

The “End of Men” and Rise of Women in the High-Skilled Labor Market*

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Abstract

We document a new finding regarding changes in labor market outcomes for men and women in the US. Since 1980, conditional on being a college-educated man, the probability of working in a cognitive/high-wage occupation has fallen. This contrasts starkly with the experience for college-educated women: their probability of working in these occupations rose, despite a much larger increase in the supply of educated women relative to men. We consider these facts in light of a general neoclassical model of the labor market. One key channel capable of rationalizing these findings is a greater increase in the demand for female-oriented skills in cognitive/high-wage occupations relative to other occupations. Using occupation-level data, we find evidence that this relative increase in the demand for female skills is due to an increasing importance of social skills within such occupations. Evidence from both male and female wages is also indicative of an increase in the demand for social skills.

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1 Introduction

A large literature documents that since 1980, and especially between 1980 and 2000, the US experienced a pronounced increase in the demand for high-skilled labor who perform cognitive tasks (see, for instance, [Violante \(2008\)](#); [Acemoglu and Autor \(2011\)](#); [Beaudry, Green, and Sand \(2016\)](#), and the references therein). In this paper, we show that the gains in the high-skilled labor market have not been distributed equally across genders.

In [Section 2](#), we document a deterioration in the employment outcomes of high-skilled men since 1980. Specifically, there has been a fall in the likelihood that a college-educated male is employed in a high-wage/cognitive occupation (what we call a “good job” and define in detail below). This is in stark contrast to the experience for high-skilled females whose likelihood of working in a good job rose. This is especially striking given that the supply of high-skilled women increased much more than it did for men during this period. These divergent gender trends are not due to compositional shifts across occupations, with employment growth in good jobs being concentrated in female-dominated ones. Rather, we find that this divergence is accounted for by an increase in the female share of employment in essentially all good jobs.¹ This motivates us to study these changes as macro phenomena, affecting high-wage/cognitive occupations broadly.

To shed light on the forces capable of rationalizing the divergent gender patterns, we study a general model of the market for high-skilled workers in [Sections 3](#) and [4](#). The model is sufficiently flexible to allow for gender differences in: (a) the supply of workers, (b) occupational choice, (c) discrimination, and (d) labor productivity, both in terms of levels and changes over time. Under a minimal set of assumptions, we show that the facts regarding occupational outcomes and the distribution of wages can be rationalized by three model channels. One channel is a greater increase in the demand for female-oriented skills relative to male skills—what we refer to as greater *female bias*—in high-wage/cognitive occupations relative to others.

Motivated by this model prediction, we explore the relationship of this channel to changes observed in occupational skill requirements. Evidence from the psychology and neuroscience literatures indicate that women have a comparative advantage in tasks requiring social and interpersonal skills (see, for instance, [Hall \(1978\)](#); [Feingold \(1994\)](#); [Baron-Cohen, Knickmeyer, and Belmonte \(2005\)](#); [Chapman et al. \(2006\)](#); [Woolley et al. \(2010\)](#); [Koenig et al. \(2011\)](#)). As such, we study whether the demand for social skills has changed over time. Specifically, our hypothesis is that the importance of social skills has become

¹See also [Blau, Brummund, and Liu \(2013\)](#) and [Hsieh et al. \(2013\)](#) who document declining occupational segregation by gender.

greater *within* high-wage/cognitive occupations relative to other occupations, and that this is a force increasing the demand for women relative to men in good jobs.²

In Section 5, following the literature that characterizes occupations as task bundles (Autor, Levy, and Murnane 2003; Gathmann and Schönberg 2010), we use two data sources to measure the importance of social skills within an occupation and, importantly, its change over time. The first data source is the Dictionary of Occupational Titles (DOT, hereafter); the second is a database of newspaper job advertisements by Atalay et al. (2017). Our measurement is based on the extent to which workers in an occupation are required to possess skills in performing tasks that are social or interpersonal in nature (defined in detail below). Consistent with our model analysis, high-wage/cognitive occupations have experienced both an increase in the importance of social skills and an increase in the female share of employment relative to other occupations. Moreover, this relationship between changes in the importance of social skills and female share is robust to the inclusion of other measures of occupational task change considered in the literature.

