Brain versus Brawn: The Realization of Women’s Comparative Advantage

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April 11, 2018

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, the US labor market faced a considerable shift from more physical (“brawn”) to more intellectual (“brain”) 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) most of the narrowing gender wage gap, (2) the reversing education gap, and (3) over half of the narrowing employment gap. Crucially, the model accounts for the time-varying-path of the narrowing gender divide with an initial stagnation and a later acceleration in female wages and education rates.

Keywords: technological progress, labor demand, skills, female labor supply, gender education gap, gender wage gap, college attainment.

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*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 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.\textsuperscript{1} During the same time period the US has experienced fast technological growth mostly complementing high-skilled labor.\textsuperscript{2}

In this paper, I first document a unique type of gender-biased technological change - \textit{brain-biased} technical change - and then, using a general equilibrium model, quantify the importance of technological change in explaining the improving labor market experience of women.

The main contribution of this paper is identifying 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,\textsuperscript{3} 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 \textit{time-varying} gender convergence in wages and education can be explained by a changing technology, shifting labor requirements from physical (“brawn”) to intellectual (“brain”) abilities.

I begin by establishing four facts on brain and brawn requirements in the labor market from 1960 to 2010 that have not been previously reported. First, aggregate trends show a strong compositional shift from brawn to brain. Second, women have historically tended to work in occupations with less brawn requirements than men, especially in the case of unskilled women. Third, both skilled and unskilled women work increasingly

\textsuperscript{1}See for example Fogli and Veldkamp (2011); Ngai and Petrongolo (2017) for the former and Guvenen and Rendall (2015) for the latter.

\textsuperscript{2}See for example Acemoglu and Autor (2011); Katz and Murphy (1992).

\textsuperscript{3}See for example Becker (1994); Juhn, Murphy and Pierce (1993); Guvenen and Kuruscu (2010).
in occupations requiring a higher share of brain, but there is no similar trend for men. Fourth, there is 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.\footnote{Note, these findings across both education groups suggest a clear difference between innate brain and “brain” from schooling - two types of brain ability that will be distinguished throughout the paper.}

These facts suggest that a shift in labor demand requirements from brawn to brain, due to technical change, could have a positive effect on women’s labor force participation, education and wages if women have an innate comparative advantage in brain over brawn.\footnote{Some occupational groups document clearly how men have a comparative advantage in brawn compared to women. In sports, male 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.} 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 for educated and uneducated labor.

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. Technical change occurs at a constant rate, with BBTC starting in the 1960s and SBTC, following the literature, starting in the late 1970s.\footnote{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.}

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 rates, agents differ in their willingness to work in the labor market and devote time to home production. 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.\footnote{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.} 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.\footnote{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.}

The model is calibrated to match various 1960 US data moments on employment, wages and education; the college wage premium in 1960 and 2010; and the rise in the share of male college graduates from 1960 to 2010. The base calibration is able to replicate 53 percent of the closing aggregate gender participation gap and 57 percent of the closing married gender participation gap. It also replicates all the gender education reversal and 78 percent of the closing gender wage gap.

The base model is also able to address one of the main challenges in the literature, that is, technical change 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. Modeling not only standard SBTC but also BBTC, an innate gender biased type technical change, leads to three effects dominating at different instances in time which results in a non-linear path of convergence. More specifically, women benefit from increasing returns to brain given their comparative advantage. However, as 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. Following this period, given women’s comparative advantage in brain and the complementarity between brain and education women surpass men in college attainment and create a positive labor supply effect with sustained SBTC. In summary, the interaction between SBTC and BBTC is key in shaping the changing selection of women into the labor market, leading to a varying time-path of both the education and wage gap convergence.

Starting from the base model, I 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 equally. 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. BBTC is the main driver for the gender wage gap convergence, but SBTC and BBTC together shape the gender education reversal. In the last counterfactual, household determinants are kept at the 1960s level. Removing changes in marital matching affects the time-varying path of education, but has little effect on the aggregate results. Changing home productivity does have a small quantitative effect on the closing gaps, but does not alter the time-varying shape of the gender convergence.

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.

Galor and Weil (1996) put forth the theory that women have entered the labor market when technological change shifted labor demand away from brawn requirements - I provide a quantitative evaluation of such a theory. In addition, the quantitative model here highlights the importance that technical change biased not only towards education, but also brain over brawn, is necessary to explain the past convergence of women’s to men’s labor market experience. 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 only on men and their 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. In contrast, focusing on
physical skill contents allows us to study differences in gender.

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 com-
puters, 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.

Jones, Manuelli and McGrattan (2015) explain a large rise in female participation by an exogenously
closing wage gap. In Rendall (2018) 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 brawn and allowing for
different types of technical change, I provide a possible underlying mechanism for observed increases in
female wage returns taken as given in these studies.

Three quantitative macroeconomic studies have attempted to model an endogenously closing gender
wage gap. 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 produc-
tivity 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 is 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 account for 15 to 20 percent of aggregate output growth. 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.

3 Empirical Trends

This paper starts from the premise that women have, on average, less brawn than men. No comprehensive dataset with individuals’ 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. The surveys were developed by the US Department of Labor, who evaluated approximately 40 job requirements for more than 12,000 occupations. The 1977 and 1991 DOT measures job characteristics in: (1) general educational development; (2) specific vocational train-

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9The 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.
Figure 1: *Brain and Brawn Occupation Combinations*

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.

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 data merged with the DOT skill measures suggests a shift 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 the 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).

For details on the construction of these measures see Appendix A and Table A.1. In the appendix, I also show 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.
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 unlabeled set of lines provide 1977 DOT average changes related only to compositional changes in occupation/industry employment distributions. A diverging trend in favor of brain is evident. Most of the change is driven by the “extensive” margin, with little change of skill requirements within occupation.

