Institute for Empirical Research in Economics
University of Zurich

Working Paper Series
ISSN 1424-0459

Working Paper No. 491

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The Realization of Women's Comparative Advantage

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Revised version, June 2017

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June 28, 2017

ABSTRACT

In the last decades the US economy experienced a rise in female labor force participation, a reversal of the gender education gap and a closing of the gender wage gap. Importantly, these changes occurred at a substantially different pace over time. During the same period, workers in the US faced a considerable shift in labor demand from more physical to more intellectual skill requirements. I rationalize these observations in the context of a general equilibrium model displaying two key assumptions: (1) the demand for brain increases both within and across education groups; and (2) women have less brawn than men. Given the observed US technical change process, the model replicates (1) over half of the narrowing gender wage gap, (2) most of the narrowing employment gap, and (3) all of the reversing education gap. Crucially, the model can also account for the time-varying-path of the narrowing gender divide with an initial stagnation and a later acceleration in female wages and education rates.

JEL classification: E23, I24, J16, J23, J24.
Keywords: technological progress, labor demand, skills, female labor supply, gender education gap, gender wage gap, college attainment.

*I would like to thank, among others, Russell Cooper, Dean Corbae, Fatih Guvenen, Alessio Moro, Kjetil Storesletten, and Fabrizio Zilibotti as well as seminar and conference participants at Brandeis University, Congressional Budget Office, SED Conference in Montreal, Stanford Institute for Theoretical Economics - Summer Workshop, the University of Texas at Austin, University of Oslo, University of Zurich, Uppsala University, Wellesley College, 2nd Nordic Summer Symposium in Macroeconomics, and NEUDC Conference at Harvard University for valuable comments. Financial support from the European Research Council (ERC Advanced Grant IPCDP-229883) and and the centre of Equality, Social Organization, and Performance (ESOP) supported by the Research Council of Norway is gratefully acknowledged.

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1 Introduction

One important and dramatic social phenomena of the 20th century has been the rise in female labor force participation, coupled with a rise in broad college attainment and a closing of the gender wage gap. Many complementary theories explaining the rise in female labor force participation have been proposed. In contrast, the determinants of the evolution of female wages has remained largely unexplained and the reversal of the gender education gap has been difficult to replicate in standard economic models.[1] The main challenge is finding a mechanism that can account both for the closing gender gaps and the time-varying speed of convergence of these gaps. The gender education and wage gaps close at an accelerating speed only starting in the 1980s, although women have entered the economy at a mostly constant rate since World Ward II. One potential explanation for this acceleration is recent technical change that favored women's innate abilities. Goldin (1990, pp. 108-109), using data from the 1920s and 1930s, suggests that women's lower earnings stemmed from the rewards to strength in manufacturing. While many studies have shown that increasing human capital demand (and investment) can explain male wage divergence across education groups over the last decades,[2] the same theory has not been applied to account for the time-varying gender gaps. In this spirit, my goal is to quantify how much of the *time-varying* gender convergence in labor force participation, wages and education can be explained by a changing demand, shifting from physical labor ("brawn") to intellectual abilities ("brain").

I begin by establishing four facts on brain and brawn requirements in the labor market that have not been previously reported. First, women have historically tended to work in occupations with less brawn requirements than men, especially in unskilled jobs. Second, aggregate trends show a strong labor demand shift from brawn to brain for the unskilled, but less so for the skilled. Third, over time both skilled and unskilled women shift increasingly into occupations requiring a higher

[1] See for example Fogli and Veldkamp (2011); Ngai and Petrongolo (2017) for the former and Guvenen and Rendall (2015) for the latter.

[2] See for example Becker (1994); Juhn, Murphy and Pierce (1993); Guvenen and Kuruscu (2010).

share of brain, but there is no similar trend for men. Fourth, the data shows a strong rise in the returns to brain over brawn for both the unskilled and skilled, with the relative rise being twice as large for college educated workers.

These facts suggest that a shift in labor demand requirements from brawn to brain, due to technical change, might have a positive effect on women's labor force participation, education and wages if women have an innate comparative advantage in brain over brawn.[3] To formalize this hypothesis, I build a general equilibrium model with two key assumptions: (1) the demand for brain increases both within and across education groups; and (2) women have less brawn than men. Moreover, to capture the effect of technical change across all gender and educational attainment groups I assume two types of technical change: (1) standard skill-biased technical change (SBTC) increasing labor productivity of college-educated individuals; and (2) brain-biased technical change (BBTC) increasing labor productivity of brain over brawn inputs, both in educated and uneducated jobs.

On the labor demand side, a representative firm faces these two types of exogenous technical change, with both shifting demand towards brain inputs. Production is modeled as an aggregate constant elasticity of substitution (CES) production function of college and non-college labor. In addition, each labor-education type has a CES production function of brain- and brawn-inputs. BBTC occurs starting in the 1960s and SBTC, following the literature, starts in the late 1970s.[4]

On the supply side, overlapping generations of finitely-lived agents maximize household consumption each period. Before reaching working-age, agents first decide on obtaining a college education, and are then married with assortative mating probabilities or remain single forever. Agents are heterogenous in innate brain and brawn. Therefore, depending on current skill wage

[3]Some occupational groups document clearly how men have a comparative advantage in brawn compared to women. In sports, male brawn records tend to exhibit higher physical strength than women's equivalent records, e.g., the fastest recorded male tennis serve is 35 percent faster (Glenday, 2013). A similar conclusion can be drawn from a BBC News Online (2002) article about the British military barring women from frontline combat since they failed to pass the required physical test in 2002.

[4]Given the temporary effects of World War II on women's labor market participation and wages (see Acemoglu, Autor and Lyle, 2004) and general data availability, the quantitative analysis focuses on the 1960s onwards.

rates, agents differ in their willingness to work in the labor market and devote time to home production. With lower innate brawn endowments, women who work will generally have lower wages than men. With a fall in the returns to brawn and a rise in the returns to brain, women's comparative advantage in brain allows for a catch up in employment levels and wages. Individuals also account for expected income, a function of brain and brawn market prices, when deciding on their education. Higher ability women may stay out of the labor market when brawn is more valuable or the returns to brain are low, thus obtaining less education compared to men with the same innate brain.[5] Over time, women may then surpass men in educational attainment, given their comparative advantage, or greater dependence, in brain for higher wages. Lastly, I allow for changes in home productivity.[6]

The model is calibrated to match various 1960 US data moments on employment, wages and education; three wage trends from 1960 to 2010; and the rise in the share of male college graduates from 1960 to 2010. The base calibration is able to replicate 80 percent of the closing aggregate gender participation gap and 91 percent of the closing married gender participation gap. It also replicates all the gender education reversal and 59 percent of the closing gender wage gap.

The base model is also able to address one of the main challenge in the literature, that is, the mechanism here is not only able to replicate the closing gender gaps, but also generates a time-varying speed of convergence of the wage and education gaps. This is the consequence of three effects on women's average wages: (1) a positive skill price effect, (2) a negative labor supply effect, and (3) a positive education-labor supply effect. As these three effects dominate at different instances in time the model generates a non-linear path of convergence. More specifically, women benefit from increasing returns to brain given their comparative advantage. However, as

[5]Assortative matching in the marriage market could off-set this effect by inducing women to educate even when market returns are low in order to find a high-earning spouse. But this effect should be relatively random across the female ability distribution.

[6]That changes in home productivity can explain part of the rise in female employment is a well-established fact. Improvements in home technology, such as the invention and marketization of household appliances (see, for example, Greenwood, Seshadri and Yorukoglu, 2005, and references therein), or the improvements in baby formulas (see Albanesi and Olivetti, 2016), enabled women to enter the labor market.

all women's wages increase with BBTC, women with relatively lower brain endowments enter the labor market creating a negative selection effect, especially during the earlier period.[7] Following this period, given women's comparative advantage in brain and the complementarity between brain and education, with sustained SBTC women surpass men in college attainment and create a positive labor supply effect. In summary the interaction between both types of technical change is key in shaping the changing selection of women into the labor market, leading to a varying time-path of both for the education and wage gap convergence.

Given the success of the model in generating a large convergence in employment and consistent time-varying changes in the gender education gap and the gender wage gap, I use the model to perform three types of counterfactual experiments. First, removing SBTC, BBTC and gender differences in brawn, I show that, the model can replicate the closing gender wage gap by allowing for gender wage discrimination to initially exist and subsequently decrease at a constant rate. However, this counterfactual experiment shows that disappearing gender discrimination cannot generate a time-varying path in the convergence of wages. In order to generate a non-linear path, the model would require a shock/event that changed the level of discrimination in the 1980s. In addition, a fall in gender discrimination leads to less female college attainment than in the benchmark, as a fall in discrimination benefits all women equal. That is, falling gender discrimination does not amplify high-ability women's larger comparative advantage in brain - a skill complementary to education. The second set of counterfactuals removes SBTC and BBTC individually and in combination to provide insight into which type of technical change drives which gender gap. Traditional SBTC is the exclusive driver for the gender education reversal, but SBTC and BBTC together shape wage changes. In the last counterfactual, home productivity is kept at the 1960s level. Removing home productivity does have a small quantitative effect on the closing gaps, but does not alter the time-varying shape of the gender convergence.

[7] The effect on the gender wage gap is ambiguous. The gender gap will widen if the negative supply effect dominates and close if the positive price effect dominates.

