is set to -2.1, corresponding to the estimate of Bloom et al. (2020) for the aggregate U.S. economy and the elasticity of substitution across varieties σ is set to 1.97 to target a degree of increasing returns to scale of one third, as suggested by Jones (2021). Notice that the chosen value for ϕ embraces the view that "ideas are getting harder to find". The calibration of the model is summarized in Table 1.

[18] https://www.oecd.org/en/data/indicators/researchers.html.

[19] The controls include second degree polynomials in age and experience, as well as education, occupation, state, race, marital status, year, gender, and occupation $\times$ gender fixed effects. The estimation results are presented in Table 4.

[20] In contrast, we get estimates of 0.011 and 0.006 for lawyers and doctors, respectively.

[21] Section 5.1 shows robustness to a relatively wide range of alternative values.

Table 1: Calibration

Parameter	Symbol	Value	Source
Discount rate	ρ	0.02	Standard calibration
Retirement rate	d	$1/30$	Average work-life of 30 years
Entry rate	b	$d + 0.01$	Population growth of 1%
Fertility pref. shock shape	β	12.96	U.S. Census Bureau
STEM education cost	ϵ	0.01	OECD (2020)
Hours worked by parents	α	0.93	U.S. Census and ACS
"Greedy work" parameter	δ	0.004	U.S. Census and ACS
Pareto talent signal shape	θ_s	1.26	Bell et al. (2019)
Pareto talent noise shape	θ_n	2.81	U.S. Census and ACS
Knowledge spillover	ϕ	-2.1	Bloom et al. (2020)
Product substitution	σ	1.97	Degree of IRS $= 1/3$

Untargeted Moments. While the estimation strategy explicitly targets certain moments, Table 2 presents additional key moments that were left untargeted yet are relatively well captured by the model. For example, while the observed U.S. R&D share of GDP stood at 3.5% in 2021 (World Bank, 2021), the model predicts a value of 2.5%, which is reasonably close. Similarly, the model's prediction of a 51% employee labor share compares favorably with the 54% observed in 2016 (Giandrea and Sprague, 2017). Moreover, the estimated total factor productivity (TFP) growth of 0.3%—although somewhat lower than the 0.6% average measured between 2000 and 2019 in the U.S. (University of Groningen and University of California, Davis, 2019)—still offers a credible approximation given that measured TFP growth may capture transitional factors (Jones, 2021). However, the model overestimates the underrepresentation of women in STEM programs at 17% compared to the 35% observed in the U.S. Census and ACS. It is important to note that the macroeconomic model used here is not specifically designed to generate a comprehensive set of microeconomic predictions for detailed micro-level validation. Nonetheless, the model's ability to match several untargeted aggregate moments of the U.S. economy underscores its structural robustness and broader applicability.

Table 2: Untargeted Moments

Moment	Data	Model	Source
R&D share of GDP	3.5%	2.5%	World Bank (2021)
Employee labor share	54%	51%	Bureau of Labor Statistics (2016)
TFP growth	0.6%	0.3%	Penn World Tables 10.01 (2000–2019)
STEM gender gap	35%	17%	U.S. Census and ACS

4.2 Inferring Distortions

To infer the model's three sources of distortions, I leverage moments on (1) the research productivity gender gap, (2) the gender gap is hours worked between parents and non-parents, and (3) the underrepresentation of women in research. In addition, I assume that men face no distortions in either occupation.

The Labor Market Distortion

As detailed in Section 3.4, the average research labor supply for cohort k and gender g is inversely related to the "keep rate" of the corresponding relative labor market tax. This relationship allows me to infer the relative labor market distortion from the observed gender gap in research productivity, as illustrated in Figure 5. Accordingly, I estimate a labor market distortion of 3.3%.

The Child Penalty Distortion

The child penalty distortion is inferred from the observed gender differences in hours worked between parent and non-parent researchers (see Figure 8). In the model, the relative hours worked by a parent of gender g from cohort k, compared to a childless peer with identical characteristics, is given by $[(1-\tau^{C}_{gk})\alpha]^{1+\delta}$. Figure 8(a) shows that, in research, mothers work 4.5% fewer hours per week than their childless peers, whereas fathers work 2.7% more. By normalizing distortions to zero for men, taking the ratio of this expression for women to that for men allows us to infer a child penalty distortion of 7%.

The Exposure Distortion

Finally, given other distortions and parameter values, the exposure barrier is inferred from the gender ratio in the fraction of researchers. This ratio is estimated using two data sources: PatentsView, which shows that only 19% of the most recent cohort of patent grantees are women, and the U.S. Census and ACS, which indicates that 27% of researchers between the ages of 25 and 45 are women. Neither measure is perfect–since not all innovations are patented and the occupational classification from Ekerdt and Wu (2024) does not perfectly what we conceive to be research[22]–so I take the average of these two estimates (23%) as the benchmark.[23] Based on this benchmark, the exposure distortion is estimated at 79%.

5 Results

We now have all the necessary ingredients to answer the central questions of this paper: how costly is the misallocation of inventive talent for aggregate productivity and welfare? To answer this question, a natural counterfactual exercise is to lift all distortions faced by female researchers and compare the economy's transition path to its initial balanced growth path allocation.

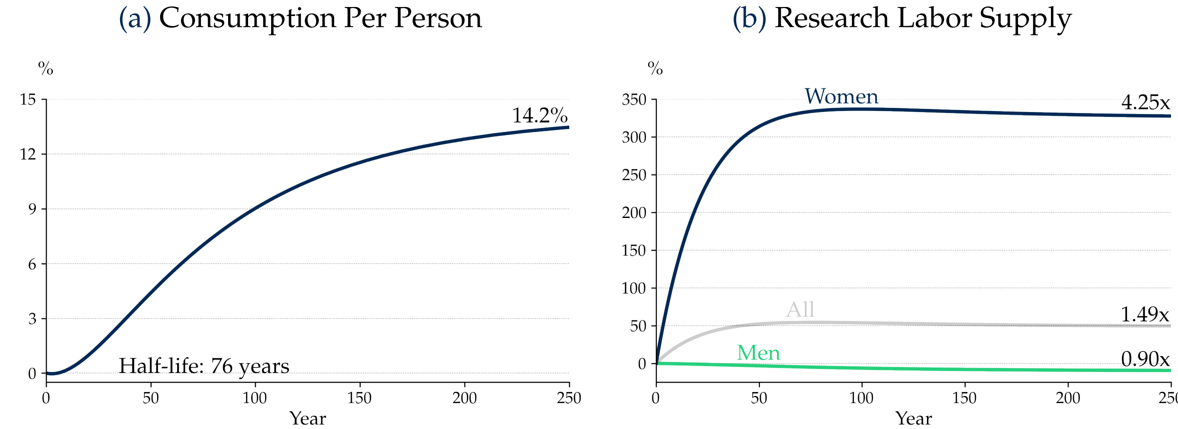
Aggregate Productivity

Panel 12(a) shows that a simultaneous withdrawal of all distortions would raise income per person by 14.2% in the long run. To get a sense of magnitudes, if we were to implement a uniform R&D subsidy of 30% in the model (absent any distortions), consumption per capita would increase by 1.5% in the long run. Although large, this productivity gain is slow to materialize, with a half-life of 76 years. This inertia is consistent with the findings of Atkeson, Burstein and Chatzikonstantinou (2019) who study the transitional dynamics of a large class of semi-endogenous growth models with a gradual accumulation of ideas. In addition, our theory further admits an overlapping generations structure with irreversible occupation choices, which directly slows down the reallocation of labor.