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 graduates (traditionally captured by SBTC). Are the observed aggregate trends simply due to men and women acquiring more education and shifting into “college-occupations” that are more brain- and less brawn intensive? Table 1 decomposes the aggregate skill trend by education and gender groups. The data is now divided by individuals (not occupations) 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 are normalized in 1960 by aggregate education groups. Both educated and uneducated men only see a modest change over time. Men, conditional on their education, work in occupations with a similar skill mix in 1960 and 2010. Assuming a college education increases an individual’s brain level and ignoring women, a model of SBTC could explain a shift towards a brain-

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11 Decompositions by broad sectors and education can be found in Appendix A (see Figure A.2).
Table 1: Change in Labor Requirements by Education and Gender

<table>
<thead>
<tr>
<th>Group</th>
<th>1960</th>
<th>2010</th>
<th>Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate</td>
<td>1.00</td>
<td>1.58</td>
<td>0.58</td>
</tr>
<tr>
<td>By Education and Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Men C+</td>
<td>1.05</td>
<td>1.01</td>
<td>-0.04</td>
</tr>
<tr>
<td>Men LTC</td>
<td>0.97</td>
<td>1.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Women C+</td>
<td>0.82</td>
<td>1.03</td>
<td>0.21</td>
</tr>
<tr>
<td>Women LTC</td>
<td>1.17</td>
<td>1.86</td>
<td>0.69</td>
</tr>
</tbody>
</table>

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 the 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.

intensive labor market. However, women are working in occupations increasingly more brain-intensive irrespective of their education. LTC women have seen the largest change with a 69 percent increase in their brain-to-brawn skill ratio. This increase of uneducated women suggests some of the aggregate trend is driven by something beyond standard SBTC (or the acquisition of a college degree). That is, the rise in brain is simply not captured by increasing educational attainment of the workforce.

Table 1 also hints at a reversal in self-selection for skilled women over time. Educated women worked in relatively lower brain occupations compared to men in 1960 (0.82 versus 1.05) pointing to a negative self-selection by ability. Since then, skilled women have seen a rise of 21 percent in their relative brain-to-brawn requirement. The change over time shows a “catching up” consistent with evidence found by Hsieh et al. (2013) in that college men and women work in similar types of occupations by 2010.

The previous evidence only provides a partial equilibrium analysis of technological change capturing changing labor requirements. To provide evidence related to relative prices, I make use of CPS wage data combined with the DOT. Using $b$ to denote brain skills and $r$ to denote brawn skills, the wage for individual $i$ in occupation $j$ is,

$$ w^t_i = w^b_j b_j + w^r_j r_j \text{ for all } t, $$

where \( w^b, w^r \) are skill prices (wage rates) and \( b_j, r_j \) are brain and brawn skill requirements by occupation.
Empirically, since skills in the data are normalized from zero to 100 on a percentile distribution,\textsuperscript{12} I proceed in two steps. Skill quantities follow from regressing individual wage residuals, $\hat{w}_{it}^j$, (controlling for region, race, and age) on brain/brawn percentiles and an individual’s education,\textsuperscript{13}

$$\hat{w}_{it}^j = \alpha_0 p_j^b + \alpha_r p_j^r + \alpha_e p_j^h e_i^j + \epsilon_i^j,$$  (2)

where $e_i^j = 1$ if the individual has a college degree (zero otherwise) and $\{p_j^b, p_j^r\}$ are the skill percentiles. Occupation-specific skills are then $b_j = p_j^b (a_h + a_e e_j)$ and $r_j = a_r p_j^r$, where $a_x$ are the coefficient estimates from Equation (2). Using these skill quantities, I estimate brain and brawn ($w_{x,t}$) skill prices for a given time period $t$ by

$$\hat{w}_{it}^j = w_{b,t} b_j + w_{r,t} r_j + \epsilon_{i,t}$$ for all $t$.  (3)

Table 2 summarizes the estimated relative brain-to-brawn wage changes.\textsuperscript{14} 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 22 percent, respectively.

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

<table>
<thead>
<tr>
<th>Group</th>
<th>1965</th>
<th>2005</th>
<th>$\Delta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate</td>
<td>-0.09</td>
<td>0.28</td>
<td>0.36</td>
</tr>
<tr>
<td>By Education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C+</td>
<td>-0.26</td>
<td>0.28</td>
<td>0.54</td>
</tr>
<tr>
<td>LTC</td>
<td>-0.09</td>
<td>0.13</td>
<td>0.22</td>
</tr>
</tbody>
</table>

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 (2) and (3) by using full-time full-year male wage residuals after controlling for experience, race and region adjusted by individuals’ survey weights from the 1968-2007 March CPS data. Due to negative or positive self-selection into the labor market female wages are not used in computing prices.

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 BBTC, which complemented women’s comparative advant-

\textsuperscript{12}A skill of zero can be interpreted as using zero percent and a skill of 100 using 100 percent of the skill available.

\textsuperscript{13}A specification also allowing for an interaction between education and brawn shows that brawn returns are not statistically different across education groups on average.

\textsuperscript{14}For consistency, only CPS wage data is used in computing wage trends. Due to the financial crisis, any data beyond 2007 is also dropped. The estimated wage rates by education are reported in Table B.1 in Appendix B. Detailed results are available from the author upon request.
tage irrespective of their educational attainment, and SBTC which incentivized women to educate.

4 Toy Model

A model with gender differences is essential to quantify the contribution of the two forces of skill- and brain-biased technical change on the observed changes in the wage and education gender gaps. The underlying forces of the model simulated in Sections 5-7 are best demonstrated in a simplified partial equilibrium version. A unit measure of men and women live for one period. Individuals decide on education at the start of the period and are then married with probability \( p^m, p^f \) before working and consuming. Assume that all single individuals and married men work. Married women decide on work by maximizing household utility, which is linear in consumption,

\[
    u(c'_i) = 1_{(w^* \geq \overline{c})} \left( w^* + \max \{ w^f, A^f_h \} - \overline{c} \right) + \left( 1 - 1_{(w^* \geq \overline{c})} \right) \left( w^* + w^f - \overline{c} \right),
\]

where \( w^* \) is the husband’s wage, \( w^f \) is the own wage, \( A^f_h \) is home production, \( \overline{c} \) is a subsistence level of consumption and \( 1_{(w^* \geq \overline{c})} \) is an indicator variable when the husband’s wages cover the subsistence level.

Wages are a function of an agent’s acquired brain and innate brawn, that is \( w^f = w^e \cdot \left( w^b \cdot \left( 1 + \epsilon^f \right) + 1_{(\epsilon = 0)} w^r \right) \).