The remainder of the paper is organized as follows. Section 2 discusses the related literature; Section 3 establishes some novel facts on labor demand requirements and related returns in the US; Section 4 presents a partial equilibrium toy model to provide insight on the theory; Section 5 generalizes the model to a general equilibrium framework for the quantitative analysis; Section 6 discusses the calibration; Section 7 provides the benchmark results and the three counterfactual exercises; and Section 8 concludes.

2 Literature Review

The paper considers changes in labor demand requirements on agents' optimal education and labor supply decisions. It connects three related strands of literature on: (1) technical change; (2) gender education; and (3) female labor supply.

Jones, Manuelli and McGrattan (2015) explain a large rise in female participation by an exogenously closing wage gap. In Rendall (2015) I use, in addition to the exogenously closing wage gap, structural change to explain rising female employment, while Olivetti (2006) does so with an exogenous increase in returns to experience for women. Thus, by modeling gender differences in innate labor market skills and allowing for technical change, I provide a possible underlying mechanism for observed increases in female wage returns taken as given in these studies.

Ngai and Petrongolo (2017) focus on determining how much of the closing gender wage and employment gaps can be explained by structural change. Productivity differences are modeled by assuming that women have a comparative advantage in services over manufacturing. The authors find that structural change can account for 20 percent of the closing gender wage gaps and half of the rise in hours worked. As explained in their paper, the theory of *brain versus brawn* can provide a micro foundation for gender productivity differences across sectors. Indeed, in Appendix A, I show that broad sectors (services/manufacturing) provide a reduced form of explicitly modeling the skill inputs of brain and brawn. However, this reduced form cannot be used to study the effects of SBTC or BBTC on gender gaps, as there are a number of low-skilled service jobs that require substantial brawn skills (e.g., waiters, cleaners). By not relying on endogenous structural transformation, I am able to contrast the effect of SBTC - a standard theory in explaining rising male wage inequality - versus BBTC on gender employment, education and wage outcomes.

Hsieh et al. (2013) study the convergence in occupational choices between men and women. Their focus in not on explaining this convergence through technical or structural change but rather a reduction in labor market frictions. Studying the same time period (1960 onwards), the authors find that decreasing frictions leading to a convergence in occupational choice accounting for 15 to 20 percent of growth in aggregate output. The theory of frictions is complementary to the mechanism proposed here.

Fogli and Veldkamp (2011) focus on the effects of cultural, social, and intergenerational learning on female labor supply. An extension aims to explain the evolution of wages through women's changing self-selection bias in the 20th century. The model is unable to match the complete wage evolution, matching either the initial stagnation or the later rise in relative female-to-male wages. In this paper, technical change complements the theory of social learning, explaining part of both the period of stagnating and the later closing gender wage gap.

The hypothesis that changing technological progress affects the gender wage gap has also been analyzed in econometric studies with different conclusions. Wong (2006) finds that SBTC has a similar impact on men's and women's wages and, therefore, cannot explain the closing wage gap. Black and Spitz-Oener (2010) quantify the contribution of changes in specific job tasks on the closing wage gap from 1979 to 1999 for West Germany. The authors find that SBTC in West Germany, especially through the adoption of computers, can explain about 41 percent of the closing wage gap. While these two studies estimate the effects of relative labor demand changes on the wage gap, both assume an inelastic labor supply. Consequently, they cannot address the non-linear path of average female-to-male wages stemming from women's self-selection bias into the labor market and changing education choices - both components that are crucial in explaining the transition of women in my theory.

In terms of methodology this paper is most closely related to Galor and Weil (1996), who suggest that women have entered the labor market when technological change shifted labor demand away from brawn requirements. A similar explanation of technical change (intellectual versus raw ability) has been used by Guvenen and Kuruscu (2010) in explaining the rise between and within male wage inequality in the US since 1970. The authors focus on men and the human capital accumulation decision over the life-cycle. The approach of skill differentiation also relates to Autor, Levy and Murnane (2003), who analyze how changes in the skill content of occupations, through recent technological change, has affected the demand for college labor. Since the authors look at recent technical change and the effect of the computer, they focus on differences in "routine" and "non-routine" tasks.

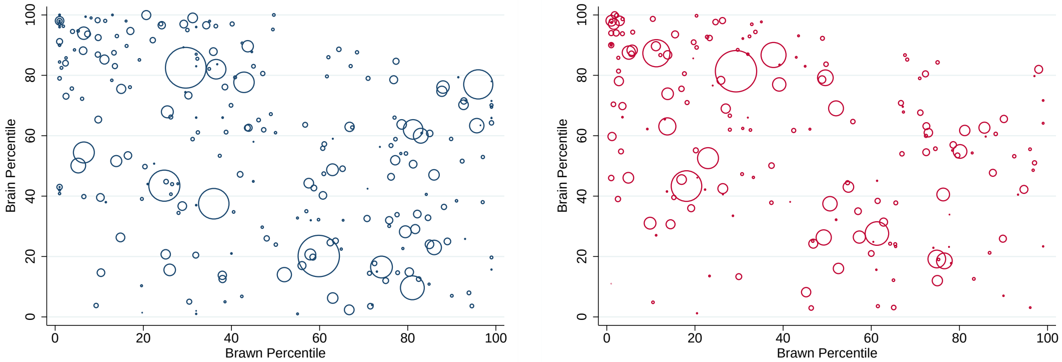
3 Empirical Trends

This project starts from the premise that women have, on average, less brawn than men. No good dataset with individual's brain and brawn skills exits. However, the Fourth Edition (1977) and Revised Fourth Edition (1991) of the Dictionary of Occupational Title (DOT) allow for a consistent construction of such measures by US census occupations.[8] The surveys were developed by the US Department of Labor, who evaluated approximately 40 job requirements for more than 12,000 occupations. Using a selected set of these 40 job requirements, I compute brain and brawn measures across occupations and time.[9] Assuming that women and men have similar levels of brain, men have a comparative advantage in the labor market if work is brawn-intensive. US Census/CPS survey data merged with the DOT skill measures suggests that labor demand (due to both SBTC and

[8]The occupational skill measures from the 1991 DOT were updated on a rolling basis from 1977 until 1991. The survey was replaced by O*net in 2001. This replacement was accompanied by a reworking of the survey method and content, making it impossible to construct consistent brain and brawn measure across the DOT surveys and O*net. Given the historic long-run perspective of this paper, I have chosen to work with the two digitalized DOT surveys covering the largest stretch of the time periods studied here.

[9]For details on the construction of measures see Appendix A.

Figure 1: *Brain and Brawn Occupation Combinations*



(a) 1977 DOT Factors in 1960 (b) 1991 DOT Factors in 2010

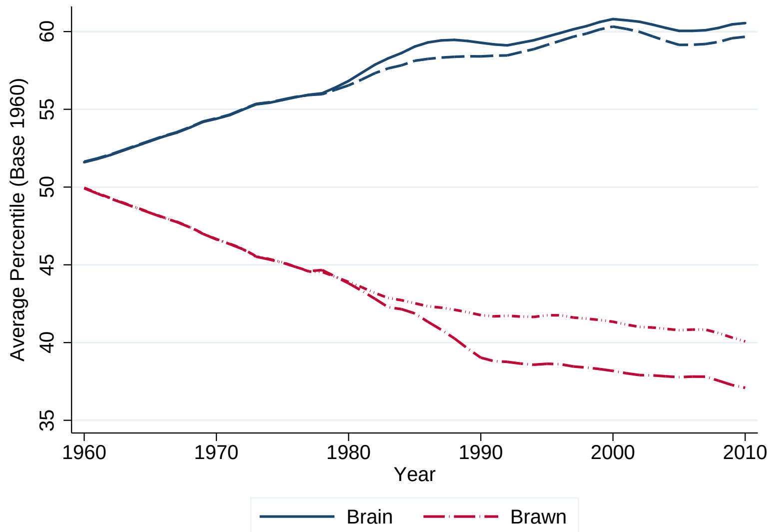
Source: 1977 and 1991 DOT skill requirements by 3-digit 1950 IPMUS occupational codes. See Appendix A for details on the computation of skill measures. Employment shares by 3-digit occupation are computed from 1960 US Census and 2010 March CPS data, respectively. Weekly hours worked, weeks worked per year and the provided survey weights for individuals aged 25-64 are multiplied to compute efficiency units of labor.

BBTC), has been shifting toward low-brawn occupations, eroding men's comparative advantage in the labor market.

Figure 1 plots occupational brain and brawn combinations weighted by the 1960 Census and 2010 CPS employed population, respectively. Since skills have no natural scale, they are normalized to percentiles of the 1960 US skill distributions using 1960 Census population weights of individuals aged 25 to 65. The size of each circle corresponds to its relative employment share, with total employment normalized to one in each year. Two facts emerge: (1) there is large variance in brain and brawn requirements across the economy; and (2) a striking disappearance of high brawn occupations by 2010 (compare the left and right panels).