[22]For instance, psychologist are classified as researchers.

[23]Because the model assumes equal employment rates for men and women, this benchmark is adjusted to reflect the actual gender differences in employment rates in the United States.

Figure 12: Consumption Per Person and Research Labor Supply



Note: Removing all barriers to female innovation could increase income per capita growth by almost 9 basis points over the next century.

This labor reallocation is depicted in Panel 12(b), which plots the path of aggregate research labor by gender in percentage deviation from their starting point. The supply of research labor by women more than quadruples, while that of men shrinks by 10%. In aggregate, research labor permanently increases by 49% within the first 50 years of the transition. As discussed in Section 3.4, raising this factor of 1.49 to the power of $\gamma = 1/3$ (the degree of increasing returns to scale) approximately recovers our long-run gain in income per person of 14.2%.

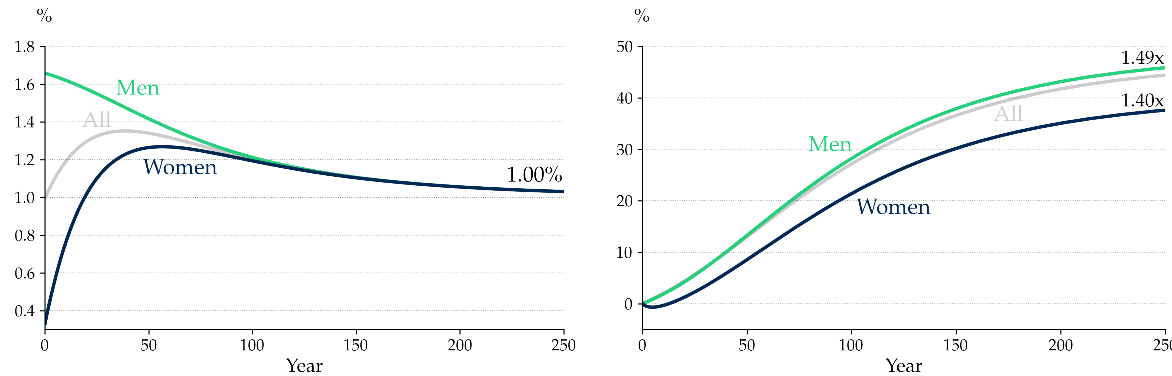
However, is this gain achieved by having *more* or *better* inventors? Figure 13 reveals the answer by tracing the path of the extensive and intensive margins of research labor supply. More specifically, Panel 13(a) plots the fraction of inventors in each gender group. About 0.33% of women are inventors in 2020, with that fraction ultimately rising to 1% after 250 years. Marginally talented men are instead being gradually pushed out of inventorship as older cohorts retire, culminating in a balanced gender representation across professions. Interestingly, the aggregate share of inventors barely rises in the long run, suggesting that most of the productivity gains from lifting distortions are achieved on the intensive margin.

To drive this point home, Panel 13(b) plots the transition path of average inventive productivity by gender, in percentage deviation from its starting point. This figure leaves no doubt that, in aggregate, the large increase in research labor is unfolding through the intensive rather than the extensive margin. However, a closer look at the dynamics *within* gender groups reveals more nuance. For women, only 23% of the 4.25-fold rise in research labor is coming from the intensive margin. In comparison, the decline in male research labor is entirely driven by their shrinking numbers, despite the counteracting rise in their average productivity from tougher competition.

Figure 13: The Extensive and Intensive Margins of Research Labor Supply

(a) Extensive Margin

(b) Intensive Margin



Note: The number of women inventors almost triples, while it shrinks by about 60% for men. However, both gender groups become more productive on average as they face more intense competition from a larger pool of talented women.

The Role of Exposure to Innovation. To illustrate the importance of the exposure distortion in driving these results, consider a hypothetical scenario where the underrepresentation of women in research is solely attributed to either the labor market or the child penalty distortions. In this experiment, I eliminate the exposure distortion by setting it to zero and exclude the research productivity gender gap moment as a target in the estimation. Consequently, the labor market distortion is inferred from the underrepresentation of women in research. Under these conditions, removing all distortions results in only a 3.6% increase in long-run consumption per person–less than a quarter of the 14.2% gain observed when the exposure distortion is at play. This stark difference arises because, if the underrepresentation were solely due to a selection mechanism, it would primarily exclude less talented women from pursuing research. In contrast, the exposure distortion suggests that even the most talented women are being deterred from entering the field, leading to a far greater loss in productivity.

Social Welfare

To assess the welfare implications of eliminating all distortions, I define the following utilitarian social welfare function, as in Calvo and Obstfeld (1988):

$$W_t(\lambda) = \int_t^\infty e^{-(\rho-n)(\tau-t)} \int_{-\infty}^{\tau} be^{-b(\tau-k)} \mathbb{E}[\ln(\lambda \cdot c_{i\tau}) + \mathbb{1}_{\{i\in\mathcal{C}_k\}} \ln(x_i)] \mathrm{d}k \mathrm{d}\tau.$$

In this expression, the fraction of people from cohort k at time τ is given by $be^{-b(\tau-k)}$, the expectation is taken over individuals within cohorts, and $\lambda > 0$ permanently multiplies the consumption of every person. Note that by changing the order of integration, we can additively separate the social welfare of surviving and future cohorts:

$$\begin{aligned} W_t(\lambda) = & \int_{-\infty}^{t} be^{-b(t-k)} \int_{t}^{\infty} e^{-(\rho+d)(\tau-t)} \mathbb{E}[\ln(\lambda \cdot c_{i\tau}) + \mathbb{1}_{\{i\in\mathcal{C}_k\}} \ln(x_i)] \mathrm{d}\tau \mathrm{d}k \qquad \text{Surviving} \\ & + \int_{t}^{\infty} be^{-(\rho-n)(k-t)} \int_{k}^{\infty} e^{-(\rho+d)(\tau-k)} \mathbb{E}[\ln(\lambda \cdot c_{i\tau}) + \mathbb{1}_{\{i\in\mathcal{C}_k\}} \ln(x_i)] \mathrm{d}\tau \mathrm{d}k \quad \text{Future.} \end{aligned}$$

With these definitions, we can ask: by what factor λ must we permanently adjust the consumption of everyone in a distorted economy to leave them as well off as if they spent the rest of their lives in an undistorted economy? The answer satisfies:

$$W_t(\lambda) = W_t^*(1)$$

where W_t and W_t^* denote social welfare in the distorted and undistorted economies, respectively. More precisely, the distorted economy is and remains on its balanced growth path, characterized by the distortions inferred for the most recent cohort. Instead, the undistorted economy starts from that same initial point but is launched on a transition path thereafter.

This exercise reveals that removing barriers to female innovation would be equivalent to permanently raising everyone's consumption by 7.2%. That figure is notably lower than the long-run income per person gain of 14.2% for two reasons. First, the transition is very slow, meaning that the higher standards of living will mostly materialize in a remote future. Second, because U.S. population growth is projected to be quite slow as well, those future gains must be discounted back to the present at a relatively high rate.