All men have equal brawn, \( r^m \), and all women have less brawn, \( r^f < r^m \). Innate brain is distributed identically for everyone, \( b^f \sim U[b_l, b_h] \). Attending college, \( \epsilon \in \{0, 1\} \), increases innate brain ability by a factor \( \epsilon > 0 \), earns a wage rate of \( w_{1,f} \), but generates a utility cost of \( \chi > 0 \). Moreover, college occupations are assumed not to require any brawn, as per the indicator function \( 1_{(\epsilon = 0)} \).\(^{15}\) Substituting for brain acquired through schooling, \( b^f(\epsilon) = b^f(1 + \epsilon^f \epsilon^f) \), and ignoring any distortion through the marriage market, the college education decision for a man is

\[
    w_{1,f} w^b \cdot \left( 1 + \epsilon^f \right) - \chi \geq w_{0,f} \left( w^b \cdot b^f + w^r \cdot r^m \right).
\]

\(^{15}\)This is not an essential assumption, but makes the exposition regarding educational choice simpler.
Normalizing the uneducated wage rate, \( w_{1,t} > w_{0,t} = 1 \), men study if and only if

\[
b' \geq \frac{\chi + w_{rt} r_m}{w_{bt} (w_{1,t} (1 + \varepsilon) - 1)} \equiv \hat{b}'_t. \tag{4}
\]

The male cut-off for education, \( \hat{b}'_t \), is an increasing function of the cost of education, but a decreasing function of the returns to education and brain, for the latter both in wages and acquired brain.

Studying the two extreme cases for women, all women work and no married women work, is most informative. Since education decisions are taken before the marriage market, assuming all women work, the decision to become educated is

\[
p^f \overline{w^1*} + w_{bt} b'(1 + \varepsilon_i) - \chi \geq p^f \overline{w^0*} + w_{bt} (b' + w_{rt} r^m),
\]

where \( \overline{w^e*} \) is the expected husband’s wage if she marries. There are two benefits to education, higher wages and assortative matching in marriage, i.e., \( \overline{w^1*} > \overline{w^0*} \). If all women work they will educated if and only if

\[
b' \geq \frac{\chi - p^f (\overline{w^1*} - \overline{w^0*}) + w_{rt} r^f}{w_{bt} (w_{1,t} (1 + \varepsilon) - 1)} \equiv \overline{b}'_t. \tag{5}
\]

This female cut-off for education, \( \overline{b}'_t \), has the same comparative statics as the male cut-off. However, given the education marriage benefit, \( p^f (\overline{w^1*} - \overline{w^0*}) \), and the lower brawn ability, women obtain more education than men, \( \hat{b}'_t > \overline{b}'_t \). With a fall in the returns to brawn, \( w_{rt} \) the female cut-off would fall even faster. If no married women work, the cut-off is instead

\[
b' \geq \frac{\chi - p^f (\overline{w^1*} - \overline{w^0*}) + (1 - p^f) w_{rt} r^f}{(1 - p^f) w_{bt} (w_{1,t} (1 + \varepsilon) - 1)} \equiv \overline{b}'_t. \tag{6}
\]

If the cost of education, \( \chi \), satisfies

\[
\chi > (\overline{w^1*} - \overline{w^0*}) + \frac{(1 - p^f)}{p^f} w_{rt} (r^m - r^f), \tag{7}
\]

this cut-off for women is larger than for men, \( \overline{b}'_t > \hat{b}'_t \). Since some women will work while others will not, the cut-off for women to obtain education lies between the two cut-offs of Equations (5) and (6),
When few women work, the cut-off will be closer to \( b_f^f \) and there will be more educated men than women, but as more women enter the labor market the cut-off will move towards \( b_f^f \) and women will surpass men in their educational attainment.

The working choice is governed by two cut-offs for each education type:

\[
b_f^f(e) \geq \frac{A^f_h - 1_{(e=0)}w_{e,f}r_f}{w_{e,f}w_{b,f}} \equiv \tilde{b}_f^{f,e} \quad \text{or} \quad \overline{c} > w_f^{e*}.
\]  

(8)

A wife must work if her spouse does not cover the subsistence level of consumption and otherwise chooses to do so when the opportunity cost of staying home is too large. Given the assumption of assortative matching, the subsistence cut-off is more likely to bind for low skilled women. Otherwise, as with the education cut-off, more women enter the labor market with a rise in the skill premium, \( w_{e,f} \) and a rise in brain returns \( w_{b,f} \).

The above shows that a rise in the skill premium and in brain returns induces women to obtain increasingly more education then men and enter the labor market. The effect on the gender wage gap will, therefore, depend on the selection of educated and uneducated women into the labor market. The average wage by education, \( e \), is

\[
\overline{w}_f^{e,e} = w_{e,f}(E(b_f^f) + 1_{(e=0)}w_{e,f}r_f).
\]  

(9)

The skill-premium, brain- and brawn returns have a direct effect on wages. As the returns to brain increase the wage gap will close as women have less brawn. Thus, for the evolution of the gender wage gap, what matters is the evolution of average brain by education level, \( E(b_f^f) \). Defining the share of women that have a spouse not covering the subsistence level by \( p^{e,1} \), average brain supplied to the market are

\[
E(b_f^{e,1}) = (1 - p^{e,1}) \frac{b_h - \max\{\tilde{b}_f^f, \tilde{b}_f^{f,1}\}}{b_h - b_l} + p^{e,1} \frac{b_h - \tilde{b}_f^f}{b_h - b_l} \quad \text{and} \quad (1)
\]  

\[
E(b_f^{e,0}) = (1 - p^{e,0}) \frac{b_h - \tilde{b}_f^{f,0}}{b_h - b_l} + p^{e,0} \frac{b_h - \tilde{b}_f^f}{b_h - b_l}.
\]  

(11)

For both equations (10) and (11), the first term captures women who have a choice of working and the
second term captures women that must work because of subsistence consumption. All cut-offs fall when the skill premium and brain returns rise, with the four effects from technical change being:

1. A fall in the average brain of educated women through a rise in (voluntary) labor force participation.
2. A fall in the average brain of educated women through a fall in the education cut-off.
3. A fall in the average brain of uneducated women through a rise in (voluntary) labor force participation and a fall in the education cut-off.
4. A rise in the average brain of uneducated women through a decrease in negative-self selection consistent with the empirical evidence in Mulligan and Rubinstein (2008).