Figure 2 shows the evolution of aggregate skill requirements. Labeled lines exploit both changes within and across occupations. That is, averages use the 1977 DOT until 1976, a weighted combination of 1977 and 1991 DOT characteristics until 1991, and 1991 DOT factor estimates from 1991 onward. The dashed lines provide 1977 DOT average changes related only to compositional changes in occupation/industry employment distributions. A diverging trend in favor of brain can be seen and is a likely indication of BBTC. Note that most of the change is driven by the "extensive" margin. However, brawn demand sees a sharper fall using both within and across

Figure 2: *Labor Requirements over Time*



Source: 1977 and 1991 DOT skill requirements by 3-digit 1950 IPMUS occupational codes. See Appendix A for details on the computation of skill measures. To compute percentile changes, employment shares by 3-digit occupation are computed from 1960 US Census and 1968-2010 March CPS data. Weekly hours worked, weeks worked per year and the provided survey weights for individuals aged 25-64 are multiplied to compute efficiency units of labor.

occupation changes, suggesting that not updating beyond 1991 due to data limitations makes this is a conservative lower bound in BBTC (i.e., any change of skills within occupations post-1991 is not captured).

Since much of the shift is due to compositional occupation changes, part of this shift towards brain could be captured by a rise of college occupations (traditional SBTC).[10] Table 1 decomposes the aggregate skill trend by education and by education/gender groups. The data is segregated by individuals with at least a four-year college degree (C+) and the working age population with no formal college degree (LTC). For comparison purposes, relative brain-to-brawn skill requirements normalized in 1960 by aggregate education groups are reported. Evidence of BBTC for non-college graduates is considerably stronger than for college graduates, with relative brain requirements increasing by 27 percent for the LTC group. In contrast, there is only a small increase for college graduates. Keeping the same education-normalization, the 1960 values suggest that

[10]Decompositions by broad sectors are left to the Appendix A (see Figure A.2).

Table 1: *Change in Labor Requirements by Education and Gender*

Group	**1960**	**2010**	**Δ**
Aggregate	1.00	1.58	0.58
By Education			
C+	1.00	1.02	0.02
LTC	1.00	1.27	0.27
By Education and Gender			
Men C+	1.05	1.01	-0.04
Men LTC	0.97	1.03	0.06
Women C+	0.82	1.03	0.21
Women LTC	1.17	1.86	0.69

Source: 1977 and 1991 DOT skill requirements by 3-digit 1950 IPMUS occupational codes. See Appendix A for details on the computation of skill measures. To compute relative labor requirements, the ratio of average brain and brawn skills by group is taken. Average skills are computed using employment shares by year computed from 1960 US Census and 2010 March CPS data as in Figure 1. The resulting ratios are normalized using the 1960 ratios by broad education group (C+ and LTC) irrespective of gender.

LTC women have always worked in relatively higher brain occupation than their male counterparts, while C+ college women have traditionally worked in relatively lower brain occupations (1.17 versus 0.97 and 0.82 versus 1.05, by education type respectively). That educated women worked in occupations requiring relatively less brain points to negative self-selection by ability in 1960. Although aggregate BBTC has been small for college graduates, skilled women have seen a sizable rise in their relative brain-to-brawn requirement of 21 percent. This change over time for college graduate women suggests a "catching up" or a change in self-selection from negative to positive. This is also consistent with evidence found by Hsieh et al. (2013) in that by 2010 college men and women work in similar types of occupations. Overall, unskilled women have seen the largest change with a 69 percent increase in their brain to brawn skill ratio.

The previous evidence only provides a partial equilibrium aspect of technological change capturing changing labor requirements. Relative prices of these inputs could also be affected. To provide some evidence related to relative prices, I make use of CPS wage data combined with the DOT. Given that the DOT only provides information on job requirements (not workers), I assume that *on average* male workers match *efficiently/correctly* to jobs. Using b to denote brain skills and

r to denote brawn skills, the wage for individual i in occupation j is,

$$w_t^i = w_{b,t}\overline{b}b_j + w_{r,t}\overline{r}r_j + \varepsilon_t^i \text{ for all } t, \tag{1}$$

where $\{w_b, w_r\}$ are skill prices (wage rates), $\{\overline{b}, \overline{r}\}$, are the total (largest) skill amount available, $\{b_j, r_j\}$ are brain and brawn percentiles,[11] and $\varepsilon_{j,t}$ is an error term. Since, $w_{b,t}\overline{b}$ and $w_{r,t}\overline{r}$ are not separately identifiable, an assumption needs to be imposed to obtain brain and brawn returns over time. To estimate $\overline{b}$ and $\overline{r}$, Equation (1) can either be estimated for a base year, assuming $w_{b,0} = w_{r,0} = 1$, or it can be estimated using all time periods jointly, implicitly assuming that average returns over the entire period equal one. The two assumptions produce similar results. Only the results to the second method are provided. To account for the effect of education on brain returns, the regression to determine $\overline{b}$ and $\overline{r}$ also includes an interaction of brain and education.[12] Skill quantities follow from regressing individual wage residuals (controlling for region, race, marital status and age) on brain, brawn and an individual's education,

$$w_t^i = \alpha_b b_j + \alpha_r r_j + \alpha_e b_j e^i + \varepsilon_t^i, \tag{2}$$

where $e^i = 1$ if the individual has a college degree and zero otherwise. Implicitly, $\{\overline{b}, \overline{r}\}$ are constant over time, similar to the data. It is conceivable that $\overline{b}$ has grown, but given data availability it is difficult to verify or estimate. Using the estimates from Equation (2), we can then estimate brain and brawn ($w_{i,t}$) skill prices for a given time period t by,

$$\overline{w}_{j,t} = w_{b,t}\left(a_b + a_e e_j\right) b_j + w_{r,t} a_r r_j + \varepsilon_{j,t} \text{ for all } t, \tag{3}$$

where a_i are the coefficient estimates from Equation (2).

[11] Since skills are normalized from zero to 100 on a percentile distribution, a skill of zero can be interpreted as using zero percent and a skill of 100 using 100 percent of the skill available.

[12] A specification also allowing for an interaction between education and brawn shows that brawn returns are on average not statistically different across education groups.

Table 2 summarizes the estimated relative brain-to-brawn wage changes.[13] On aggregate, relative returns grew by 36 percent, where the increase is more than twice as high for college educated individuals than other workers, 54 versus 21 percent, respectively.

Table 2: *Change in Relative Brain-to-Brawn Returns*

Group	**1965**	**2005**	**Δ**
Aggregate	-0.09	0.27	0.36
By Education			
C+	-0.27	0.27	0.54
LTC	-0.09	0.12	0.21

Source: 1977 and 1991 DOT skill requirements by 3-digit 1950 IPMUS occupational codes. See Appendix A for details on the computation of skill measures. Relative returns are the difference of average brain and brawn skills prices by group. Average skills prices are computed according to in Equations (1) and (2) by using wage residuals after controlling for experience, race and region of full-time full-year male workers adjusted by individuals' survey weights from 1968-2007 March CPS data.

Given the above facts, this study argues that, after World War II, women entered the labor market and their average wages improved due to the rise of brain-demand, which complemented women's comparative advantage.

4 Toy Model

The underlying forces of the model simulated in Sections 5-7 are best demonstrated in a simplified partial equilibrium version. Assume a unit measure of men and women, who are all single and live one period, with utility functions linear in consumption, $u(c_t^i) = c_t^i$, where $c_t^i = \max\{w_t^i, A_h\}$. Agent i chooses between working and earning wage w_t^i or staying at home and consuming home production A_h. Individuals decide on attending college, $e \in \{0,1\}$, to increase their innate brain ability by a factor $\varepsilon > 1$ at the beginning of the period. Attending college produces a utility cost of $\chi > 0$. Wages are a function of an agent's acquired brain and innate brawn, that is $w_t^i = w_{b,t} b^i(e) + w_{r,t} r^i$, where $b^i(e) = b^i \varepsilon$, if the individual attends college, and $b^i(e) = b^i$ otherwise. Let

[13] For consistency, only CPS wage data is used in computing wage trends. Due to the financial crisis, any data beyond 2007 is also dropped. All detailed results are available from the author upon request.

all men have equal brawn, r^m, and all women have less brawn, $r^f < r^m$. Innate brain is distributed identically for everyone, $b^i \sim U[b_l, b_h]$. Furthermore, assume that all men work, $w_{b,t}b_l + w_{r,t}r^m \geq A_h$, but women's brawn is such that low-brain women do not work, $w_{b,t}b_l + w_{r,t}r^f < A_h$. Thus, a woman works if and only if,[14]

$$b^i(e) \geq \frac{A_h - w_{r,t}r^f}{w_{b,t}} \equiv \hat{b}_t^f. \tag{4}$$

Substituting for brain acquired through schooling, $b^i(e) = b^i\varepsilon$, the college education decision for a male i is,

$$\left(w_{b,t}b^i\varepsilon + w_{r,t}r^m\right) - \chi \geq \left(w_{b,t}b^i + w_{r,t}r^m\right), \tag{5}$$

or men study if and only if,

$$b^i \geq \frac{\chi}{w_{b,t}(\varepsilon - 1)} \equiv \hat{b}_t^{m,e}. \tag{6}$$

The male cut-off for education, $\hat{b}^{m,e}$, is an increasing function of the cost of education, but a decreasing function of the returns to brain, both in wages and acquired brain. If all women work, women would have the same cut-off, $\hat{b}^{f,e} = \hat{b}^{m,e}$. However, since some women remain home if r^f is low enough, the education decision follows from,

$$\max\left\{\left(w_{b,t}b^i\varepsilon + w_{r,t}r^f\right), A_h\right\} - \chi \geq \max\left\{\left(w_{b,t}b^i + w_{r,t}r^f\right), A_h\right\}. \tag{7}$$

The cut-off is a function of home productivity, $\hat{b}^{f,e}(A_h)$. Moreover, this cut-off is greater than or equal to the male cut-off, $\hat{b}^{f,e}(A_h) \geq \hat{b}^{m,e}$, since women who choose to stay home gain nothing from education, but still pay the cost, χ. In an economy with high returns to brawn this outcome is more likely.