Of this 7.2% consumption-equivalent welfare variation, 95% comes from higher mean consumption, while the rest comes from lower consumption inequality and utility from children. This does not imply, however, that those gains are evenly shared in the economy. Indeed, carrying out this welfare calculation separately for different demographic groups shows that removing all distortions is equivalent to an 8.6% increase in consumption for future cohorts, as opposed to a more modest 1% increase for surviving cohorts.

Notably, the current generation of female inventors stands to gain from this experiment, with a potential 1.3% increase in their consumption-equivalent welfare. On the flip side, not everyone benefits: surviving cohorts of male inventors would face a 1.7% decline in their consumption. Those distributional consequences should remind us that when the costs of an intervention are concentrated and borne today, while its benefits are diffuse and materialize tomorrow, we ought to think carefully about its implementability.

5.1 Robustness to Parameter Values

In this section, our main findings are revisited with alternative parameter values. In particular, I discuss their robustness to the degree of increasing returns to scale γ, the talent signal parameter θ_s, the demographic parameters b and d, and the knowledge spillover parameter ϕ. Note here that for consistency, I recalibrate the estimated parameters and distortions when varying parameter values.

As discussed in Jones (2021), the overall degree of increasing returns to scale in the economy is both notoriously challenging to measure and fundamental in providing practical answers to some of our most pressing macroeconomic questions. Despite the sparsity of empirical work on the matter, there have been some valuable quantification attempts. Jones (2002) estimates values ranging from about 0.05 to 0.33 through a time-series econometric analysis. Peters (2021) instead leverages the pseudo-random resettlement of 8 million ethnic Germans into West Germany after the Second World War to estimate a value of nearly 0.6. Given this wide range of estimates, I calculate the long-run percentage gain in consumption per capita after eliminating all distortions, which ranges from about 2% to almost 27% for γ going from 0.05 to 0.6.[24]

The shape parameter for the research talent signal, θ_s, is similarly important because it determines the degree to which firms can economize on the total number of inventors by relying heavily on a few exceptionally talented researchers. If we consider a higher value of $\theta_s = 2$ (instead of $\theta_s = 1.26$), which implies greater scarcity of superstar inventors, the long-run gain in consumption per capita would decrease to 8.7% from 14.2%.

I further assess the results' robustness to a set of parameters that speed up or slow down the transition toward a new balanced growth path. The demographic parameters b and d play precisely this role by dictating the cohort turnover rate. The knowledge spillover parameter ϕ does so by disciplining the degree of autocorrelation in the stock of ideas. In Table 3, I set d to values that correspond to an expected working life of 20 and 40 years and calculate the transition's half-life and the welfare gain from eliminating distortions.[25] Interestingly, the demographic parameters have virtually no effect on long-run consumption per capita. However, letting the expected working life vary by 10 years shifts the transition's half-life by roughly 6 to 8 years. In present value terms, this translates to counterfactual welfare gains of 7.6% or 6.9% instead of our baseline figure of 7.2%.

For the knowledge spillover parameter ϕ, I select alternative values of 0.5 and -6.2, the latter being the lower bound of the estimates in Bloom et al. (2020). Importantly, here, when varying ϕ, I adjust σ to keep the degree of increasing returns to scale constant to $\gamma = 1/3$.

[24]Here again, the rule of thumb of raising the 50% increase in research labor supply to the power of γ approximately recovers the long-run gain in income per person.

[25]In particular, when varying d, I vary b by the same amount to keep the population growth rate constant. This isolates the counterfactual calculation from variations in the social discount rate.

Table 3: Consumption per Person, Half-Lives, and Welfare: The Role of d and ϕ

Parameter	Value	Consumption Per Person Gain (%)	Half-Life (years)	Welfare Gain (%)
Baseline		14.2	75.7	7.16
d	1/20	14.3	68.1	7.60
	1/40	14.2	81.3	6.85
ϕ	0.5	14.2	78.2	6.92
	-6.2	14.2	75.3	7.22

Note: This table shows the long run percentage gain in income per person, its half-life and the percentage welfare gain from removing all distortions in 2020 for different values of d and ϕ. When varying d and ϕ, I respectively adjust b and σ as to keep population growth n and the degree of increasing returns to scale γ constant.

That is precisely why variations in ϕ lead to no changes in long-run living standards in Table 3. Hence, this robustness exercise can alternatively be viewed as a sensitivity analysis to the parameter σ instead of ϕ. Although lower values for the knowledge spillover parameter seem to barely change our results, a higher value of $\phi = 0.5$ raises the transition's half-life by about 3 years, which shrinks welfare gains by 24 basis points.

6 Theoretical Extensions

In which directions could we extend our model, and how may these refinements influence our results? This section is an attempt to answer this question with seemingly important ingredients that were left out of the model.

Role Models and Affirmative Action

Previously, we noted that the exposure distortion was intended to encapsulate barriers such as the relative scarcity of relevant role models for young girls compared to young boys. What if we were to delineate this more explicitly within the model? By doing so, part of what is currently captured under the exposure distortion would be redefined as a technological friction, emphasizing the importance of role models in molding career aspirations. Such friction would have to be modeled as a technological constraint on the environment. Hence, achieving a more efficient talent allocation could be a longer journey, as women would only gradually join the ranks of inventors, in turn inspiring the next generation to do so.

To incorporate the influence of role models in the model, an individual's exposure to innovation is still represented as a Bernoulli random variable. However, its mean parameter now also depends on the proportion of individuals from each gender who opted for research in prior generations:

$$e_i \sim \text{Bernoulli}\big((1-\tau_{gk}^E) \cdot I_{gk}^{\xi_g} \cdot I_{\neg gk}^{\xi_{\neg g}}\big).$$

From the point of view of a person i of gender g, I_{gk} denotes the fraction of inventors of the same gender, whereas $I_{\neg gk}$ denotes that for the opposite gender. The parameters ξ_g and $\xi_{\neg g}$ capture the gender-specific relevance of role models while τ_{gk}^E is the exposure distortion net of the role model frictions.

Note that this formulation introduces a subtle yet significant externality within the model. Specifically, the occupational decisions of earlier generations of inventors resonate and influence the career choices of subsequent cohorts, but the former are not compensated for this externality. This market failure opens the door to affirmative action on the grounds of efficiency considerations, an issue I will revisit shortly.

In this extension of the model, the average research labor supply in each occupation is unchanged, but the proportion of individuals of gender g and cohort k opting for research is now multiplied by the term $I_{gk}^{\xi_g} \cdot I_{\neg gk}^{\xi_{\neg g}}$. Hence, part of what was previously inferred as the exposure distortion is now captured by technological frictions from role models. To infer the residual exposure distortion, one must discipline the role model parameters ξ_g and $\xi_{\neg g}$. To do so, I borrow estimates from Bell et al. (2018) who regress the fraction of children in a commuting zone who go on to patent in a specific technological field on the fraction of individuals of each gender from that commuting zone who were granted a patent in that same technological field.[26] In this extended model, the exposure distortion is subtly tempered relative to the baseline, and its interpretation becomes less straightforward. Nevertheless, conducting the counterfactual analysis in the environment, I find a slightly more modest increase in long-run income per person of 10.6% which translates to a consumption-equivalent welfare gain of 3.8%.