However, there is also a positive education effect from (3) to (1) on aggregate brain as more women educated and acquire $e$. So the aggregate (across education) effect is ambiguous.

In summary there are three forces that govern the evolution of the gender wage gap with SBTC and BBTC:

- The **Price Effect**: women benefit more (lose less) from a relative fall in brawn wages $w_{rt}$.
- The **Ability Effect**: lower ability women enter the market and obtain education.
- The **Education Effect**: Education attainment increases brain by a factor of $e$.

The price and education effects close the wage gap, while the ability effect widens the wage gap. The ability effect is stronger when women’s labor force participation and education levels are low, but weakens as labor force participation and education rates converge. Education rates converge as SBTC accelerates in the late 1970s (Heathcote, Storesletten and Violante, 2010). Therefore, the closing of the gender wage gap is slow at first, but accelerates as the price and education effects begin to dominate. These results suggest that a model differentiating between brain and brawn labor requirements, and the related technical change, 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, $B^e_t$ and $R^e_t$ 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:

$$Y_t = \sum_{e=0,1} \alpha^e_t \left( \gamma^e_t (B^e_t)^{\phi_e} + (1 - \gamma^e_t) (R^e_t)^{\phi_e} \right)^{1/\phi_e}.$$  \hspace{1cm} (12)

The share parameters on education type, $\alpha^e_t$, satisfy $\alpha^1_t + \alpha^0_t = 1$; $\gamma^e_t$ is the share parameter on brain; $\varepsilon_\phi = \frac{1}{1-\phi_e}$ 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 $\alpha^1_t$ represents exogenous SBTC and a rise in $\gamma^e_t$ is exogenous BBTC. With intermediate output $Y^e_t = (\gamma^e_t (B^e_t)^{\phi_e} + (1 - \gamma^e_t) (R^e_t)^{\phi_e})^{1/\phi_e}$, the college wage premium is

$$\frac{w^1_t}{w^0_t} = \frac{\alpha^1_t}{\alpha^0_t} \left( \frac{Y^1_t}{Y^0_t} \right)^{\phi_e - 1}. $$ \hspace{1cm} (13)

Similarly, the brain premium by education is

$$\frac{w^e_{b,t}}{w^e_{r,t}} = \frac{\gamma^e_t (B^e_t)^{\phi_e - 1}}{1 - \gamma^e_t (R^e_t)^{\phi_e}}. $$ \hspace{1cm} (14)
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 (14) the relative demand of inputs is

\[
\frac{B^e_t}{R^e_t} = \left( \frac{\gamma^e_t w^e_t}{(1 - \gamma^e_t) w^e_{b,t}} \right)^{\varepsilon_b - 1}.
\]

The brain premia, \( \frac{w^e_{b,t}}{w^e_{f,t}} \), 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. College increases innate brain abilities. 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

\[
U_p(c_t, h_t) = \frac{1}{\xi} \ln \left( \left( c_t - \bar{c} \right)^{\xi} + h_t^{\xi} \right),
\]

subject to a standard budget constraint and the home production technology

\[
c_t \leq \omega^{m}_{e,t} \ell^{m}_t + \omega^{f}_{e,t} \ell^{f}_t \quad \text{and} \quad h_t = A^m_h (1 - \ell^{m}_t) + A^f_h \left( 1 - \ell^{f}_t \right),
\]

where the superscripts stand for male or female, \( \frac{1}{1-\xi} \) is the elasticity of substitution between market and home goods, and home productivity is allowed to differ by gender. From the toy model, the consumption subsistence level is necessary to account for the fact that married, but not single, educated and unedu-
cated women had similar labor supplies in 1960 and that self-selection by education into the labor market has moved from negative to positive (Mulligan and Rubinstein, 2008). Agent \( i \) earns wage, \( \omega_{i,t}^g = w_{e_i}^g b_i (1 + e_i) + w_{r_i}^g r_i \) for \( e_i \in \{0, 1\} \) and \( g \in \{f, m\} \), a function of his/her innate brain and brawn abilities, and educational attainment, \( e_i \). 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 and, given a positive subsistence level \( \bar{c} > 0 \), the primary earner always works, while the secondary earner works if

\[
\omega_i^2 > \left( (\omega_j^1)^{\xi} + (A^2_h)^{\xi} \right)^{\frac{1}{\xi}} - \omega_j^1 \quad \text{or} \quad \omega_j^1 < \bar{c},
\]

where the superscript denotes the primary and secondary earner.\(^{16}\)

5.2.2 Single Households

Given the subsistence requirements and the discrete labor decision, single agents always work in this setup. 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 \( 1_{p_s} \) denotes households with these additional resources. Single agents then solve the maximization problem:

\[
U_s(c_t, h_t) = \begin{cases} 
\ln(c_t - \bar{c}) & \text{if } 1_{p_s} = 0; \\
\max\{\ln(c_t), \ln(h_t)\} & \text{if } 1_{p_s} = 1,
\end{cases}
\]

subject to a standard budget constraint and the home production technology

\[
c_t \leq \omega_{h,t}^g \ell_t \quad \text{and} \quad h_t = A^g_{h,t}(1 - \ell_t),
\]

\(^{16}\)Notice if home production is zero, Equation (16) simplifies to \( U_p(c_t, h_t) = \ln((c_t - \bar{c})) \) with \( \xi > 0 \). That is, this specification allows for one- and dual-income households.
where the subsistence requirement is adjusted for the economies of scale, \( 2 > \psi > 1 \). 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

\[
\omega_s^g \geq A_{s,h}^g.
\]  

(23)