[14] Given the empirical evidence on women's self-selection into work changing from negative to positive (Mulligan and Rubinstein, 2008), the general equilibrium model is amended to allow for potential changes in selection through assortative matching in marriage.

4.1 Evolution of Labor Supply and Wages under BBTC

Given the above assumptions, men's labor force participation equals one and women's equals,

$$LFP_t^f = \int_{\hat{b}_t^f}^{b_h} dF(b) = \frac{b_h - \hat{b}_t^f}{b_h - b_l}. \tag{8}$$

If BBTC raises $\frac{w_{b,t}}{w_{r,t}}$, this leads to a fall in $\hat{b}_t^f$ and a rise in female employment, i.e., BBTC closes the gender employment gap. Similarly, with relative low brain returns and $\hat{b}_t^{f,e}(A_h) > \hat{b}_t^{m,e}$, BBTC closes the gender education gap.

Using Equation (4), if one becomes educated (high χ), average female wages are,

$$\overline{w}_t^f = w_{b,t}E(b^f) + w_{r,t}r^f = 0.5\left(w_{b,t}b_h + w_{r,t}r^f + A_h\right), \tag{9}$$

where $E(b^f)$ is the average brain supply of women conditional on the working population.

$$E(b^f) = \frac{\int_{\hat{b}_t^f}^{b_h} b\, dF(b)}{LFP_t^f} = 0.5\left(b_h + \hat{b}_t^f\right). \tag{10}$$

Similarly, male wages (without education) are,

$$\overline{w}_t^m = w_{b,t}E(b^m) + w_{r,t}r^f = 0.5w_{b,t}(b_h + b_l) + w_{r,t}r^m, \tag{11}$$

where $E(b^m) = 0.5(b_h + b_l)$ given that all men work. There are three forces that govern the evolution of the gender wage gap with BBTC:

1. The *Price Effect*: women benefit more (loose less) from falling brawn wages $w_{r,t}$
2. The *Supply Effect*: lower ability women will enter the market
3. The *Education Effect*: non-working women have no incentive to obtain education. However, once more women enter the labor market, they are more likely then men to obtain education,

increasing women's relative brain supplies.

The price effect follows from comparative statics on Equations (9) and (11),

$$
\begin{aligned}
\frac{\partial \overline{w}_t^m}{\partial w_{r,t}} = r^m \quad &> \quad \frac{\partial \overline{w}_t^f}{\partial w_{r,t}} = 0.5 r^f > 0 \\
\frac{\partial \overline{w}_t^m}{\partial w_{b,t}} = 0.5\,(b_h + b_l) \quad &> \quad \frac{\partial \overline{w}_t^f}{\partial w_{b,t}} = 0.5 b_h > 0.
\end{aligned}
\tag{12}
$$

Given women's lower brawn endowment, $r^f < r^m$, a fall in $w_{r,t}$ closes the gender wage gap. However, rising returns to brain lead to a smaller increase in female wages, $b_l > 0$. The result is driven by the supply effect,

$$
\frac{\partial E(b^m)}{\partial w_{b,t}} = 0 > \frac{\partial E(b^f)}{\partial w_{b,t}} = -0.5 \frac{\hat{b}_t^f}{w_{b,t}},
\tag{13}
$$

with lower ability (brain) women entering the market as brain returns rise. The education effect can counteract the negative *Supply Effect* as women surpass men in acquired brain.

In summary, the price and education effect closes the wage gap, while the supply effect widens the wage gap. The supply effect is stronger when women's labor force participation and education levels are low, but weakens as labor force participation and education rates converge. Therefore, the closing of the gender wage gap is slow at first, but accelerates as the *Price* and *Education Effect* begin to dominate. These results suggest that a model differentiating between brain and brawn labor requirements should replicate the initial US employment, education, and wage differences across gender. It should also reproduce the subsequent evolution of the gender gaps in education and wages, including some initial "stagnation" in average female wages as observed during the 1960s and 1970s, and a later reversal through increasing female education attainment.

5 General Equilibrium Model

The general equilibrium model is based on the previous one period model with some modifications to account for key labor market facts across marital status. The economy consists of overlapping generations who live for four periods, with a unit measure of both men and women in aggregate, and a representative competitive firm. There is no population growth and agents only marry within generations.

5.1 Aggregate Production

Agents supply two labor inputs, brain and brawn to a labor market segregated by education. The aggregate production function has constant elasticity of substitution in (1) the two inputs, B_t^e and R_t^e with $e \in \{0,1\}$ (the aggregate labor supplies of brain and brawn by education, with the superscript equal to one denoting college labor), and (2) across education levels,

$$Y_t = \left\{ \sum_{j=0,1} \alpha_t^j \left(\gamma_t^j (B_t^j)_j^{\phi} + (1-\gamma_t^j)(R_t^j)_j^{\phi} \right)^{\phi/\phi_j} \right\}^{1/\phi}. \tag{14}$$

The share parameters on education type, α_t^e, satisfy $\alpha_t^1 + \alpha_t^0 = 1$, γ_t^e is the share parameter on brain, $\varepsilon_\phi = \frac{1}{1-\phi}$ is the elasticity of substitution between the education groups, and $\varepsilon_\phi^e = \frac{1}{1-\phi_e}$ is the elasticity of substitution between the two skill inputs. A rise in α_t^1 represents exogenous SBTC and a rise in γ_t^e is exogenous BBTC. With intermediate output $Y_t^e = \left(\gamma_t^e (B_t^e)^{\phi_e} + (1-\gamma_t^e)(R_t^e)^{\phi_e}\right)^{1/\phi_e}$ and $\alpha_t = \alpha_t^1$ ($\alpha_t^0 = 1 - \alpha_t$), the college wage premium is,

$$\frac{w_t^1}{w_t^0} = \frac{\alpha_t}{1-\alpha_t} \left(\frac{Y_t^1}{Y_t^0} \right)^{\phi - 1}. \tag{15}$$

Similarly, the brain premium by education is,

$$\frac{w^e_{b,t}}{w^e_{r,t}} = \frac{\gamma^e_t}{1-\gamma^e_t}\left(\frac{B^e_t}{R^e_t}\right)^{\phi_e - 1}. \tag{16}$$

For the model to generate a rise in the relative demand for brain through BBTC, the two inputs must be substitutes, $\varepsilon^e_\phi > 1$. From Equation (16) the relative demand of inputs is,

$$\frac{B^e_t}{R^e_t} = \left(\frac{\gamma^e_t w^e_{r,t}}{(1-\gamma^e_t) w^e_{b,t}}\right)^{\varepsilon_{\phi_e} - 1}. \tag{17}$$

The brain premia, $\frac{w^e_{b,t}}{w^e_{r,t}}$, rise as long as an outward shift in labor supply does not offset the increase in labor demand.

5.2 Households: Preferences, Marriage and Education

At the beginning of "life," individuals choose to attend college by paying a cost χ. College increases innate brain abilities by a factor $\varepsilon > 1$. However, when making the college decision, agents do not have prefect information over their true innate brain ability, which is only revealed at the start of their working life. After the education decision is made, but before entering the labor market, an exogenous probability determines marital status (remain single forever or married). Marriage rates are education-specific to match the assortative mating in educational attainment (from the US). Households collectively decide on who will work in the market or home and consume a final market good and home production.

5.2.1 Married Households

Agents only decide on the extensive margin of labor supply, $\ell_i = \{0,1\}$. Market and home produced goods are imperfect substitutes. A married household maximizes,

$$U_p(c_t, h_t) = \frac{1}{\zeta} \ln\left((c_t - \bar{c})^{\zeta} + h_t^{\zeta}\right). \tag{18}$$

subject to a standard budget constraint and the home production technology,

$$c_t \leq \omega_{e_i,t}^m \ell_t^m + \omega_{e_i,t}^f \ell_t^f \quad \text{and} \tag{19}$$

$$h_t = A_h\left(1 - \ell_t^m + 1 - \ell_t^f\right), \tag{20}$$

where the superscripts stand for male or female, $\frac{1}{1-\zeta}$ is the elasticity of substitution between market and home goods, and $\bar{c}$ is a consumption subsistence level. The consumptions subsistence level is necessary to account for the fact that married, but not single, educated and uneducated women had similar labor supplies in 1960 and that self-selection into the labor market has moved from negative to positive (Mulligan and Rubinstein, 2008). Agent i earns wage, $\omega_{e_i,t}^g = (1-\tau^g) w_t^{e_i} (w_{b,t}^{e_i} b_i (1 + e_i \varepsilon_i) + w_{r,t}^{e_i} r_i)$ for $e_i \in \{0,1\}$ and $g \in \{f, m\}$, a function of his/her innate brain and brawn abilities, educational attainment, e_i, and gender-specific labor market discrimination, τ^g. As in the partial equilibrium model, brawn is common within gender, with men having more than women, $r^m > r^f$, while brain comes from a gender-neutral log-normal distribution, $\ln(b_i) \sim N(\mu_b, \sigma_b^2)$. By assumption men and women are perfect substitutes in home production. Therefore, spouses specialize with the higher wage earner entering the labor market first. Given a positive subsistence level $\bar{c} > 0$, the primary earner always works, while the secondary earner works if,

$$\omega_t^2 > \left(\left(\omega_t^1\right)^{\zeta} + A_h^{\zeta}\right)^{\frac{1}{\zeta}} - \omega_t^1 \quad \text{or} \quad \omega_t^1 < \bar{c}, \tag{21}$$

where the superscript denotes the primary and secondary earner.