Section 6 explores the relationship between skill content and occupation wage premia. We use wage data to demonstrate an overall increase in the demand for social skills. We show that the return to social skills, conditional on other characteristics of occupations, increased significantly between 1980 and 2000. Moreover, social skills importance explains a growing proportion of variation in occupational wages. In addition, we use occupational wage premia to rule out the possibility that the DOT-based findings of Section 5 are driven by reverse causality (i.e., that the measured importance of social skills in high paying occupations increased as a reaction to increased female employment). Finally, we offer wage evidence suggesting fruitful avenues of research in identifying specific mechanisms through which the demand for social skills has risen.

Our paper contributes to the vast literature that studies differences in labor market outcomes between men and women. This literature has predominantly focused on the gender pay gap (see e.g. Blau and Kahn (2017); Goldin (2014) and the references therein). Our analysis instead focuses on occupational employment outcomes (rather than wage outcomes conditional on employment), and in particular the employment outcomes within the high-skill segment of the labor market. Our approach is most closely related to papers that explore the role of comparative advantage and changes in task composition in accounting for changes in gender gaps. For example, Bacolod and Blum (2010) and Black and Spitz-

²Our interest in social skills is motivated by the recent work of Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) who emphasize the importance of the *level* of social skills in understanding occupational employment growth trends. However, our emphasis is on the *change* in social skill importance over time within occupations, a distinction we turn to in Section 5.

Oener (2010) study how changes in the demand for different tasks contribute to the closing of the gender wage gap. Various papers, including Galor and Weil (1996), Welch (2000), Beaudry and Lewis (2014), Bhalotra, Fernández, and Venkataramani (2015), Yamaguchi (2016), and Rendall (2017) suggest that women have a comparative advantage at tasks that involve “brains” as opposed to “brawn”, and link the decrease in the demand for physical tasks to the shrinking of the gender wage gap. Ngai and Petrongolo (2017) consider a model of structural transformation, where female relative hours and wage gains are driven by “between industry” changes towards the service-producing sector, while Olivetti and Petrongolo (2014) show that industry structures play an important role in accounting for international differences in gender outcomes.³

2 Divergence in High-Skilled Labor Market Outcomes

The occupational distribution of employment differs greatly between high- and low-skilled workers. A college education allows one to work in occupations that would otherwise be difficult to obtain with less schooling. In this section we present the divergent gender trends in terms of employment likelihood in these desirable, “good jobs”—a deterioration for high-skilled men, and an improvement for high-skilled women.

We consider a number of categorizations of what a good job is, and show that our results are robust across definitions. Our first definition comes from the *job polarization* literature. We partition occupations at the 3-digit Census Occupation Code level as either cognitive, routine, or manual (see, for instance, Autor and Dorn (2013), Cortes (2016), Jaimovich and Siu (2012), Cortes et al. (2015), Beaudry, Green, and Sand (2016)). We categorize *cognitive* occupations—which include, for example, general managers, physicians, financial analysts, computer software engineers, and economists—as good jobs. These “white-collar” occupations place emphasis on “brain” (as opposed to “brawn”) activities, and perform tasks that require greater creativity, analysis and problem-solving skills than others. Not surprisingly, these tend to occupy the upper-tail of the occupational wage distribution. Routine occupations (e.g., machine operators and tenders, secretaries and administrative assistants) tend to occupy the middle of the wage distribution, and manual occupations (e.g., janitors and building cleaners, personal and home care aides) the bottom (see Goos and Manning (2007), Acemoglu and Autor (2011)). Our second definition looks directly at an occupation’s wage ranking. We consider good jobs to be those in the *top quartile*

³See also Burstein, Morales, and Vogel (2015) on the link between computer use and the closing of the gender wage gap, and Juhn, Ujhelyi, and Villegas-Sanchez (2014) on the relationship between trade liberalization and gender inequality in labor market outcomes in Mexico.

of the occupational wage distribution, where the mass of each occupation is based on its share of aggregate hours.⁴ Obviously, there is a significant amount of overlap in 3-digit level occupations across these definitions.