### 5.2.3 Marriage Market

Marriage is determined by chance, but varies with educational attainment. Women at time \( t \) marry with probability \( p_{e,t}^f \) 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., \( p_{j,j,t}^f > p_{j,k,t}^f \) with \( \sum_{e^* = 0,1} p_{e^*,e^*,t}^f = 1 \). Only agents of the same generation marry, and only 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 \( \lambda_{g,e}^{f,e} \) 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

\[
p_{e,t}^m = \frac{\sum_{e^* = 0,1} \lambda_{e,t}^{f,e} p_{e^*,e^*,t}^f p_{e,e,t}^f p_{e^*,e^*,t}^f}{\lambda_{t}^{m,e}},
\]

\[
p_{e,1,t}^m = \frac{\sum_{e^* = 0,1} \lambda_{e,t}^{f,1} p_{e^*,e^*,t}^f p_{e,e,t}^f p_{e^*,e^*,t}^f}{\sum_{e^* = 0,1} \lambda_{e,t}^{f,1} p_{e^*,e^*,t}^f p_{e,e,t}^f p_{e^*,e^*,t}^f} \quad \text{and} \quad p_{e,0,t}^m = 1 - p_{e,1,t}^m.
\]

### 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 \( \varepsilon > 0 \). However, when making the college decision, agents do not have perfect information over their true innate brain ability, which is only revealed at the start of their working life.\footnote{Allowing for uncertainty on ability avoids perfect sorting into education by brain ability consistent with empirical evidence. Moreover, this reduces the computational burden, as education decisions can be computed from a representative agent problem.} 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, $E\left(V^g_1\right) - X \geq E\left(V^g_0\right)$. More specifically,

$$p^g_{1,t} \sum_{e^* = 0,1} \left( p^g_{1,e^*} V^g_{p,1,e^*} \right) + (1 - p^g_{1,t}) V^g_{s,1} - p^g_{0,t} \sum_{e^* = 0,1} \left( p^g_{0,e^*,t} V^g_{p,0,e^*} \right) - (1 - p^g_{0,t}) V^g_{s,0} \geq X,$$

(24)

where $V^g_{p,1,e^*} (V^g_{p,0,e^*})$ is the value function of an educated (uneducated) agent married to a spouse of education $e^* = \{0, 1\}$ and $V^g_{s,e}$ is the value function of an agent that remains single forever with education $e = \{0, 1\}$. Equation (24) 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 $\{w_{e,t}, w_{bh,t}, w_{rd,t}\}_{(e=0,1)}$, is defined by:

1. The demand for market goods, $c_i$, the production of household goods, $h_i$, the time allocation of labor, $\ell^g_i$, and the initial education choice, $e^g_i$, that maximize household utility;

2. 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 calibrated 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 $a^1$; (2) BBTC through an increase in $\{n^1, n^0\}$; (3) falling marriage rates; and (4) changes in home productivity.\(^{18}\)

\(^{18}\)Duernecker and Herrendorf (2018) 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.
Agents work for 40 years (or 4 periods) and discount at an annual factor 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 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, $g_{A_0} = 0.004$ before 1978 and $g_{A_1} = 0.015$ 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

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

where $L^e_{j,t}$ are employment shares of occupation $j$ and education $e$.\(^{19}\) To estimate the elasticity parameter $\phi^e$, BBTC is assumed log-linear,\(^{20}\)

$$\ln \left( \frac{y^e_t}{1 - y^e_t} \right) = b^*_e t + \eta^e_t. \quad (26)$$

Taking the natural logarithm of the relative wage Equation (14), and inserting Equation (26), leads to the following regression by education group:

$$\ln \left( \frac{w^e_t}{w^e_{t-1}} \right) = a^1_e t + a^2_e \ln \left( \frac{E^e_{b,t}}{E^e_{r,t}} \right) + \nu^e_t, \quad (27)$$

where $a^1_e = \phi^e - 1$. 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 $\phi^1 = \phi^0 = 0.88$. In addition, BBTC or the evolution of $y^e_t$ is given by the coefficient $a_1$ and Equation (26).

The subsistence scaling parameter is set according to OECD scales, $\psi = 1.5$. The share parameter for educated labor is set to $g^e_0 = 0.5$. The mean brain, $\mu_b$, is normalized to zero while male brawn, $r^m$, is

---

\(^{19}\)Employment shares, $L^e_{j,t}$, include 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.

\(^{20}\)See also Krusell et al. (2000) for a similar estimation.
Table 3: Elasticity Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Aggregate</th>
<th>C+</th>
<th>LTC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_2$</td>
<td>-0.123**</td>
<td>-0.120**</td>
<td>-0.121**</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.017)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>$a_1$</td>
<td>0.011**</td>
<td>0.015**</td>
<td>0.005**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

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. The 1968-2010 March CPS data are used for wage and efficiency units; see Table 1 and 2 for details on the computation of wage rates and efficiency units of labor.

normalized to one, such that men have on average the same innate brain and brawn endowments. Home productivity is allowed to differ only for married women, $A^f_h \geq A^m_h = A^m_{s,h} = A^f_{s,h} = A_h$. SBTC, $g\alpha$, is estimated to match the rise in the college wage premium and the rise in male educational attainment from 1960 to 2010. All remaining parameters $\{a^e_f, y^e_0, r^f, A^f_h, A_h, p_s, \bar{c}, \sigma_b, \gamma, \mu_X, \sigma_X\}$ 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, $\{\mu_X, \sigma_X\}$, are matched to education shares. The shares of young males with a college degree in 1960 provides a one-to-one mapping for the average cost of education. The variance in educational cost, $\sigma_X$, is used to match the lower education share of women in 1960. The production share parameters, $\{a^e_1, y^e_0\}$, are matched to the college wage premium and the labor force participation of men.\(^{21}\) The productivity parameters $\{r^f, \sigma_b, \gamma\}$ 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, $\sigma_b$,\(^{22}\) and the difference between the gender wage gap for college versus non-college workers is informative on the additional returns to education, $\gamma$. The parameters governing participation $\{\bar{c}, A^f_h, A_h, p_s\}$ are matched to all remaining labor force participation targets and the difference between the selection-corrected (using the Heckman correction framework) and uncorrected married gender

\(^{21}\)Given the log-linear specification, the coefficient on brain $y^e_f = \frac{\gamma \exp(a^e_f t)}{1 - \gamma + \gamma \exp(a^e_f t)}$.