It was previously mentioned that this extension of the model introduces an externality: the current generation of individuals do not internalize that their occupation choice will influence the fraction of individuals in future cohorts who will have the opportunity to consider research as a career path (Chung, 2000; Mookherjee, Ray and Napel, 2010; Genicot and Ray, 2017). As such, the rationale behind subsidies to inventor wages goes beyond merely harnessing knowledge spillovers–it also serves as a corrective measure for this

[26]The results of this regression are presented in Table 5 for both girls and boys. Bell et al. (2018) estimate statistically insignificant cross-gender coefficients but significant own-gender coefficients of 2.232 and 1.693 for girls and boys, respectively. To ensure coherence with the model, these estimates are first translated in elasticity form and then averaged to obtain parameter values of $\epsilon_g = 0.24$ and $\epsilon_{\neg g} = 0$.

externality. This role model externality introduces the potential for transitional gender-specific optimal policy. Indeed, given an initially skewed gender composition, a welfare-maximizing planner might temporarily consider implementing *differential* wage subsidies for female researchers to expedite the transition towards a more efficient allocation of talent, trading off a slightly worse allocation of talent today in order to access a larger pool of talent in a nearer future.

Technological Field Heterogeneity

Given the considerable heterogeneity in gender composition across technological fields shown in Figure 3(b), an important question arises: Could inventive talent be misallocated not only between research and production but also among these distinct technological areas? Quantifying this potential source of misallocation accurately would require detailed information on the relative importance of each technological field to overall innovation, which is not obvious at all.

More precisely, the research sector could combine research labor R_{ft} from different fields indexed by $f \in \{1, \ldots, F\}$ according to a Cobb-Douglas technology:

$$\dot{M}_t = M_t^{\phi} R_t \quad \text{where} \quad R_t = \prod_{f=1}^{F} R_{ft}^{\nu_f} \quad \text{and} \quad \sum_{f=1}^{F} \nu_f = 1$$

where the parameters $\boldsymbol{\nu} \in [0,1]^F$ would govern the relative importance of each field in the production of new ideas. On the other side of this market would be individuals born with a vector of inventive talent signals $\mathbf{z}_i^s$ over those fields, drawn from a multivariate Pareto distribution with cumulative distribution function G_s:

$$G_s(\mathbf{z}^s) = 1 - \left(\sum_{f=1}^{F} {z_f^s}^{\frac{-\theta}{1-\varrho}} \right)^{1-\varrho}.$$

The shape parameter $\theta > 1$ would measure the degree of talent dispersion *across* individuals whereas $\varrho \in [0,1)$ would determine their correlation between technological fields *within* individuals. In particular, talent draws are perfectly correlated across fields when $\varrho \to 1$, or completely independent when $\varrho = 0$.

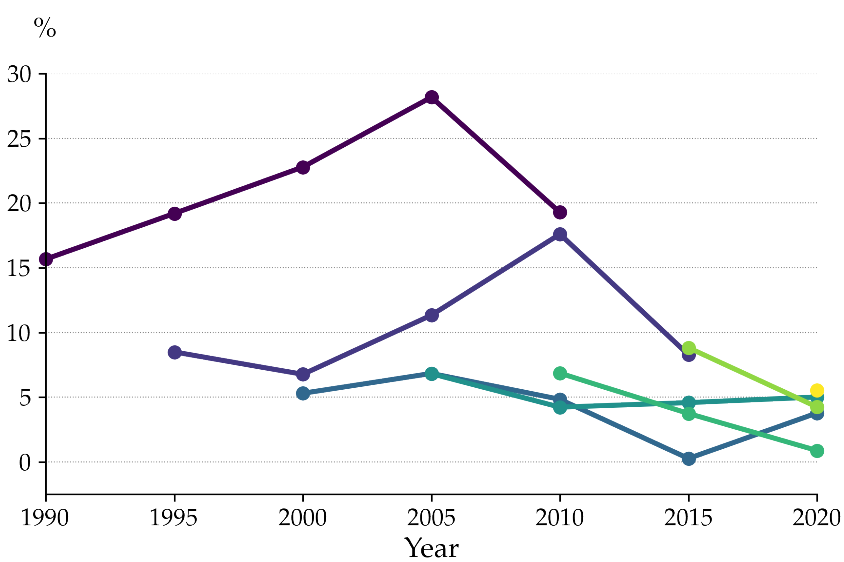
For this field-specific heterogeneity to be quantitatively significant, fields with the greatest underrepresentation of women would also need to be among the most critical for overall innovation. Given that the latter is difficult to measure empirically, it seemed to be more productive to focus on talent misallocation between research and production (rather than across fields), which aligns more directly with available empirical evidence.

“On-The-Job” Human Capital

It may be particularly challenging for women to remain at the technological frontier if childcare and household responsibilities disproportionately fall on them (Kim and Moser, 2021; Kaltenberg, Jaffe and Lachman, 2023). To reflect this possibility within the model, one could incorporate gender-specific human capital depreciation as a simplified representation of these gender-related barriers to skill retention. Under perfect foresight, it is straightforward to show that this distortion would still operate through selection. That is, if gendered barriers to human capital maintenance constituted a prominent explanation for the scarcity of women in research, the model would imply that women would be more productive than their male colleagues at the onset of their careers (before their human capital would depreciate).

Along those lines, Figure 14 plots the inventive productivity gender gap across different cohorts over time. Two observations emerge. First, the diminishing productivity advantage observed among women over time is primarily a cohort effect. Second, although more recent cohorts exhibit a somewhat larger productivity advantage for women at the onset of their careers, the magnitude of this advantage remains modest. These findings suggest that gendered barriers to skill retention are unlikely to be the dominant explanation for the underrepresentation of women in research.

Figure 14: The Life-Cycle of the Inventive Productivity Gender Gap



Note: This figure illustrates the evolution of the inventive productivity gender gap across different cohorts over the career lifecycle.

Occupational Preferences

Could gender differences in intrinsic preferences for innovation be a plausible candidate explanation for the underrepresentation of women among inventors? Under the assumption that individuals still select into occupations based on their talent, broadening the model in this direction makes clear that this force yet again operates through selection. Indeed, if women disliked careers in innovation, only the most talented would pursue them despite their perceived disamenities.

An alternative possibility is that individuals self-select into occupations based on those preferences rather than their innate talent. If selection into invention was indeed purely based on these heterogeneous preferences, all distortions would have equivalent implications for aggregate productivity, as they would all influence only the extensive rather than the intensive margin of research labor supply. Hence, the quantitative results would remain unchanged, but their interpretation would differ: what I label an exposure distortion could instead reflect other distortions operating through preference-based sorting. In that case, the policy prescriptions would change even though the macroeconomic consequences would not.

7 Conclusion

What are the macroeconomic consequences of missing out on half of our brightest inventive minds? To answer this question, I develop a model of semi-endogenous growth in which individuals with heterogeneous inventive talent can choose between a career in research or production. However, three gendered barriers can deter or prevent women from pursuing their comparative advantage. They may face different forms of discrimination in the labor market, a larger professional penalty from parenthood, or lack the opportunities and role models to become researchers.

Interpreting micro-level data on U.S. researchers through the lens of this framework, I find that the recent underrepresentation of women cannot be explained by distortions that only operate through selection on ability or family considerations. Women and men inventors are just too similarly productive, and the labor supply gender gap between parents and non-parents among R&D workers is too narrow for such distortions to play a prominent role. From a policy perspective, this may suggest that we ought to focus our attention and resources on bottlenecks that may manifest earlier along the innovation pipeline such as the lack of relevant role models.