5.2.2 Single Households

Given the subsistence requirements and the discrete labor decision, single agents always work in this set-up. To ensure the model is consistent with the data, some agents have the option of staying at home with probability $p_s \geq 0$. This can be thought of as the government providing benefits equal to the subsistence requirements for a "random" fraction of agents or some single agents having other means of covering the subsistence requirement (e.g., living with their parents, inheritance). The indicator function $\mathbf{1}_{p_s}$ denotes households with these additional resources. Single agents then solve the maximization problem,

$$U_s(c_t, h_t) = \begin{cases} \ln\left(c_t - \frac{\bar{c}}{\psi}\right) & \text{if} \quad \mathbf{1}_{p_s} = 0; \\ \max\left\{\ln\left((c_t\right), \ln(h_t)\right\} & \text{if} \quad \mathbf{1}_{p_s} = 1, \end{cases} \tag{22}$$

subject to a standard budget constraint and the home production technology,

$$c_t \leq \omega^g_{e_i,t} \ell_t \quad \text{and} \tag{23}$$

$$h_t = A_h \left(1 - \ell_t\right), \tag{24}$$

where the subsistence requirement is adjusted for the economies of scales, $2 > \psi > 1$. Single households cover less subsistence expenditure than married households, but not necessarily half of the amount, given economies of scale in marriage. The fraction $1 - p_s$ of single agents must work, while the fraction p_s works if and only if

$$\omega^g_{e_i,t} \geq A_h + \frac{\bar{c}}{\psi}. \tag{25}$$

5.2.3 Marriage Market

Marriage is determined by chance, but varies with educational attainment. Women at time t marry with probability $p^f_{e,t}$ for $e \in \{0,1\}$. To capture assortative matching in education, the probability that a woman of education $j \in \{0,1\}$ marries a man with the same educational background j is strictly greater than marrying another man, $k \neq j$, i.e., $p^f_{j,j,t} > p^f_{j,k,t}$ with $\sum_{k=0,1} p^f_{j,k,t} = 1$. Only agents of the same generation marry, after the education decision has taken place. Therefore, in each period there will be a new fraction of young agents with and without a college degree. Denote these fractions of each gender/education type by $\lambda^{g,e}_t$ with $g = \{f,m\}$ for female/male and $e = \{0,1\}$ for LTC/C, respectively. At time t for a consistent equilibrium, male marriage probabilities are,

$$p^m_{e,t} = \frac{\sum_{k=0,1} \lambda^{f,k}_t p^f_{k,t} p^f_{k,e,t}}{\lambda^{m,e}_t},$$
$$p^m_{e,1,t} = \frac{\lambda^{f,1}_t p^f_{1,t} p^f_{1,e,t}}{\sum_{k=0,1} \lambda^{f,k}_t p^f_{k,t} p^f_{k,e,t}} \quad \text{and} \quad p^m_{e,0,t} = 1 - p^m_{e,1,t}.$$

5.2.4 Education Choice

Individuals choose education when young and single. Education carries a utility cost $\chi \sim N(\mu_\chi, \sigma_\chi)$, but increases innate brain ability by a factor of $\varepsilon > 1$. If the value function of an agent of gender g with education e at the beginning of life is defined as V^g_e, an individual goes to college if and only if, $E\left(V^g_1\right) - \chi \geq E\left(V^g_0\right)$. More specifically,

$$p^g_{1,t} \sum_{k=0,1} \left(p^g_{1,k,t} V^g_{p,1,k}\right) + (1-p^g_{1,t}) V^g_{s,1} - p^g_{0,t} \sum_{k=0,1} \left(p^g_{0,k,t} V^g_{p,0,k}\right) - (1-p^g_{0,t}) V^g_{s,0} \geq \chi, \tag{26}$$

where $V^g_{p,1,k}$ ($V^g_{p,0,k}$) is the value function of an educated (uneducated) agent married to a spouse of education $k = \{0,1\}$ and $V^g_{s,e}$ is the value function of an agent that remains single forever with education $e = \{0,1\}$. Equation (26) shows the two benefits of education: (1) higher wages in future periods and (2) assortative matching in marriage.

5.3 Decentralized Equilibrium

An equilibrium, given wages $\{w^e_t, w^e_{b,t}, w^e_{r,t}\}_{(e=0,1)}$, is defined by:

1. The demand for market goods, c_i, the production of household goods, h_i, the supply of labor, ℓ^g_i, and the initial education choice e^g_i, that maximize household utility;

2. The demand for labor inputs, B^e and R^e for $e \in \{0,1\}$, that maximize the final good's profit function; and

3. Markets clearing,

   (a) The labor market, $B^e_{hh} = B^e$ and $R^e_{hh} = R^e$ for $e \in \{0,1\}$; and

   (b) The goods market, $C_{hh} = Y$,

   where B^e_{hh} and R^e_{hh} are aggregate household labor skill supplies obtained by integrating labor supply over the brain and brawn distribution of all agents and C_{hh} is aggregate market consumption obtained by integrating over all households.

6 Calibration

The model is calibrate to the 1960's US economy and then simulated until 2010 at 10 year-intervals. I allow for four exogenous trends: (1) SBTC through a increase in α_t; (2) BBTC through an increase in $\{\gamma^1_t, \gamma^0_t\}$; (3) falling marriage rates; and (4) changes in home productivity.[15]

Agents work for 40 years (or 4 periods) and discount at an annual rate of $\beta = 0.98$. The two standard elasticity parameters, $\{\phi, \zeta\}$, are taken from previous studies. The elasticity parameter of college to non-college labor is set to $\phi = 0.60$, the value estimated by Autor, Katz and Kearney (2008) for the US from 1963 to 2005. Following Ngai and Pissarides (2008), the elasticity

[15] Bridgman (2016) and Moro, Moslehi and Tanaka (2017) find that falling relative home-to-market productivity in the late 1970s is an important driver of market versus home labor decisions.

parameter of market to non-market consumption is set to $\zeta = 0.57$. The growth in home (relative to market) productivity is set following Bridgman (2016). Before 1978, home productivity growth outpaces market productivity by 0.4 percent, and after 1978 it grows 1.5 percent more slowly. Thus, $g_{A_h,0} = 0.004$ before 1978 and $g_{A_h,1} = -0.015$ thereafter.

The remaining elasticity parameters $\{\phi^1, \phi^0\}$ are estimated using a similar approach as Katz and Murphy (1992, pg. 69). Having determined returns to brain and brawn in Section 3, average brain and brawn efficiency units can be computed as,

$$E^e_{b,t} = \sum_j \bar{b} b_j L^e_{j,t} \quad \text{for } e \in \{0,1\}, \tag{27}$$

where $L^e_{j,t}$ are employment shares of occupation j and education e. In computing wage rates, only wages of full-time-full-year workers are included,[16] while $L^e_{j,t}$ includes all individuals with working hours of at least 260 per year. Individuals are weighted by their CPS weights and hours worked per year to compute total annual factor supplies. To estimate the elasticity parameter ϕ^e BBTC is assumed log-linear,[17]

$$\ln\left(\frac{\gamma^e_t}{1-\gamma^e_t}\right)_t = b^e_0 + b^e_1 t + \eta^e_t. \tag{28}$$

Taking the natural logarithm of the relative wage Equation (16), and inserting Equation (28), leads to the following regression by education group,

$$\ln\left(\frac{w^e_b}{w^e_r}\right)_t = a^e_1 t + a^e_2 \ln\left(\frac{E^e_b}{E^e_r}\right)_t + v^e_t, \tag{29}$$

where $a_2 = \phi^e - 1$. Table 3 provides the regression estimates in aggregate and for both education groups separately. Given the results across all estimation groups, I assume a common elasticity parameter of $\phi^1 = \phi^0 = 0.88$.

[16] Full-time-full-year workers are defined as working at least 1,400 hours per year.

[17] See also Krusell et al. (2000) for a similar estimation.

Table 3: *Elasticity Parameters*

Variable	Aggregate	C+	LTC
a_2	-0.123**	-0.120**	-0.121**
	(0.033)	(0.017)	(0.041)
a_1	0.011**	0.015**	0.005**
	(0.002)	(0.002)	(0.002)
Significance levels :	† : 10%	∗ : 5%	∗∗ : 1%

Source: 1977 and 1991 DOT skill requirements by 3-digit 1950 IPMUS occupational codes. See Appendix A for details on the computation of skill measures. 1968-2010 March CPS data for wage and efficiency units see Table 1 and 2 for details on the computation of wage rates and efficiency units of labor.