\(^{22}\)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.
Table 4: Model Parameters

<table>
<thead>
<tr>
<th>Estimated</th>
<th>Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>share on C+ output</td>
<td>0.39</td>
</tr>
<tr>
<td>$\gamma_0^0$</td>
<td>share on LTC brain/brawn</td>
<td>0.48</td>
</tr>
<tr>
<td>$r^f$</td>
<td>female brawn</td>
<td>0.27</td>
</tr>
<tr>
<td>$\sigma_b$</td>
<td>std. dev. brain</td>
<td>0.61</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>education brain increment</td>
<td>0.44</td>
</tr>
<tr>
<td>$\tau$</td>
<td>subsistence consumption</td>
<td>0.35</td>
</tr>
<tr>
<td>$A_{1,b}$</td>
<td>married women home productivity</td>
<td>2.51</td>
</tr>
<tr>
<td>$A_{1,h}$</td>
<td>general home productivity</td>
<td>0.47</td>
</tr>
<tr>
<td>$p_s$</td>
<td>singles’ work requirement</td>
<td>0.39</td>
</tr>
<tr>
<td>$\mu_X$</td>
<td>mean cost of education</td>
<td>1.96</td>
</tr>
<tr>
<td>$\sigma_X$</td>
<td>std. dev. cost of education</td>
<td>0.98</td>
</tr>
<tr>
<td>$g_{\alpha}$</td>
<td>SBTC growth rate</td>
<td>0.01</td>
</tr>
</tbody>
</table>

**Predetermined**

| $\phi^1$ | elasticity parameter C+ brain/brawn | 0.88   |
| $\phi^0$ | elasticity parameter LTC brain/brawn| 0.88   |
| $\phi$   | elasticity parameter C+ vs LTC      | 0.60   |
| $\zeta$  | elasticity parameter consumption    | 0.57   |
| $g_{\phi}$ | BBTC growth rate on LTC    | 0.005  |
| $g_{\phi}$ | BBTC growth rate on C+    | 0.015  |
| $g_{A_{1,0}}$ | home-to-market productivity growth rate before 1978 | 0.004 |
| $g_{A_{1,1}}$ | home-to-market productivity growth rate after 1978 | -0.015 |

**Normalized**

| $\mu_b$  | mean brain            | 0      |
| $r^m$    | male brawn            | 1.0    |
| $\gamma_0^f$ | share on C+ brain/brawn | 0.5   |

wage gap. Lastly, the change in the log wage premium and rise in the share of educated men provide a direct mapping for SBTC.\(^{23}\) Targets are matched well. The largest discrepancy is between the married labor force participation in the data and model of 0.33 versus 0.52. A calibration that allows for differences in education cost by gender in 1960 can remedy this discrepancy.\(^{24}\)

### 7 Results

The economy is simulated for six periods from 1960 to 2010. In addition to the estimated and calibrated growth rates, marriage rates are adjusted to match US marriage trends.\(^{25}\) Table 6 documents aggregate time

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\(^{23}\)SBTC is set to start only after 1978 consistent with the evidence from Heathcote, Storesletten and Violante (2010).

\(^{24}\)As the results of the two version are otherwise similar, I proceed with the more restricted calibration.

\(^{25}\)See Appendix Table B.2 in B for the evolution of marriage rates.
Table 5: Data Targets and Model Moments

<table>
<thead>
<tr>
<th>1960s Target</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Young Male C+</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Young Female C+</td>
<td>0.07</td>
<td>0.08</td>
</tr>
<tr>
<td>Rise in Young Male C+</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>Single Female LFP</td>
<td>0.68</td>
<td>0.69</td>
</tr>
<tr>
<td>Single Female C+ LFP</td>
<td>0.89</td>
<td>0.87</td>
</tr>
<tr>
<td>Single Male LFP</td>
<td>0.87</td>
<td>0.88</td>
</tr>
<tr>
<td>Male LFP</td>
<td>0.95</td>
<td>0.98</td>
</tr>
<tr>
<td>Married Female LFP</td>
<td>0.33</td>
<td>0.52</td>
</tr>
<tr>
<td>Gender Wage Gap</td>
<td>-0.54</td>
<td>-0.56</td>
</tr>
<tr>
<td>Gender Wage Gap Difference C+ to LTC</td>
<td>0.14</td>
<td>0.13</td>
</tr>
<tr>
<td>Married Gender Wage Gap Difference Corrected to Average</td>
<td>0.10</td>
<td>0.07</td>
</tr>
<tr>
<td>Male College Premium</td>
<td>0.42</td>
<td>0.49</td>
</tr>
<tr>
<td>Variance in Log Male Wages</td>
<td>0.10</td>
<td>0.12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Growth Target</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Growth in Male College Wage Premium</td>
<td>0.32</td>
<td>0.37</td>
</tr>
</tbody>
</table>


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. The first four columns report the difference between men and women (e.g., fraction C+ women minus fraction C+ men for each year). The last two columns report the difference between 2010 and 1960 (e.g., fraction C+ in 2010 minus fraction C+ in 1960).26

Having estimated a rise in BBTC from the data (see Table 3) and calibrated a rise in SBTC by only targeting a rise in male education rates, the model generates closing gaps for education, employment and wages as in the US. The model is able to replicate over 50 percent (0.41 versus 0.22) 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 57 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 gender-difference necessary to

26Due to rounding when reporting statistics in Tables 5 and 6 the values do not match exactly.
generate a reversal in the gender education gap is that women have 27 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 by ability and education 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 seven percentage points smaller. The model produces the same change in self-selection as in the data (from negative to positive), where the difference goes from three to negative one percentage points. With this changing self-selection of women, the benchmark replicates 78 percent of the closing gender wage gap (0.23 over 0.29) and almost all the gender gap for married individuals (0.25 over 0.26).