Our analysis uses the 5% samples of the 1980 and 2000 decennial censuses, made available by IPUMS (see [Ruggles et al. \(2010\)](#)). We restrict attention to the 20-64 year old, civilian, non-institutionalized population. We define the *high-skilled* as those with at least a college degree in terms of educational attainment.⁵ As is well known, this twenty year period saw an increase in the high-skilled population: a near doubling, from 20.97 million to 40.80 million, of individuals with at least a college degree. Despite this massive increase, the probability that a high-skilled individual was employed in a cognitive (COG) occupation did not fall; it remained constant at 61.1%, as their employment in such jobs also doubled. This constancy masks divergent trends in the COG employment likelihood across genders.

Table 1 presents the key statistics motivating our analysis. In 1980, 66% of high-skilled men worked in cognitive occupations. Over the next 20 years, this proportion *fell* by 3 percentage points (pp) to 63%.⁶ This fall in the probability of working in a good job was not observed among women. By contrast, the fraction of high-skilled women working in COG jobs *increased* by 4.6 pp between 1980 and 2000. This improvement in the likelihood of COG employment occurred despite a much larger increase in the number of college-educated women relative to men.

Moreover, this divergence in gender trends is pervasive, and is not driven by changes within narrow segments of the national market for high-skilled labor. For instance, when we disaggregate the US data by metropolitan statistical area (as defined by IPUMS), we find that the likelihood of working in a good job increases for high-skilled women relative to men in 93% of localities.⁷ We provide further discussion regarding the pervasiveness and robustness of this divergence in gender trends below.

⁴As is standard, we compute individual-level wages from the Census as total annual wage and salary income, divided by (weeks worked last year \times usual hours worked per week). Annual income in 1980 is multiplied by 1.4 for top-coded individuals (see [Firpo, Fortin, and Lemieux \(2011\)](#)). We restrict attention to those who report positive income and working ≥ 250 annual hours. Throughout our analysis, we exclude individuals in farming/forestry/fishing occupations. 3-digit occupations are ranked by their median wage, and assigned to percentiles according to their position in the hours-weighted distribution of employment.

⁵To match occupations across Census Occupation Coding systems, we use a crosswalk based on [Meyer and Osborne \(2005\)](#) and [Autor and Dorn \(2013\)](#), and discussed in [Cortes et al. \(2015\)](#); details are available upon request. Given changes in the census questionnaire over time, we define high-skilled workers as those with at least four years of college attainment in 1980, and those with at least a bachelor’s degree in 2000.

⁶Given the very large sample sizes in IPUMS, the standard errors for these proportions are miniscule, in the fourth decimal place.

⁷Moreover, of the 7% where the relative increase is greater for men, in only five MSAs does the probability of working in a COG occupation rise for men and fall for women in absolute terms (namely, Augusta-Aiken, GA-SC; Charleston-N.Charleston, SC; Gadsden, AL; Kokomo, IN; Macon-Warner Robins, GA).

Table 1: High-Skilled Occupational and Employment Status: 1980–2000

	1980	2000	% Difference		
			Total	Explained	Unexplained
Male					
<i>Total (000's)</i>	<i>12080</i>	<i>20340</i>			
Cognitive (%)	66.2	63.3	−2.9	+0.4	−3.3
Routine (%)	23.0	21.9	−1.1		
Manual (%)	3.0	4.1	+1.1		
Not Working (%)	7.8	10.7	+2.9		
Female					
<i>Total (000's)</i>	<i>8890</i>	<i>20470</i>			
Cognitive (%)	54.2	58.8	+4.6	−0.4	+5.0
Routine (%)	15.7	15.9	+0.2		
Manual (%)	2.9	3.8	+0.9		
Not Working (%)	27.2	21.5	−5.7		

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 and 2000 decennial censuses. Employment categorized by occupational task content. See text for details.