The subsistence scaling parameter is set according to OECD scales, $\psi = 1.5$, the share parameter for educated labor is set to $\gamma_0^1 = 0.5$, mean brain, μ_b, is normalized to zero while male brawn, r^m, is normalized to one, such that men have on average the same innate brain and brawn endowments, and labor market discrimination, τ^f, is set to zero.[18] SBTC and BBTC, $\{g_\alpha, g_{\gamma^0}, g_{\gamma^1}\}$, are estimated to jointly match: (1) the rise in the college wage premium; and (2) the rise in the relative brain premia by education group. The variance in education cost, σ_χ is calibrated to match the rise in male educational attainment from 1960 to 2010. All remaining parameters $\{\alpha_0, \gamma_0^0, r^f, A_{h,p}, A_{h,s}, p_s, \bar{c}, \sigma_b, \varepsilon, \tau^f, \mu_{\chi_m}, \mu_{\chi_f}\}$ are calibrated by matching 1960s data targets (see Table 4 for all parameter values).

Parameters are calibrated jointly by minimizing the distance between data targets and model moments (see Table 5), with some targets naturally more informative for certain parameters than others. Below follows an outline of the general strategy. Education parameters, $\{\mu_{\chi_m}, \mu_{\chi_f}, \sigma_\chi\}$, are matched to education shares. The shares of young males and females with a college degree in 1960 provide a one-to-one mapping for the average cost of education by gender μ_{χ_g}. The rise in the share of male college graduates is informative of the variance in educational cost σ_χ. The production share parameters, $\{\alpha_0, \gamma_0^0\}$, are matched to the college wage premium and the

[18]Even when allowing for general labor market discrimination, $\tau^f > 0$, the model does well in matching all targets by calibrating such discrimination close to zero. That is, the model does not require discrimination to match the selected targets.

Table 4: *Model Parameters*

Estimated	Type	Value
ϕ^1	elasticity parameter C+ brain/brawn	0.88
ϕ^0	elasticity parameter LTC brain/brawn	0.88
α_0	share on C+ output	0.40
γ_0^0	share on LTC brain/brawn	0.41
r^f	female brawn	0.44
σ_b	std. dev. brain	0.66
ε	education brain increment	1.22
$\bar{c}$	subsistence consumption	0.44
$A_{h,p}$	married women home productivity	2.13
A_h	general home productivity	0.45
p_s	singles' work requirement	0.57
μ_{χ_m}	men's mean cost of education	0.74
μ_{χ_f}	women's mean cost of education	1.33
σ_χ	std. dev. cost of education	0.89
g_α	SBTC growth rate	0.010
g_{γ^0}	BBTC growth rate on LTC	0.003
g_{γ^1}	BBTC growth rate on C+	0.005
Predetermined		
$g_{A_h,0}$	home-to-market productivity growth rate before 1978	0.004
$g_{A_h,1}$	home-to-market productivity growth rate after 1978	-0.015
ϕ	elasticity parameter C+ vs LTC	0.60
ζ	elasticity parameter consumption	0.57
Normalized		
μ_b	mean brain	0
r^m	male brawn	1.0
τ^f	female market discrimination	0
γ_0^1	share on C+ brain/brawn	0.5

labor force participation of men. The productivity parameters $\{r^f, \sigma_b, \varepsilon\}$ are matched to wage-education differences. The gender wage gap determines female brawn, r^f, the variance in log male wages determines variance in innate brain, σ_b,[19] and the difference between the gender wage gap for college versus non-college workers is informative on the additional returns to education, ε. The parameters governing participation $\{\bar{c}, A_{h,p}, A_h, p_s\}$ are matched to all remaining labor

[19]The model abstracts form idiosyncratic shocks, which are present in the data. Therefore, instead of matching the log wage variance in the US data when calibrating the standard deviation of brain, I follow Guvenen and Kuruscu (2010) in matching the residual variance of 0.104, defined as variance less idiosyncratic shocks.

force participation targets and the difference between the selection-corrected (using the Heckman correction framework) and uncorrected married gender wage gap. Lastly, the change in log wage premia provide direct mappings for SBTC and BBTC by education group.[20] Targets are matched

Table 5: *Data Targets and Model Moments*

1960s Target	**Data**	**Model**
Young Male C+	0.11	0.11
Young Female C+	0.07	0.09
Rise in Male C+	0.22	0.17
Single Female LFP	0.68	0.67
Single Female C+ LFP	0.89	0.88
Single Male LFP	0.87	0.88
Male LFP	0.95	0.97
Married Female LFP	0.33	0.33
Gender Wage Gap	-0.54	-0.47
Gender Wage Gap Difference C+ to LTC	0.14	0.14
Married Gender Wage Gap Difference Corrected to Average	0.10	0.09
Male College Premium	0.42	0.47
Variance in Log Male Wages	0.10	0.10
Growth Target		
Log Growth in male college wage premium	0.32	0.32
Log Growth in brain premium C+	0.54	0.54
Log Growth in brain premium LTC	0.21	0.21

Source: 1960 US Census and 2010 March CPS data merged with 1977 and 1991 DOT skill requirements by 3-digit 1950 IPMUS occupational codes. All data targets are 10-year moving averages. The sample consists of men and women aged 25-64 adjusted with survey weights.

well. The largest discrepancy is between the average gender wage gap in the data and model of -0.54 versus -0.47. However, the difference between the gender wage gaps in college-to-LTC groups and the selection corrected versus uncorrected married wage gap are all matched.

7 Results

The economy is simulated for six periods from 1960 to 2010. In addition to the calibrated growth rates, marriage rates are adjusted to match US marriage trends. Table 6 documents aggregate time

[20] SBTC is set to start only after 1978 consistent with the evidence from Heathcote, Storesletten and Violante (2010).

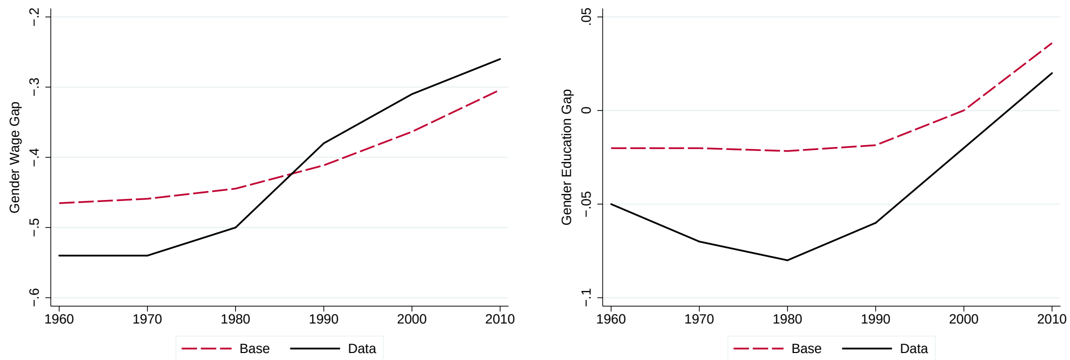
trends of the US versus the simulated economy. As the aim of the model is to understand gender differences, the results are presented in terms of three gender gaps: (1) education, (2) employment, and (3) wages.

Table 6: *Gender Gaps over Time*

	1960		**2010**		$\Delta_{2010-1960}$	
	Data	**Model**	**Data**	**Model**	**Data**	**Model**
Education						
Fraction C+	-0.05	-0.02	0.02	0.04	0.06	0.06
Employment						
All	-0.54	-0.57	-0.14	-0.24	0.41	0.33
Single	-0.19	-0.20	-0.03	-0.15	0.15	0.05
Married	-0.63	-0.67	-0.20	-0.28	0.43	0.39
Wage						
All	-0.54	-0.47	-0.26	-0.30	0.29	0.17
Selection-Adjusted All	-0.41	-0.44	-0.32	-0.32	0.09	0.12

The model generates closing gaps for education, employment and wages as in the US. The calibration is able to replicated over 80 percent (0.41 versus 0.33) of the observed rise in female labor force participation from 1960 to 2010. This increase in female labor force participation is mostly generated by married woman, replicating 91 percent of the data (in almost equal portions by educational attainment - not reported here). The benchmark is able to replicate all the reversal in the education gap. The model does not rely on differences in education costs over time, by gender, or gender-specific labor market discrimination (see for example Heathcote, Storesletten and Violante, 2010; Cerina, Moro and Rendall, 2017) to replicate the gender education reversal. Instead the only model gender-difference necessary to generate a reversal in the gender education gap is that women have 44 percent of male innate brawn - a skill important in the 1960's labor market, but not in 2010. Lastly, the model is consistent with the fact that women have moved from being negatively self-selected to positively self-selected over this time period. In the data, the uncorrected gap is 13 percentage points larger than the corrected gap in 1960, but by 2010 the uncorrected gap is instead seven percentage points smaller. The model produces the same change

Figure 3: *Evolution*



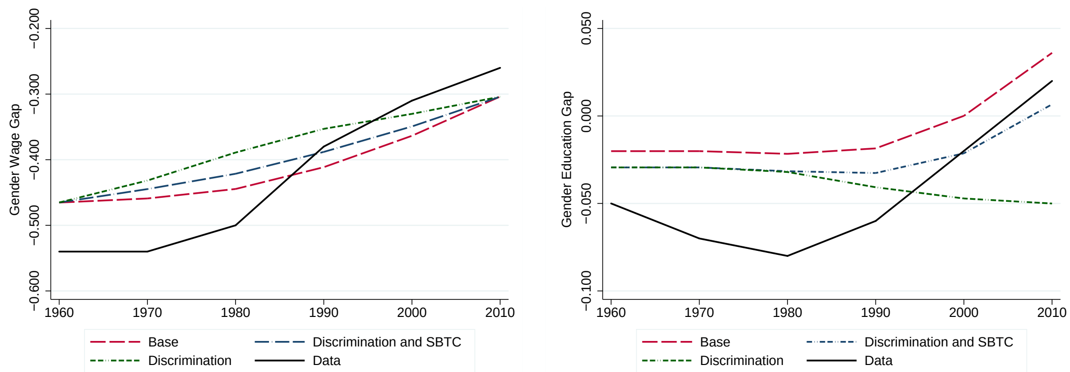
(a) The Gender Wage Gap

(b) The Gender Education Gap

in self-selection as in the data (from negative to positive), where the difference goes from three percent points to negative two percentage points. With this changing self-selection of women, the benchmark replicates over half of the closing gender wag gap (0.17 over 0.29).