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 transition’s relative slopes. Figure 3 shows the evolution of the gender wage and education gaps - both having time-varying paths. The US gender wage gap closes on average by 0.2 percentage points per annum from 1960 to 1980, and then accelerates to a rate of 0.8 percentage points per annum from 1980 to 2010. In the model, the respective rates are 0.2 and 0.6 percentage points per annum - growth more than triples 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 1980/1990 and a per annum change of 0.4 after 1990. As I will discuss later (see Figure 5), this acceleration

### Table 6: Gender Gaps over Time

<table>
<thead>
<tr>
<th></th>
<th>1960 Model</th>
<th>2010 Data</th>
<th>2010 Model</th>
<th>( \Delta_{2010-1960} ) Data</th>
<th>( \Delta_{2010-1960} ) Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction C+</td>
<td>-0.05</td>
<td>-0.04</td>
<td>0.02</td>
<td>0.06</td>
<td>0.09</td>
</tr>
<tr>
<td>Fraction Young C+</td>
<td>-0.07</td>
<td>-0.04</td>
<td>0.07</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td><strong>Employment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>-0.54</td>
<td>-0.42</td>
<td>-0.14</td>
<td>-0.21</td>
<td>0.41</td>
</tr>
<tr>
<td>Single</td>
<td>-0.19</td>
<td>-0.20</td>
<td>-0.03</td>
<td>-0.14</td>
<td>0.15</td>
</tr>
<tr>
<td>Married</td>
<td>-0.63</td>
<td>-0.48</td>
<td>-0.20</td>
<td>-0.24</td>
<td>0.43</td>
</tr>
<tr>
<td><strong>Wage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>-0.54</td>
<td>-0.56</td>
<td>-0.26</td>
<td>-0.34</td>
<td>0.29</td>
</tr>
<tr>
<td>Married</td>
<td>-0.58</td>
<td>-0.57</td>
<td>-0.32</td>
<td>-0.32</td>
<td>0.26</td>
</tr>
<tr>
<td>Selection-Adjusted All</td>
<td>-0.41</td>
<td>-0.53</td>
<td>-0.32</td>
<td>-0.35</td>
<td>0.09</td>
</tr>
</tbody>
</table>
is only partially driven by the delayed (post-1978) onset of SBTC.

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, $g_{1960}^1 > g_{1960}^0$ and $\varepsilon > 0$. 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 $r_f = r_m = 1.0$, $g_\nu = g_\nu^1 = 0$ and $g_\alpha = 0$ and estimate a labor market discrimination, $\{\tau_{1960}, \tau_{2010}^e\}$, to match the change in the gender wage gap from 1960 to 2010. A woman now earns wage, $w_{e_i,t}^f = (1 - \tau_t^e)w_{e_i,t}(w_{b_i}^e b_i (1 + e_i \varepsilon_i) + w_{r_i}^e)$ for $e_i \in \{0, 1\}$, where the gender-specific labor market discrimination, $\tau^e$, is potentially education specific.

Figure 4 shows the resulting gender wage and education gap evolution assuming gender discrimination decreases monotonically. Three experiments are computed: (1) with SBTC, $g_\alpha > 0$, which is labeled “Discrimination and SBTC,” (2) without SBTC, $g_\alpha = 0$, labeled “Discrimination,” and (3) without SBTC, but
Figure 4: Counterfactual: Labor Market Discrimination

(a) The Gender Wage Gap

(b) The Gender Education Gap

where discrimination is allowed to differ by education for all time periods, labeled “Discrimination by skill.” This last counterfactual instead of matching the aggregate change in the gender wage gap from 1960 to 2010 is matched to the change in the education-specific gender wage gaps. Allowing for a linear decrease in labor market discrimination leads to an almost linear gender wage gap closing (see Figure 4 left panel). Without SBTC and BBTC, the gender wage gap closes in a slightly inverted U-shape. Allowing for skill-specific discrimination also shows a linear trend over time, in addition to a gap that is 6.2 percentage points larger compared to the baseline model in 2010.

Removing SBTC, BBTC and gender differences in brawn eliminates women’s extra incentive to educate (see Figure 4 right panel). With SBTC still present, the gender education gap does not close until 1990, but then closes one-third less than in the benchmark. Without any technical change, the gender education gap closes even less. 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, $\tau$, and average brawn equals average brain for all education groups. Instead, allowing for education-specific discrimination generates a closing education gap more similar to the benchmark model, but this closing gap is not enough to decrease the gender wage gap. This suggests that both educational changes and BBTC play an important role in closing the gender wage gap.
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 and BBTC explain a similar portion of the reversal in the gender education gap. In contrast, the gender wage gap convergence is explained mostly by BBTC. The main difference is that SBTC affects only the late acceleration of later period. Without SBTC, fewer high-ability women enter the labor market, i.e., in the benchmark, women surpass men in educational attainment only after 2000. This is consistent with the timing of the three effects highlighted in the partial equilibrium model of Section 4. Thus, the positive education effect, coupled with a higher skill premium, only dominates in later decades.

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 an almost 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 Household Counterfactual

Household composition has shifted significantly in the last decades, affecting the education decision of women (Guvenen and Rendall, 2015). The evolution of gender gaps with the “marriage market” fixed at 1960 are reported in Table 7 (see Column “NoM”). Marriage rates had no effect on the education gap, but without changes in marriage rates the employment gap would close even more as would the gender wage gap of married women. While the path of convergence remains unchanged for employment and wage gaps, the gender education gap now closes in a more uniform way. This is most evident for the education rates of

Table 7: Gender Gaps over Time: Household Counterfactuals

<table>
<thead>
<tr>
<th></th>
<th>Data (Base)</th>
<th>Model (NoM)</th>
<th>Model (NoHP)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction C+</td>
<td>0.06</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>Fraction Young C+</td>
<td>0.14</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td><strong>Employment</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>0.41</td>
<td>0.22</td>
<td>0.28</td>
</tr>
<tr>
<td>Single</td>
<td>0.15</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>Married</td>
<td>0.43</td>
<td>0.25</td>
<td>0.34</td>
</tr>
<tr>
<td><strong>Wage</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>0.29</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>Married</td>
<td>0.26</td>
<td>0.25</td>
<td>0.29</td>
</tr>
<tr>
<td>Selection-Adjusted All</td>
<td>0.09</td>
<td>0.18</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Notes: “Base” refers to the benchmark results, “NoM” to the counterfactual without changes in marriage probabilities, and “NoHP” to the counterfactual without changes in home productivity.
the young, aged 25 to 34 (see Figure 7 right panel).