I then take advantage of the general equilibrium structure of this theory to quantify the aggregate implications of lifting all barriers to female innovation. This calculation reveals that U.S. income per person would increase by 14.2% in the long run. Taking transition dynamics into account, eliminating all distortions would be equivalent to permanently raising everyone's consumption by 7.2%. Those economy-wide gains are mostly achieved by bringing better rather than more people into the process of innovation. Indeed, as barriers fall, new generations of ingenious women join the ranks of inventors, thus driving out marginally talented men.

This paper leaves the door open to many exciting avenues for future research. Which specific policies would be most effective in expanding access to inventive opportunities for young girls? Can data on inventor earnings, educational attainment, or childhood test scores provide more direct empirical evidence on various gendered distortions? Are people from low-income families and minority backgrounds facing the same obstacles to innovation as women? How much more prosperous would we be if we opened the doors of innovation to other underrepresented groups? Those are all outstanding but potentially fruitful questions that await future study.

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A Theoretical Appendix

A.1 The Individual's Problem

The Consumption-Saving Problem. Taking prices as given, the consumption-saving problem of an individual i is to choose their consumption of each product over time to maximize lifetime utility:

$$U_i = \max_{\{\{c_{jit}\}_{j=0}^{M_t}\}_{t=k}^{\infty}} \int_k^{\infty} e^{-(\rho+d)(t-k)}[\ln(c_{it}) + \mathbb{1}_{\{i\in\mathcal{C}_t\}} \ln(x_i)]\mathrm{d}t$$

subject to equation (4) and the flow budget constraint:

$$\dot{a}_{it} = r_t a_{it} + (1 - \mathbb{1}_{\{i\in\mathcal{R}_t\}}\tau^L_{gt})w^o_t \ell^o_i - c_{it}.$$

With Dixit and Stiglitz (1977) preferences over the differentiated products, we obtain the usual individual demand functions:

$$c_{jit} = c_{it}/p^{\sigma}_{jt}, \quad \forall j \in [0, M_t].$$

The current-value Hamiltonian of the consumption-saving problem is:

$$\mathcal{H}_t = \ln(c_{it}) + \nu_t[r_t a_{it} + (1 - \mathbb{1}_{\{i\in\mathcal{R}_t\}}\tau^L_{gt})w^o_t \ell^o_i - c_{it}]$$

where ν_t is the costate variable and $\lim_{t\to\infty} e^{-(\rho+d)(t-k)}\nu_t a_{it} = 0$. The first-order necessary conditions are:

$$\frac{\partial \mathcal{H}_t}{\partial c_{it}} = c_{it}^{-1} - \nu_t = 0 \quad \text{and} \quad \frac{\partial \mathcal{H}_t}{\partial a_{it}} = \nu_t r_t = (\rho + d)\nu_t - \dot{\lambda}_t.$$

Combining those equations, we obtain the Euler equation and the No-Ponzi condition:

$$\frac{\dot{c}_{it}}{c_{it}} = r_t - \rho - d \quad \text{and} \quad \lim_{t\to\infty} e^{-\int_k^t r_{t'}\mathrm{d}t'} a_{it} = 0.$$

Integrating the flow budget constraint using both equations delivers:

$$c_{it} = (\rho + d)(a_{it} + h_{it})$$

where h_{it} is the human wealth of individual i at time t:

$$h_{it} \equiv (1 - \mathbb{1}_{\{i\in\mathcal{R}_t\}}\tau^L_{gt})\omega^o_t \ell^o_i \quad \text{where} \quad \omega^o_t \equiv \int_t^{\infty} e^{-\int_t^{t'} r_{t''}\mathrm{d}t''} w^o_{t'}\mathrm{d}t'.$$

Using the individual's Euler equation and the initial condition for financial wealth, we can express consumption in period t from the point of view of period k as:

$$c_{it} = (\rho + d)(1 - \mathbb{1}_{\{i \in \mathcal{S}_t\}}\epsilon)h_{ik}e^{\int_k^t (r_{t'} - \rho - d)\mathrm{d}t'}.$$

Substituting this equation in the definition of lifetime utility:

$$U_i = \frac{\ln[(\rho + d)(1 - \mathbb{1}_{\{i \in \mathcal{S}_t\}}\epsilon)h_{ik}] + \mathbb{1}_{\{i \in \mathcal{C}_t\}}\ln(x_i) - 1}{\rho + d} + \Delta_k$$

where Δ_k is defined for convenience as:

$$\Delta_k \equiv \int_k^\infty e^{-(\rho+d)(t-k)} \int_k^t r_{t'}\mathrm{d}t'\mathrm{d}t.$$

The Fertility Choice Problem. A person will decide to have children if and only if the expected lifetime utility from doing so is higher than that of not having children. This delivers a threshold on the preference shock x_i above which a person will choose to have children:

$$\underline{x}_{gk}^o \equiv \begin{cases} 1/[(1 - \tau_{gk}^C)\alpha]^{1+\delta} & \text{if } o = R, \\ 1/\alpha & \text{if } o = P. \end{cases}$$

The Occupation Choice Problem. Conditional on receiving exposure to innovation and their education choice, a person will choose to work in research if and only if the expected lifetime utility from doing so is higher than that of working in production. Once again, we consider three cases. If $x_i < \underline{x}_g^P$, such that individual i would never choose to have children, then the talent threshold above which they would choose to work in research is:

$$\underline{z}_{gk}^N \equiv \frac{1}{1 - \tau_{gk}^L} \cdot \frac{\omega_k^P}{\omega_k^R}.$$

If $x_i > \underline{x}_g^R$, such that individual i would always choose to have children regardless of their occupation, then the threshold is:

$$\underline{z}_{gk}^A \equiv \frac{1}{(1 - \tau_{gk}^C)^{1+\delta}\alpha^\delta} \cdot \underline{z}_{gk}^N > \underline{z}_{gk}^N.$$

Finally, if $x_i \in (\underline{x}_g^P, \underline{x}_g^R]$, such that individual i would only choose to have children if they were to work in production, then that threshold is:

$$\underline{z}_{gk}^D(x) \equiv \alpha x \cdot \underline{z}_{gk}^N \in (\underline{z}_{gk}^N, \underline{z}_{gk}^A].$$

The Education Choice Problem. A person will choose to enroll in STEM if and only if the expected lifetime utility from doing so is higher than otherwise. There are two important considerations that determine this choice. First, individuals recognize that even after receiving a STEM education, they can still opt to work in production. Second, they make this education choice behind the veil of ignorance regarding their talent noise shock: although they observe their talent signal, the noise shock has not yet been realized.