Figure 3 shows the evolution of the gender wage and education gaps - both having time-varying paths. Not only is the model able to replicate a substantial part of the aggregate change between 1960 and 2010, the simulation is also consistent with the relative change in slopes of the transition. The US gender wage gap closes on average by 0.2 percentage points per annum from 1960 to 1980, and than accelerates to a rate of 0.8 percentage points per annum from 1980 to 2010. In the model the respective rates are 0.1 and 0.5 percentage points per annum. As the model explains over half of the closing wage gap, the per annum rates almost coincide with their respective slopes. In both cases, growth more than quadruples from the earlier to later period. In comparing the gender education gap in the data between 1960 and 1990 there is no overall growth, and between 1990 and 2010 growth changes to 0.4 percentage points per annum. In the model, there is virtually no growth prior to 1990 and a per annum change of 0.3 after 1990.

Figure 4: *Counterfactual: Labor Market Discrimination*



(a) The Gender Wage Gap

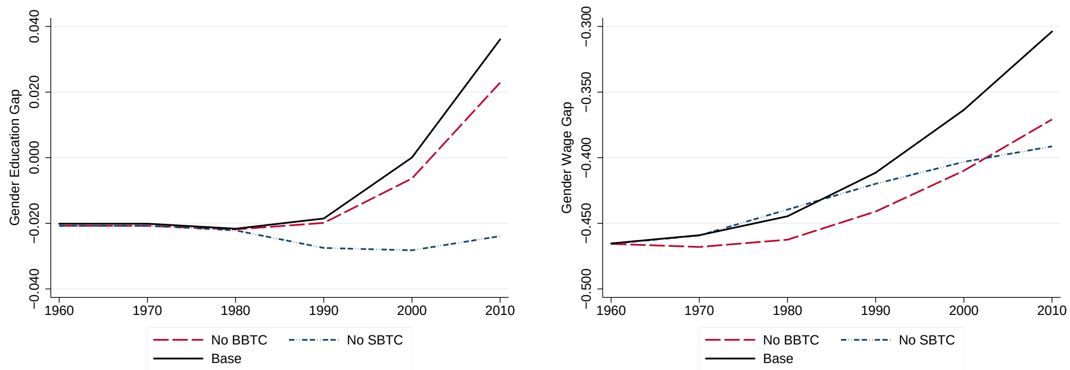
(b) The Gender Education Gap

7.1 Discrimination Counterfactual

The model relies on a gender difference in brawn skills to replicate the initial gender gaps in employment, education and wages in 1960. Over time, technical change biased toward brain closes all three gender gaps and produces realistic time-varying paths for education and wages. SBTC increases the value of brain indirectly as educated jobs always require relatively less brawn, $\gamma^1_{1960} = 0.5 > \gamma^0_{1960} = 0.4$ and $\varepsilon > 1.0$. BBTC directly decreases the value of brawn-to-brain for each education group. Instead of modeling technical change and gender differences through skills, the empirical literature has attributed much of the unexplained gender wage gap between men and women to labor market discrimination. In this spirit, we can use the benchmark calibration by setting $r^f = r^m = 1.0$, $g_{\gamma^0} = g_{\gamma^1} = 0$ and $g_\alpha = 0$ and estimate a labor market discrimination, $\{\tau^f_{1960}, \tau^f_{2010}\}$, to match the change in the gender wage gap from 1960 to 2010.

Figure 4 shows the resulting gender wage and education gap evolution assuming gender discrimination decreases monotonically. Two experiments are computed, one with and one without SBTC, i.e., $g_\alpha > 0$ which is labeled "Discrimination and SBTC" and $g_\alpha = 0$ which is labeled "Discrimination." Allowing for a linear decrease in labor market discrimination leads to an almost linear gender wage gap closing (see left panel). Without SBTC and BBTC the gender wage gap closes in a slightly inverted U-shape. With SBTC still present, as in the benchmark, the gender

Figure 5: *Counterfactual: Varying Technical Change*



(a) The Gender Education Gap

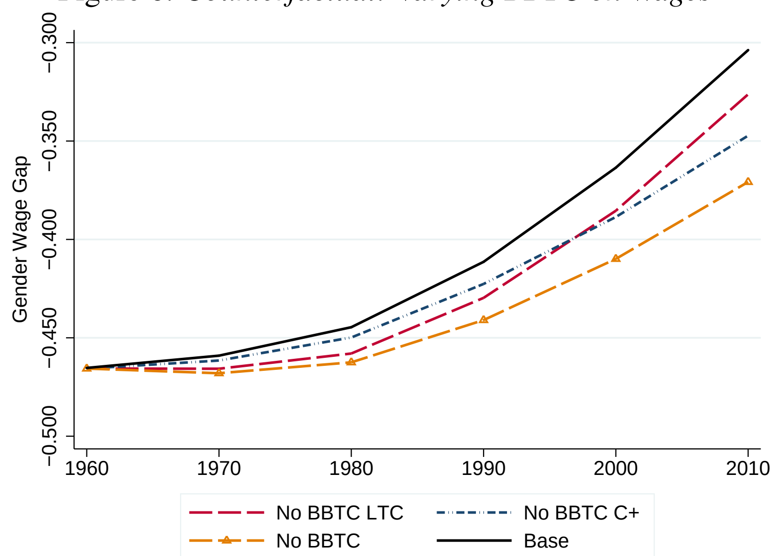
(b) The Gender Wage Gap

education gap does not close until 1990, but then closes one third less than the benchmark. The lower educational attainment of women is a consequence of removing part of the demand shift towards women's comparative advantage in brain. With a fall in labor market discrimination, there is no additional amplification mechanism towards the brain input of educated labor, as both educated and uneducated women benefit equally from the fall in discrimination, τ^f and average brawn equals average brain for all education groups. That is, removing SBTC, BBTC and gender differences in brawn eliminates women's extra incentive to educate. Without any technical change the gender education gap widens slightly.

7.2 Technical Change Counterfactual

Having established that both SBTC and BBTC matter for the time-varying evolution of the education and wage gaps, it is relevant to quantify the importance of each type of technical change in driving these gender gaps. Figure 5 simulates the gender gap in education and wages by shutting down either BBTC or SBTC using the benchmark calibration. SBTC explains all the reversal in the gender education gap. BBTC has very little explanatory power on its own. In contrast, the gender wage gap convergence is explained by both BBTC and SBTC together. The main difference is that SBTC affects only the later acceleration of the transition. Without SBTC, fewer high-ability

Figure 6: *Counterfactual: Varying BBTC on Wages*



women enter the labor market, i.e., in the benchmark, women surpass men in educational attainment only after 1990. This is consistent with the timing of the three effects highlighted in the partial equilibrium model of Section 4. Thus, the positive supply effect through education only dominates in later decades - removing SBTC removes the positive supply effect.

Since the model allows for different BBTC across education groups, it is possible to further analyze the impact of BBTC separately for uneducated and educated labor. Figure 6 shuts down each type of BBTC independently. BBTC for the uneducated generates a constant closing of the gap. As with SBTC, the rise in BBTC for educated workers explains a larger portion of the closing gap in the last two decades.

7.3 Home Productivity Counterfactual

In light of recent evidence that changes in home productivity matter for market versus home hours allocation (Bridgman, 2016; Moro, Moslehi and Tanaka, 2017), the base model allows for changing home productivity. The following counterfactual sets changes in home productivity to zero, $g_{A_h,0} = g_{A_h,1} = 0$, and computes changes in the three gender gaps. The results in Table 7 show that home productivity is not a main driver in the evolution of the employment or wage gaps, and explains, at most, one-third of the closing gender education gap (see Column "NoHP"). Moreover, the time-varying gender wage gap path does not change, with the growth rate between the first and second subperiods still quadrupling (subperiods not reported here). Similarly, the growth rate for the education gap remains at zero percent prior to 1990, only showing positive growth from 1990 to 2010.

Table 7: *Gender Gaps over Time: No Home Productivity*

	$\Delta_{2010-1960}$		
	Data	**Model**	
		(Base)	**(NoHP)**
Education			
Fraction C+	0.06	0.06	0.04
Employment			
All	0.41	0.33	0.30
Single	0.15	0.05	0.03
Married	0.43	0.39	0.35
Wage			
All	0.29	0.17	0.14
Selection-Adjusted All	0.09	0.12	0.10

Notes: "Base" refers to the benchmark results and "NoHP" to the counterfactual without changes in home productivity.

8 Conclusion

The purpose of this study is to assess the importance of labor demand changes on women's labor force participation, education and wages. For proper policy development, it is necessary to establish the extent to which the female labor market experience has been shaped by discrimination or other factors. This study focuses on the changes in occupational brain and brawn requirements, without ignoring the effects of standard SBTC usually used to explain most wage changes for men since the 1970s.