Finally, we note that these changes in occupational employment occurred alongside corresponding gender trends in participation. For college-educated men, the fall in the likelihood of working in a good job was accompanied by a nearly equal rise in the fraction not working (unemployed or out of the labor force). Of course, this does not imply that those who otherwise would have been in COG found themselves not working. Neither is the fall in cognitive employment an obvious or immediate consequence of declining participation among men. Consider a simple model where labor market outcomes are determined by selection on labor market ability, with the most able workers employed in COG, and those with the lowest ability not working. The rise in non-employment would have meant a disproportionate fall in the fraction employed in manual jobs. By contrast, 1980-2000 saw a disproportionate fall in male employment probability in cognitive jobs. Similarly, the rising participation rate of high-skilled women would have been felt disproportionately at the lower end of the occupational wage distribution. By contrast, the rise in female employment probability was reflected disproportionately in good jobs.⁸ This is further indication of the role of gender-specific processes that favored high-skilled women relative to their male counterparts in good jobs.

⁸We return to the issue of selection, and the joint determination of non-employment and, conditional on employment, occupational outcomes, in a more nuanced model in Subsection 3.2 and Appendix B.

In the rightmost columns of Table 1, we study whether this fall in COG employment probability among men can be attributed to changes in demographic characteristics. Denoting π_i as a dummy variable that takes on the value of 1 if individual i works in a COG occupation and 0 otherwise, we consider a simple linear probability model for working in a COG occupation in year t :

$$\pi_{it} = X_{it}\beta + \epsilon_{it}, \quad (1)$$

for $t \in \{1980, 2000\}$. Here, X_{it} denotes standard demographic controls for age (five year bins), race (white, black, hispanic, other), and nativity. The fraction working in COG reported in the first two columns of Table 1 are simply the sample averages:

$$\frac{1}{N} \sum_i^N \pi_{it} = \bar{\pi}_t. \quad (2)$$

As such, the “Total % Difference,” $\bar{\pi}_{2000} - \bar{\pi}_{1980}$, can be decomposed into a component that is explained by changes in the demographic composition of men over time, and a component unexplained by composition change. This latter component owes to changes in estimated coefficients, $\hat{\beta}$, reflecting changes in the propensities to work in COG for specific demographic groups (see [Oaxaca \(1973\)](#) and [Blinder \(1973\)](#)). We perform this Oaxaca-Blinder decomposition separately by gender.⁹

Demographic change predicts that (high-skilled, working age) males should have *increased* their probability of working in the cognitive occupational group modestly, by 0.4 pp. This is due largely to the shift toward 40-54 year olds (as prime-aged men are more likely to be COG than either the young or old) between 1980 and 2000. Hence, the observed fall is more than 100% due to the unexplained component, i.e., a fall in the propensity of high-skilled males to work in good jobs. Though not displayed here, we find that this fall is particularly acute among the prime-aged. The decomposition result for females stands in stark contrast. Demographic change predicts a 0.4 pp fall in the fraction of women in COG jobs. Hence, more than all of the observed rise is due to the unexplained component. Though not displayed here, we find that the increase in the propensity to work in good jobs is very widespread across women from different demographic groups (the main exception being young black women). The largest propensity increases are experienced by women aged 25-34 and 45-59.

These divergent trends are robust to alternative definitions of good jobs. Table 2 presents the same labor market statistics as Table 1, this time delineating jobs by their place in the occupational wage distribution of 1980. The likelihood of a high-skilled, working age man

⁹We implement this from a pooled regression over both time periods. Results in which coefficient estimates are obtained for either the 1980 or 2000 period are essentially unchanged.