The expected lifetime utility from not completing a STEM education is given by:

$$U_i^P = \frac{\ln[(\rho+d)\omega_k^P] + \mathbb{1}_{\{i\in\mathcal{C}_t\}}\ln(\alpha x_i) - 1}{\rho+d} + \Delta_k$$

The expected lifetime utility from enrolling in a STEM program is instead:

$$U_i^S = \int_{\vartheta_n}^{\infty} \max\{U_i^R(z^n), U_i^P\}\mathrm{d}G_n(z^n) + \ln(1-\epsilon)/(\rho+d)$$

where $U_i^R(z^n)$ is the expected lifetime utility of a researcher with talent noise shock z^n net of student debt:

$$U_i^R(z^n) = \frac{\ln[(\rho+d)(1-\tau_{gk}^L)\omega_k^R z_i^s z^n] + \mathbb{1}_{\{i\in\mathcal{C}_t\}}\ln\{[(1-\tau_{gk}^C)\alpha]^{1+\delta}x_i\} - 1}{\rho+d} + \Delta_k$$

Therefore, a person will opt for STEM if and only if $U_i^S > U_i^P$, which we can rewrite as:

$$\int_{\vartheta_n}^{\infty} \max\{U_i^R(z^n) - U_i^P, 0\}\mathrm{d}G_n(z^n) > -\ln(1-\epsilon)/(\rho+d).$$

Substituting the expressions for $U_i^R(z^n)$ and U_i^P in this inequality, we obtain:

$$\int_{\underline{z}_i^n}^{\infty} \ln(z^n/\underline{z}_i^n)\mathrm{d}G_n(z^n) > -\ln(1-\epsilon)$$

where $\underline{z}_i^n$ is defined as:

$$\underline{z}_i^n \equiv \frac{\omega_k^P\{1+\mathbb{1}_{\{i\in\mathcal{C}_t\cap\mathcal{P}_t\}}(\alpha x_i - 1)\}}{(1-\tau_{gk}^L)\omega_k^R z_i^s\{1+\mathbb{1}_{\{i\in\mathcal{C}_t\cap\mathcal{R}_t\}}[(1-\tau_{gk}^C)^{1+\delta}\alpha^{1+\delta}x_i - 1]\}} > \vartheta_n.$$

This inequality delivers individual talent signal thresholds above which someone would enroll in a STEM program:

$$z_i^s > \frac{\Gamma\omega_k^P[1+\mathbb{1}_{\{i\in\mathcal{C}_t\cap\mathcal{P}_t\}}(\alpha x_i - 1)]}{(1-\tau_{gk}^L)\omega_k^R\{1+\mathbb{1}_{\{i\in\mathcal{C}_t\cap\mathcal{R}_t\}}[(1-\tau_{gk}^C)^{1+\delta}\alpha^{1+\delta}x_i - 1]\}}$$

where $\Gamma \equiv [-\theta_n \ln(1-\epsilon)]^{1/\theta_n}/\vartheta_n$. Given the realizations of preference shocks for children, we obtain three regions. If $x_i < \underline{x}_g^P < \underline{x}_g^R$, such that individual i would never choose to have children regardless of their occupation, then the talent signal threshold above which they would complete a STEM education is:

$$\underline{z}_{gk}^{s\text{-N}} \equiv \Gamma \cdot \frac{1}{1-\tau_{gk}^L} \cdot \frac{\omega_k^P}{\omega_k^R}.$$

If $x_i > \underline{x}_g^R$, such that individual i would always choose to have children regardless of their occupation, then the threshold is:

$$\underline{z}_{gk}^{s\text{-A}} \equiv \frac{1}{(1-\tau_{gk}^C)^{1+\delta}\alpha^\delta} \cdot \underline{z}_{gk}^{s\text{-N}} > \underline{z}_{gk}^{s\text{-N}}.$$

Finally, if $x_i \in (\underline{x}_g^P, \underline{x}_g^R]$, such that individual i would only choose to have children if they were to work in production, then that threshold is a function of their preference shock for children:

$$\underline{z}_{gk}^{s\text{-D}}(x) \equiv \alpha x \cdot \underline{z}_{gk}^{s\text{-N}} \in (\underline{z}_{gk}^{s\text{-N}}, \underline{z}_{gk}^{s\text{-A}}].$$

A.2 The Firm's Problem

Taking the demand function for its product and the wage paid to production workers as given, the intermediate firm's problem is to choose its product's price and production labor demand to maximize profits:

$$\pi_{jt} = \max_{p_{jt}, l_{jt}} \{p_{jt} y_{jt} - w_t^P l_{jt}\}.$$

Firms thus set their price to a constant markup μ above marginal cost:

$$p_{jt} = \mu \cdot w_t^P \quad \text{where} \quad \mu \equiv \frac{\sigma}{\sigma - 1}$$

which implies that profits are perfectly symmetric across firms:

$$\pi_{jt} = \frac{C_t}{\sigma M_t}, \quad \forall j \in [0, M_t].$$

Symmetry in labor demand also implies that firms produce:

$$y_{jt} = \frac{L_t}{M_t}.$$

A.3 The Research Sector's Problem

Taking wages and the measure of products as given, the research sector's problem is to choose a patent price and research labor to maximize profits:

$$\max_{q_t, R_t} \{q_t M_t^{\phi} R_t - w_t^R R_t\}.$$

Hence, the first-order condition for research labor implies:

$$q_t M_t^{\phi} = w_t^R.$$

Since there is free-entry in the intermediate sector, the final sector sets the price of a patent to extract all rents from the commercialization of an idea:

$$q_t = \int_t^{\infty} e^{-\int_t^{t'} r_{t''} \mathrm{d}t''} \pi_{t'} \mathrm{d}t'.$$

Differentiating with respect to time and using the expression for a firm's profits, we obtain the law of motion for the price of a patent:

$$\dot{q}_t = r_t q_t - \frac{C_t}{\sigma M_t}.$$

A.4 Aggregation

Before characterizing the aggregation, it will be useful to first note that the CDF of (total) talent conditional on the talent signal exceeding a threshold $\underline{z}$ is given by:

$$\begin{aligned}
\mathrm{P}(z^s \cdot z^n \leq z | z^s > \underline{z}) &= \frac{\mathrm{P}(z^s \cdot z^n \leq z \cap z^s > \underline{z})}{\mathrm{P}(z^s > \underline{z})} \\
&= \frac{\mathrm{P}(z^n \leq z/z^s \cap z^s > \underline{z})}{\mathrm{P}(z^s > \underline{z})} \\
&= \frac{\int_{\underline{z}}^{\infty} G_n(z/z^s) g_s(z^s) \mathrm{d}z^s}{1 - G_s(\underline{z})} \\
&= \theta_s \underline{z}^{\theta_s} \int_{\underline{z}}^{z/\vartheta_n} [1 - (\vartheta_n z^s / z)^{\theta_n}] z^{s - \theta_s - 1} \mathrm{d}z^s \\
&= 1 - \frac{\theta_n (\vartheta_n \underline{z}/z)^{\theta_s} - \theta_s (\vartheta_n \underline{z}/z)^{\theta_n}}{\theta_n - \theta_s}.
\end{aligned}$$

Therefore, the fraction of researchers among individuals of gender g and cohort k who would never choose to have children is:

$$I_{gk}^{N} \equiv (1-\tau_{gk}^{E})\cdot \mathrm{P}(z > \underline{z}_{gk}^{N} | z^{s} > \underline{z}_{gk}^{s\text{-}N})\cdot \mathrm{P}(z^{s} > \underline{z}_{gk}^{s\text{-}N}) = (1-\tau_{gk}^{E})[(1-\tau_{gk}^{L})\omega_{k}^{R}/\omega_{k}^{P}]^{\theta_{s}}\mathcal{I}$$

where the constant $\mathcal{I}$ is defined as:

$$\mathcal{I} \equiv \frac{\theta_{n}\vartheta_{n}^{\theta_{s}} - \theta_{s}\vartheta_{n}^{\theta_{n}}\Gamma^{\theta_{n}-\theta_{s}}}{\theta_{n}-\theta_{s}}.$$