I establish a considerable rise in brain and fall in brawn requirements from the 1977/1991 DOT. The model presented in this paper is successful in explaining a significant portion of the closing gender gaps. Calibrating the model to the 1960's US economy shows that SBTC, BBTC and improvements in home technology are able to replicate the rise in female labor force participation, the reversal of the gender education gap, and over half of the closing gender wage gap. Turning to the time-varying path of the gender gaps in education and wages, the model shows that technical change, unlike labor market discrimination, is able to replicate the general patterns seen in the US data. That is, the model generates both the initial stagnation and later rise of the post-World War II gender education and wage gaps. The shape of the transition is, in large part, driven by changing selection and educational attainment due to SBTC and BBTC. More specifically, SBTC plays the dominant role in shaping the reversal of the gender education gap. In contrast, both SBTC and BBTC are necessary to generate the convergence between male and female wages. While BBTC has a fairly constant effect on the closing gender wage gap, as suggested by the partial equilibrium model, SBTC is essential in providing the later accelerated positive supply effect of educated women.

Nonetheless, roughly 40 percent of the closing wage gap remains unexplained. Thus, the theory put forth here is likely complementary to a host of other theories, such as increasing gender-biased returns to experience, a decrease in labor market frictions and social learning.

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A Appendix: Skill Measures

The 1977 and 1991 DOT measures job characteristics in: (1) general educational development; (2) specific vocational training; (3) required worked aptitudes; (4) temperaments or adaptability requirements; (5) physical strength requirements; and (6) environmental conditions.[21] General educational development measures the formal and informal educational attainment required to perform a job effectively by rating reasoning, language and mathematical development. Each reported level is primarily based on curricula taught in the US, where the highest mathematical level is advanced calculus, and the lowest level only requires basic operations, such as adding and subtracting two-digit numbers. Specific vocational preparation is measured in the number of years a typical employee requires to learn the job tasks essential to perform at an average level. Eleven aptitudes required of a worker (e.g., general intelligence, motor coordination, numerical ability) are rated on a five point scale, with the first point/level equivalent to the top ten percent of the population and the fifth level compromising the bottom ten percent of the population. The remaining 90 percent are split into three equal parts to make up the remaining levels. Ten temperaments required of a worker are reported in the DOT, where the temperament type is reported without any numerical rating. An example of a temperament is the ability to influence people in their opinions or judgments. Physical requirements include a measure of strength required on the job, rated on a five point scale from sedentary to very heavy, and the presence or absence of physical tasks such as climbing, reaching, or kneeling. Lastly, environmental conditions measure occupational exposure (presence or absence) to environmental conditions, such as extreme heat, cold and noise. The characteristics reported in the DOT capture the heterogeneity across occupations and industries. While they measure different specific job requirements, they can be grouped into broader categories of skills in terms of their common underlying dimensions.

I compute brain using the average of standardized general educational development and spe-

[21]Data and documentation is available from the Inter-university Consortium for Political and Social Research (ICPSR).

cific vocational training. The brawn measure is composed of the average between physical strength requirements and environmental conditions (see Table A.1 for actual measures). To combine different DOT variables, the original job requirements are rescaled. Vijverberg and Hartog (2005) provide a detailed methodology for rescaling DOT variables. Pre-1977 skills are computed with 1977 DOT job characteristics, post-1991 skills use only 1991 DOT job characteristics, and a linearly weighted combination of both DOT job characteristics is used between 1977 and 1991. I

Table A.1: *DOT Job Requirements*

Job Characteristic	**Avg.**[1]	**PCA**[2]
Brawn Factor		
Climbing/Balancing	x	x
Stooping/Kneeling/Crouching/Crawling	x	x
Strength Requirement	x	x
Environmental Exposure[3]	x	x
Indoor or Outdoor Work	x	x
Brain Factor		
Reasoning Development	x	x
Mathematical Development	x	x
Language Development	x	x
Specific Vocational Preparation	x	x
General Intelligence		x
Verbal Aptitude		x
Numerical Aptitude		x
Clerical Aptitude		x
Talking and Hearing		x

[1] Average of normalized variables.
[2] Estimated using maximum-likelihood principal component analysis.
[3] Environmental conditions, such as the presence of heat, cold, and humidity, were combined to one variable prior to the estimation.

show below that using the aptitude measures related to intellectual abilities (see bottom of Table A.1) and reducing the DOT data-dimensionality via principal component analysis does not alter the labor demand time trends observed for the US. That is, the brain and brawn measures are robust to different specifications.

To obtain population representative estimates, the occupations in the DOT must be weighted. In the 1977 DOT, the *Committee on Occupational Classification and Analysis of the National Academy of Sciences funded by the Department of Labor and the Equal Employment Opportunity Commission* merged the 12,431 1977 DOT jobs to 7,289 unique occupation-industry pairs from the 1970 United States Census. The reduction from 12,431 to 7,289 is the result of more detailed occupational classifications in the DOT. For example, while there is only one "waiter/waitress" category in the census classification, the DOT contains multiple categories, such as "waiter/waitress formal," "waiter/waitress, head," "waiter/waitress, take out." Given data availability, it is impossible to weight these finer occupational classifications by the actual workforce. Thus, the over 7,000 resulting occupational skill measures are merged with the 1960 US Census and the 1968 to 2010 Current Population Survey (CPS) to compute labor market trends.[22] Since skills have no natural scale, they are normalized to percentiles of the 1960 US skill distributions, respectively.[23]

Figure A.1 compares the brain and brawn estimates with the alternative specification using principle component analysis. Only a small discrepancy between the two brain measures exists. In conclusion, it is unlikely that *ad hoc* selection of measures used in the data analysis are driving the results.

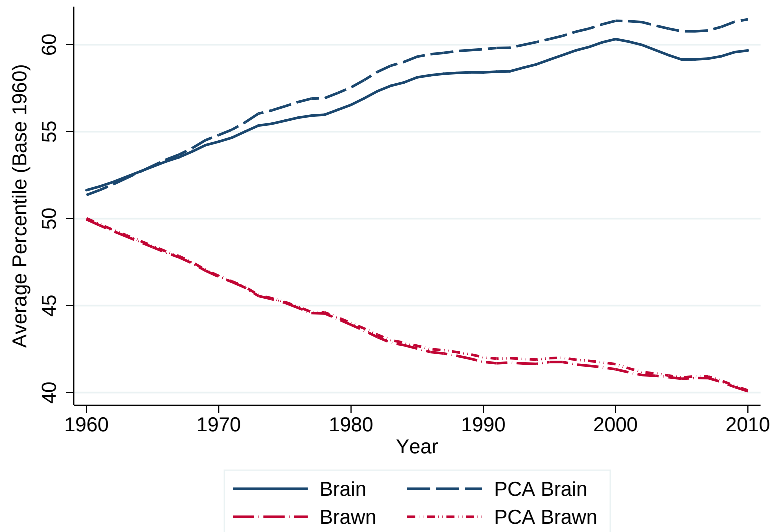
A.1 Brain versus Brawn across Sectors

Figure A.2 splits Figure 1 by broad sectors. The service sector is less brawn intensive in both 1960 and 2010 compared to the industrial sector. However, splitting the economy by sectors is not a perfect fit for studying why women may have benefited from changes in labor demand over time.

[22] Census and CPS data is obtained from the IPUMS-USA (Ruggles et al., 2010) and the IPUMS-CPS project (King et al., 2010). The IPUMS projects provide a consistent 1950 US Census classification of occupations and industries over the years, which is used in merging 1977 and 1991 DOT factors.

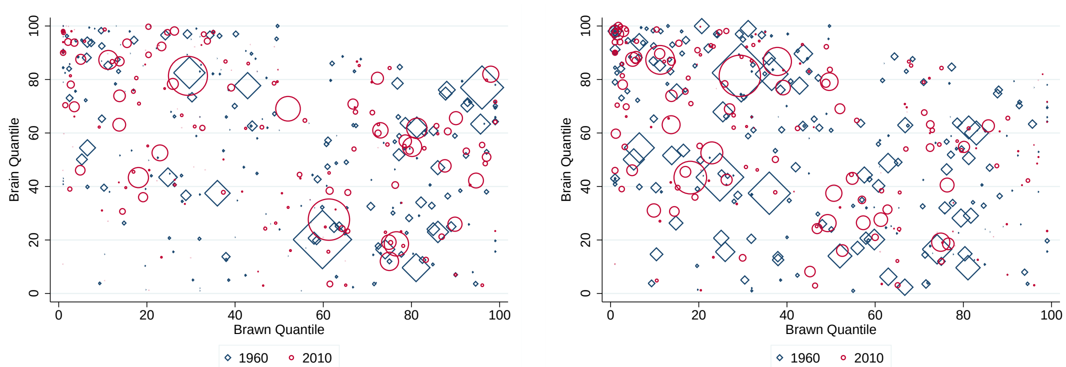
[23] For details on the normalization see Autor, Levy and Murnane (2003). The scaling is done for both the 1977 and 1991 DOT skill measures to allow for consistent comparisons over time. Measures are assigned a percentile rank for the US using 1960 Census population weights of individuals aged 25 to 65.

Figure A.1: *Evolution with PCA*



Source: See Figure 2 for details.

Figure A.2: *Brain and Brawn across Sectors*



(a) Industry

(b) Services

Source: See Figure 1 for details.