Table 2: High-Skilled Occupational and Employment Status: 1980–2000

	1980	2000	% Difference		
			Total	Explained	Unexplained
Male					
<i>Total (000's)</i>	<i>12080</i>	<i>20340</i>			
Top 25%	59.9	55.9	-4.0	+0.6	-4.6
Bottom 75%	32.3	33.4	+1.1		
Not Working (%)	7.8	10.7	+2.9		
Female					
<i>Total (000's)</i>	<i>8890</i>	<i>20470</i>			
Top 25%	39.7	40.7	+1.0	-0.2	+1.2
Bottom 75%	33.1	37.8	+4.7		
Not Working (%)	27.2	21.5	-5.7		

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 and 2000 decennial censuses. Employment categorized by ranking in occupational wage distribution of 1980. See text for details.

being employed in a top quartile occupation fell by 4 percentage points between 1980 and 2000. Again, changes in demographic composition would have predicted the opposite. By contrast, the likelihood for women increased.¹⁰

In Appendix Table A.1, we present the analogue of Table 2, this time delineating jobs by their place in the occupational wage distribution of 2000. Again, the divergent gender trends are obvious. The male probability falls by approximately 3 pp, while the female probability rises by 3 pp; in both cases, more than 100% of the change is due to the unexplained component. Finally, Appendix Table A.2 contains the analogue of Table 1 for individuals with at least some post-secondary education. Again, the results hold, indicating that these divergent gender trends are robust to the definition of high- versus low-skilled. In summary, we find this to be clear evidence that the probability of being employed in a good job has fallen for high-skilled men, while it has risen for women.

2.1 Between or Within Occupations

These divergent gender trends in the employment likelihood, along with the increase in the number of high-skilled women relative to men, imply that there has been a pronounced

¹⁰We have replicated our analysis for the top quintile and decile of the distribution. The nature of our results are unchanged, and for brevity, are made available upon request.

Table 3: High-Skilled Female Share of Employment: Decomposition

	Observed		Between	Within
	1980	2000		
Cognitive	37.7%	48.4%	36.2%	49.4%
Top 25%	32.8%	42.3%	29.6%	44.6%

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 and 2000 decennial censuses. See text for details.

increase in the female share of employment in good jobs. Here, we investigate whether this is simply due to a shift “between” occupations, with employment growth in good jobs being concentrated in female-dominated ones. If this were the case, it would suggest a study of the specific forces leading to a disproportionate increase in such occupations.

To address this, we perform a simple within-vs-between decomposition of the rising share of female employment in the cognitive occupation group. Let F_t^{COG} denote female employment in all COG occupations at time t , and E_t^{COG} denote total employment in these jobs. The female share of employment, σ_t , is simply:

$$\sigma_t \equiv \frac{F_t^{COG}}{E_t^{COG}} = \sum_{j \in COG} \left(\frac{F_t^j}{E_t^j} \right) \times \left(\frac{E_t^j}{E_t^{COG}} \right) \quad (3)$$

where $\left(F_t^j / E_t^j \right)$ is the female share of employment in 3-digit occupation j , and $\left(E_t^j / E_t^{COG} \right)$ is the 3-digit occupation’s share of COG employment at time t .

The first row of Table 3 indicates that between 1980 and 2000, the female share of COG employment increased from approximately 38% to 48%. By how much would σ_t have increased if there were only between-occupation changes? We construct a counterfactual by holding all $\left(F_t^j / E_t^j \right)$ ’s at their 1980 values, and allowing only $\left(E_t^j / E_t^{COG} \right)$ values, the occupational shares, to change as observed in the data. This is reported in the third column of Table 3: the female share would have actually fallen.

The fourth column presents results for a counterfactual in which $\left(E_t^j / E_t^{COG} \right)$ values are held at their 1980 values, and only $\left(F_t^j / E_t^j \right)$ values vary as in the data. This over-predicts the increase in σ_t . Hence, all of the change in the female share is due to a broad-based increase in female representation *within* 3-digit level cognitive occupations. Indeed, the female share of employment increased in 92% of 3-digit level COG occupations between 1980 and 2000.

The second row of Table 3 presents the decomposition for employment in the top quartile occupations of 1980. Again, the increase in σ_t is due to “within” occupation changes, with

the female share increasing in 91% of top quartile 3-digit level occupations. We view this evidence, combined with the results from the previous subsection as pointing to a “macro” force, improving the labor market prospects of high-skilled females relative to males in good jobs, irrespective of the specific granular occupation.