The fraction of researchers among individuals of gender g and cohort k who would always choose to have children is:

$$I_{gk}^{A} \equiv (1-\tau_{gk}^{E})\cdot \mathrm{P}(z > \underline{z}_{gk}^{A} | z^{s} > \underline{z}_{gk}^{s\text{-}A})\cdot \mathrm{P}(z^{s} > \underline{z}_{gk}^{s\text{-}A}) = [(1-\tau_{gk}^{C})^{1+\delta}\alpha^{\delta}]^{\theta_{s}} I_{gk}^{N}.$$

The fraction of researchers among individuals of gender g and cohort k who would only choose to have children if they were to work in production is:

$$\begin{aligned} I_{gk}^{D} &\equiv (1-\tau_{gk}^{E})\cdot \frac{\int_{\underline{x}_{gk}^{P}}^{\underline{x}_{gk}^{R}} \mathrm{P}(z > \underline{z}_{gk}^{D}(x) | z^{s} > \underline{z}_{gk}^{s\text{-}D}(x))\cdot \mathrm{P}(z^{s} > \underline{z}_{gk}^{s\text{-}D}(x))\beta x^{-\beta-1}\mathrm{d}x}{\int_{\underline{x}_{gk}^{P}}^{\underline{x}_{gk}^{R}} \beta x^{-\beta-1}\mathrm{d}x} \\ &= \frac{\beta}{\beta+\theta_{s}}\cdot \frac{1-[(1-\tau_{gk}^{C})^{1+\delta}\alpha^{\delta}]^{\beta+\theta_{s}}}{1-[(1-\tau_{gk}^{C})^{1+\delta}\alpha^{\delta}]^{\beta}}\cdot I_{gk}^{N}. \end{aligned}$$

Therefore, the total share of researchers among individuals of gender g and cohort k is:

$$I_{gk} = I_{gk}^{N}[1-(1/\underline{x}_{gk}^{P})^{\beta}] + I_{gk}^{A}(1/\underline{x}_{gk}^{R})^{\beta} + I_{gk}^{D}[(1/\underline{x}_{gk}^{P})^{\beta} - (1/\underline{x}_{gk}^{R})^{\beta}].$$

The average labor supply by researchers of gender g and cohort k who would never choose to have children is:

$$Z_{gk}^{N} \equiv \frac{\int_{\underline{z}_{gk}^{N}}^{\infty} z\mathrm{P}(z|z^{s} > \underline{z}_{gk}^{s\text{-}N})\mathrm{d}z}{\mathrm{P}(z > \underline{z}_{gk}^{N} | z^{s} > \underline{z}_{gk}^{s\text{-}N})} = \frac{\mathcal{Z}\omega_{k}^{P}}{(1-\tau_{gk}^{L})\omega_{k}^{R}}$$

where the constant $\mathcal{Z}$ is defined as:

$$\mathcal{Z} \equiv \frac{\theta_{n}\theta_{s}[(\vartheta_{n}\Gamma)^{\theta_{s}}/(\theta_{s}-1) - (\vartheta_{n}\Gamma)^{\theta_{n}}/(\theta_{n}-1)]}{\theta_{n}(\vartheta_{n}\Gamma)^{\theta_{s}} - \theta_{s}(\vartheta_{n}\Gamma)^{\theta_{n}}}.$$

The average labor supply by researchers of gender g and cohort k who would always choose to have children is:

$$Z_{gk}^{A} \equiv \frac{\int_{\underline{z}_{gk}^{A}}^{\infty} z[(1-\tau_{gk}^{C})\alpha]^{1+\delta}\mathrm{P}(z|z^{s} > \underline{z}_{gk}^{s\text{-}A})\mathrm{d}z}{\mathrm{P}(z > \underline{z}_{gk}^{A}|z^{s} > \underline{z}_{gk}^{s\text{-}A})} = \alpha Z_{gk}^{N}$$

The average labor supply by researchers of gender g and cohort k who would only choose to have children if they were to work in production is:

$$Z_{gk}^{D} \equiv \frac{\int_{\underline{x}_{gk}^{P}}^{\underline{x}_{gk}^{R}} \frac{\int_{\underline{z}_{gk}^{D}(x)}^{\infty} z\mathrm{P}(z|z^{s} > \underline{z}_{gk}^{s\text{-}D}(x))\mathrm{d}z}{\mathrm{P}(z > \underline{z}_{gk}^{D}(x)|z^{s} > \underline{z}_{gk}^{s\text{-}D}(x))} \beta x^{-\beta-1}\mathrm{d}x}{\int_{\underline{x}_{gk}^{P}}^{\underline{x}_{gk}^{R}} \beta x^{-\beta-1}\mathrm{d}x} = \frac{\beta}{\beta-1} \cdot \frac{1-[(1-\tau_{gk}^{C})^{1+\delta}\alpha^{\delta}]^{\beta-1}}{1-[(1-\tau_{gk}^{C})^{1+\delta}\alpha^{\delta}]^{\beta}} \cdot Z_{gk}^{N}.$$

The fraction of individuals from cohort k in period t is equal to $be^{-b(t-k)}$. Denoting average consumption within cohort k as $c_t(k)$ delivers the following expression for average consumption in the economy:

$$c_t = \int_{-\infty}^{t} be^{-b(t-k)} c_t(k)\mathrm{d}k.$$

Differentiating with respect to time and using the Euler equation:

$$\dot{c}_t = (r_t - \rho - d)c_t - b[c_t - c_t(t)].$$

Substituting in the consumption function and the asset market clearing condition:

$$\dot{c}_t = (r_t - \rho - d)c_t - b(\rho + d)[q_t M_t / N_t + H_t - H_t(t) - a_t(t)]$$

where $a_t(t)$ is the average financial wealth across the most recent cohort, and H_t and $H_t(t)$ denote average human wealth across all cohorts and in the most recent one, respectively. Average human wealth H_t across all cohorts is given by:

$$H_t \equiv \frac{\sum_g \omega_t^{P} L_{gt}}{2N_t} + \frac{\sum_g (1-\tau_{gt}^{R})\omega_t^{R} R_{gt}}{2N_t}$$

where the laws of motion for L_t and R_{gt} are given by:

$$\dot{L}_{gt} = L_{gt}(t) - dL_{gt} \quad \text{and} \quad \dot{R}_{gt} = R_{gt}(t) - dR_{gt}$$

and where we have the additional definitions:

$$
\begin{aligned}
L_t(t) &\equiv [1-(1/\underline{x}_{gt}^P)^\beta + \alpha(1/\underline{x}_{gt}^P)^\beta](1-I_{gt})bN_t, \\
R_{gt}(t) &\equiv \{Z_{gt}^N I_{gt}^N[1-(1/\underline{x}_{gt}^P)^\beta] + Z_{gt}^A I_{gt}^A(1/\underline{x}_{gt}^R)^\beta + Z_{gt}^D I_{gt}^D[(1/\underline{x}_{gt}^P)^\beta - (1/\underline{x}_{gt}^R)^\beta]\}bN_t.
\end{aligned}
$$