Moreover, in light of recent evidence that changes in home productivity matter for market versus home hours allocation (Duernicker and Herrendorf, 2018; Moro, Moslehi and Tanaka, 2017), the base model allows for changing home productivity. The following counterfactual sets changes in home productivity to zero, \( g_{Ah,0} = g_{Ah,1} = 0 \), 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, education or wage gaps (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 tripling (subperiods not reported here). Similarly, the growth rate for the education gap remains at zero percent prior to 1990, only showing positive growth from 1980/1990 to 2010.

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 changing household composition are able to replicate the closing gender wage gap, the reversal of the gender education gap, and over half of the rise in female labor force participation. 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 and BBTC play a complementary role in shaping the reversal of the gender education gap. In contrast, BBTC has a fairly constant effect on the closing gender wage gap, as suggested by the partial equilibrium model, while SBTC is essential in providing the later accelerated positive supply effect of educated women.

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

References


## Appendix: Skill Measures

As explained in the text, the 1977 and 1991 DOT measure 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.\(^{27}\) The general educational development group 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. The specific vocational training 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.

To combine different DOT variables, the original job requirements are rescaled. Vijverberg and Hartog (2005) provide a detailed methodology for rescaling DOT variables. Pre-1976 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 are used between 1977 and 1991.

To obtain population representative estimates, the occupations in the DOT must be weighted. In the

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\(^{27}\)Data and documentation is available from the Inter-university Consortium for Political and Social Research (ICPSR).
### Table A.1: DOT Job Requirements

<table>
<thead>
<tr>
<th>Job Characteristic</th>
<th>Avg.¹</th>
<th>PCA²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Brawn Factor</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Climbing/Balancing</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Stooping/Kneeling/Crouching/Crawling</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Strength Requirement</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Environmental Exposure³</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Indoor or Outdoor Work</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td><strong>Brain Factor</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reasoning Development</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Mathematical Development</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Language Development</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Specific Vocational Preparation</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>General Intelligence</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Verbal Aptitude</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Numerical Aptitude</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Clerical Aptitude</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Talking and Hearing</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>

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.

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.²⁸ Since skills have no natural scale, they are normalized to percentiles of the 1960 US skill distributions, respectively.²⁹

²⁸Census 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.
²⁹For details on the normalization see Autor, Levy and Murnane (2003). The scaling is done for both the 1977 and 1991 DOT
Figure A.1: *Evolution with PCA*

![Graph showing evolution with PCA](image)

Source: See Figure 2 for details.

Figure A.1 compares the brain and brawn estimates with an alternative specification using principle component analysis (see Table A.1 for measures used). 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 and Education

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.

The same is true when splitting the economy by college and non-college educated workers (see Figure A.3). College workers are employed in occupations with less brawn and more brain requirements. However, even college graduates work in occupation that require some brawn and the share of these workers decreases from 1960 to 2010.

### B Appendix: Additional Data

Table B.1 reports the 5-year moving average relative brain-to-brawn log wage returns by education from Equation (3). Both series show an almost (excluding 1980) monotonic upward movement.

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.2: *Brain and Brawn across Sectors*

(a) Industry

(b) Services

Source: See Figure 1 for details.

Figure A.3: *Brain and Brawn by Education*

(a) College

(b) Less than College

Source: See Figure 1 for details.

Table B.2 summarizes the marriage rates over time. Columns (1) and (2) are the share of married women with a college or no-college education, respectively. Column (3) is the share of C+ women married to a C+ man, while Column (4) is the share of LTC women married to a C+ man. US data shows a decrease in overall marriages rates and an increase in assortative mating.

---

Table B.2: Summary of Marriage Rates

<table>
<thead>
<tr>
<th>Year</th>
<th>College Education</th>
<th>Less than College</th>
</tr>
</thead>
<tbody>
<tr>
<td>1960</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

30 Therefore, the share of C+ women married to a LTC man is one minus Column (3) and the share of LTC women married to a LTC man is one minus Column (4).
Table B.1: *Relative Brain to Brawn Returns over Time*

<table>
<thead>
<tr>
<th>Year</th>
<th>C+</th>
<th>LTC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1965</td>
<td>-0.26</td>
<td>-0.09</td>
</tr>
<tr>
<td>1970</td>
<td>-0.13</td>
<td>0.03</td>
</tr>
<tr>
<td>1975</td>
<td>-0.10</td>
<td>-0.01</td>
</tr>
<tr>
<td>1980</td>
<td>-0.24</td>
<td>-0.13</td>
</tr>
<tr>
<td>1985</td>
<td>-0.15</td>
<td>-0.07</td>
</tr>
<tr>
<td>1990</td>
<td>-0.06</td>
<td>-0.07</td>
</tr>
<tr>
<td>1995</td>
<td>0.10</td>
<td>-0.06</td>
</tr>
<tr>
<td>2000</td>
<td>0.29</td>
<td>0.16</td>
</tr>
<tr>
<td>2005</td>
<td>0.28</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Source: See Table 2 for details.

Table B.2: *Female Marriage Rates over Time*

<table>
<thead>
<tr>
<th>Year</th>
<th>C+</th>
<th>LTC</th>
<th>C+: M C+</th>
<th>LTC: M C+</th>
</tr>
</thead>
<tbody>
<tr>
<td>1960</td>
<td>0.73</td>
<td>0.80</td>
<td>0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>1970</td>
<td>0.77</td>
<td>0.79</td>
<td>0.06</td>
<td>0.10</td>
</tr>
<tr>
<td>1980</td>
<td>0.71</td>
<td>0.73</td>
<td>0.11</td>
<td>0.13</td>
</tr>
<tr>
<td>1990</td>
<td>0.67</td>
<td>0.67</td>
<td>0.15</td>
<td>0.13</td>
</tr>
<tr>
<td>2000</td>
<td>0.68</td>
<td>0.64</td>
<td>0.21</td>
<td>0.12</td>
</tr>
<tr>
<td>2010</td>
<td>0.67</td>
<td>0.60</td>
<td>0.27</td>
<td>0.11</td>
</tr>
</tbody>
</table>