Average human wealth $H_t(t)$ across the most recent cohort is given by:

$$
H_t(t) \equiv \frac{\sum_g \omega_t^P L_{gt}(t)}{2bN_t} + \frac{\sum_g (1-\tau_{gt}^R)\omega_t^R R_{gt}(t)}{2bN_t}.
$$

To find an expression for the average financial wealth of the most recent cohort, it is useful to first note that the probability that a person decides to pursue research conditional on completing a STEM degree is independent of one's fertility preferences and given by:

$$
S^R \equiv \frac{\theta_n(\vartheta_n\Gamma)^{\theta_s} - \theta_s(\vartheta_n\Gamma)^{\theta_n}}{\theta_n - \theta_s}.
$$

The average financial wealth of the most recent cohort is then:

$$
a_t(t) = \sum_g \{a_{gt}^N(t)[1-(1/\underline{x}_{gt}^P)^\beta] + a_{gt}^A(t)(1/\underline{x}_{gt}^R)^\beta + a_{gt}^D(t)[(1/\underline{x}_{gt}^P)^\beta - (1/\underline{x}_{gt}^R)^\beta]\}/2
$$

where we have the additional definitions:

$$
\begin{aligned}
a_{gt}^N(t) &= -\epsilon\omega_t^P(1/\underline{z}_{gt}^{s\text{-}N})^{\theta_s}[1+(\mathcal{Z}-1)S^R], \\
a_{gt}^A(t) &= -\epsilon\omega_t^P(1/\underline{z}_{gt}^{s\text{-}A})^{\theta_s}\alpha[1+(\mathcal{Z}-1)S^R], \\
a_{gt}^D(t) &= -\epsilon\omega_t^P(1/\underline{z}_{gt}^{s\text{-}N})^{\theta_s}\frac{\beta}{\beta+\theta_s}\cdot(1/\underline{x}_{gt}^P)^\beta[1-(\underline{x}_{gt}^P/\underline{x}_{gt}^R)^{\beta+\theta_s}][(1-S^R)/\underline{x}_{gt}^P + S^R\mathcal{Z}_{gt}^D],
\end{aligned}
$$

and where the term $\mathcal{Z}_{gt}^D$ is defined as:

$$
\mathcal{Z}_{gt}^D \equiv \frac{\beta\mathcal{Z}}{\beta-1}\cdot\frac{1-(\underline{x}_{gt}^P/\underline{x}_{gt}^R)^{\beta-1}}{1-(\underline{x}_{gt}^P/\underline{x}_{gt}^R)^\beta}.
$$

Finally, the laws of motion for Δ_t, ω_t^P and ω_t^R are:

$$
\dot{\Delta}_t = (\rho+d)\Delta_t - \frac{r_t}{\rho+d}, \quad \dot{\omega}_t^P = r_t\omega_t^P - w_t^P \quad \text{and} \quad \dot{\omega}_t^R = (r_t+\delta)\omega_t^R - w_t^R.
$$

Define the normalized variable $x_t^* \equiv x_t e^{-g_x t}$ such that g_x is the balanced growth rate of variable x_t and let $N_t^* = 1$ for all t. Then, collecting the above and performing some simple substitutions, we obtain the system of ordinary differential-algebraic equations describing the dynamics of the equilibrium allocation:

$$
\begin{aligned}
\dot{c}_t^* &= (r_t - \rho - d - g_c)c_t^* - b(\rho + d)[q_t^* M_t^* + H_t^* - H_t^*(t) - a_t^*(t)],\\
\dot{L}_{gt}^* &= L_{gt}^*(t) - bL_{gt}^*,\\
\dot{R}_{gt}^* &= R_{gt}^*(t) - bR_{gt}^*,\\
\dot{\omega}_t^{P*} &= (r_t - g_c)\omega_t^{P*} - w_t^{P*},\\
\dot{\omega}_t^{R*} &= (r_t - g_c)\omega_t^{R*} - w_t^{R*},\\
\dot{M}_t^* &= M_t^{*\phi} \textstyle\sum_g R_{gt}^*/2 - g_M M_t^*,\\
\dot{q}_t^* &= (r_t - g_q)q_t^* - c_t^*/(\sigma M_t^*),\\
\dot{\Delta}_t &= (\rho + d)\Delta_t - r_t/(\rho + d),\\
w_t^{R*} &= q_t^* M_t^{*\phi},\\
w_t^{P*} &= (c_t^* M_t^*)^{1/\sigma}/\mu,\\
c_t^* &= M_t^{*1/(\sigma-1)} \textstyle\sum_g L_{gt}^*/2,
\end{aligned}
$$

where we have the additional definitions:

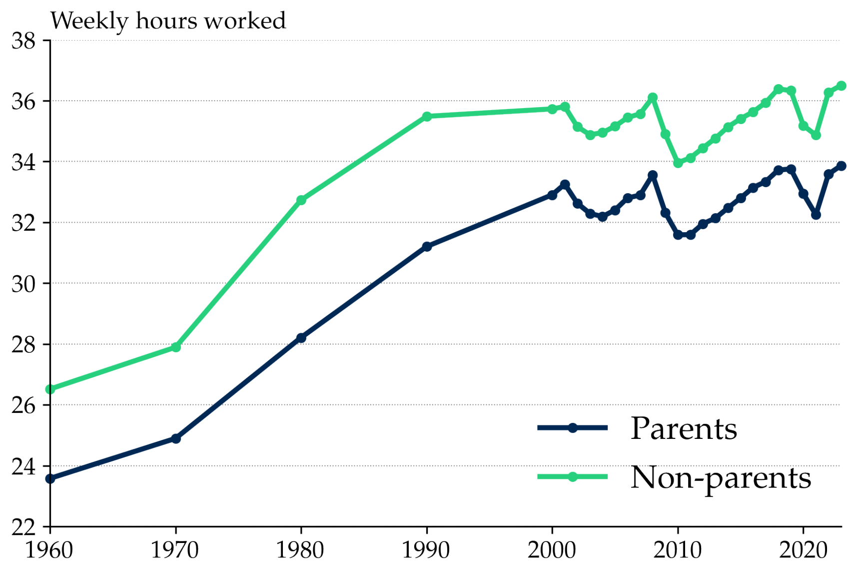
$$
g_c \equiv \frac{n}{(\sigma - 1)(1 - \phi)}, \quad g_M \equiv \frac{n}{1 - \phi}, \quad \text{and} \quad g_q \equiv n + g_c - g_M.
$$

The steady state of the model is found by setting all time derivatives to zero and solving the resulting nonlinear system of equations.

B Empirical Appendix

B.1 Additional Figures and Tables

Figure B.1: Weekly Hours Worked by Parenting Status



Note: Parents work less than their childless peers. Author's calculation using data from the U.S. Decennial Census and ACS.

Table 4: "Greedy Work" Parameter Estimation

Variable	Coefficient
Intercept	2.762
	(0.007)
ln(hours)	-0.064
	(0.000)
ln(hours) $\times$ Researcher	0.004
	(0.000)
ln(hours) $\times$ Lawyer	0.006
	(0.000)
ln(hours) $\times$ Doctor	0.011
	(0.000)
Observations	11,852,518

Note: The controls include second degree polynomials in age and experience, as well as education, occupation, state, race, marital status, year, gender, and occupation $\times$ gender fixed effects.