3 Model

Here we present a simple equilibrium model of the market for high-skilled workers. The goal is to explore, within a neoclassical framework, the forces capable of generating the findings of Section 2. The model is intentionally general, allowing for gender differences in the supply of high-skilled workers, the distribution of cognitive work ability, wages, occupational outcomes, and their changes over time. In Section 4, we use the model to illuminate the forces capable of rationalizing the falling share of high-skilled men and the rising share of high-skilled women working in “good jobs,” between 1980 and 2000. For the purposes of exposition and quantitative analysis, we label good jobs as cognitive occupations.¹¹

3.1 Labor Demand

Our theoretical results can be derived from a very general specification of the demand for labor. In particular, we assume that high-skilled labor is combined with other inputs to produce real output, Y_t , via:

$$Y_t = G(f^C(Z_{Mt}^C L_{Mt}, Z_{Ft}^C L_{Ft}), f^O(Z_{Mt}^O E_{Mt}, Z_{Ft}^O E_{Ft}), \mathbb{K}_t). \quad (4)$$

Here, $f^C(\cdot)$ represents “cognitive labor services,” which are produced from effective labor in the *cognitive* occupation, L_{gt} , for $g = \{M, F\}$ where M stands for male, and F stands for female. As we discuss below, high-skilled individuals are endowed with different abilities in cognitive work, implying that the amount of effective labor differs from the measure, or “number,” of employed workers. Effective labor is augmented by gender-specific productivity, Z_{Ft}^C and Z_{Mt}^C .

The employment of high-skilled males and females who work in the non-cognitive or *other* occupation, E_{Mt} and E_{Ft} , produces “other labor services,” $f^O(\cdot)$. Here too there is gender-specific productivity, Z_{Mt}^O and Z_{Ft}^O .

Finally, \mathbb{K}_t is a vector of all other factor inputs (which may include capital, low-skilled labor, etc.) at date t . We assume that the function G is constant returns to scale, with

¹¹Our results hold for other definitions explored in Section 2; for brevity, these are available upon request.

$G_1, G_2 > 0$, $G_{11}, G_{22} < 0$, $f_1^i, f_2^i > 0$ and $f_{11}^i, f_{22}^i \leq 0$ for $i = C, O$.¹²

The representative firm hires factor inputs in competitive markets. There is discrimination towards women in the labor market; we model this as a tax representing preference-based discrimination as in the seminal work of [Becker \(1957\)](#). Hence, the firm's problem is to solve:

$$\max_{\substack{L_{Mt}, L_{Ft}, \\ E_{Mt}, E_{Ft}, \mathbb{K}_t}} Y_t - (1 + \tau_t^C)w_{Ft}L_{Ft} - w_{Mt}L_{Mt} - (1 + \tau_t^O)p_{Ft}E_{Ft} - p_{Mt}E_{Mt} - \mathbf{r}_t\mathbb{K}_t. \quad (5)$$

For generality, the discriminatory “wedge” against high-skilled women in the cognitive occupation, $(1 + \tau_t^C)$, may differ from that in the other occupation, $(1 + \tau_t^O)$. Maximization results in standard labor demand functions for L_{Mt} , L_{Ft} , E_{Mt} and E_{Ft} :

$$w_{Mt} = Z_{Mt}^C G_1(\cdot) f_1^C(Z_{Mt}^C L_{Mt}, Z_{Ft}^C L_{Ft}), \quad (6)$$

$$w_{Ft} = \frac{Z_{Ft}^C}{1 + \tau_t^C} G_1(\cdot) f_2^C(Z_{Mt}^C L_{Mt}, Z_{Ft}^C L_{Ft}), \quad (7)$$

$$p_{Mt} = Z_{Mt}^O G_2(\cdot) f_1^O(Z_{Mt}^O E_{Mt}, Z_{Ft}^O E_{Ft}), \quad (8)$$

$$p_{Ft} = \frac{Z_{Ft}^O}{1 + \tau_t^O} G_2(\cdot) f_2^O(Z_{Mt}^O E_{Mt}, Z_{Ft}^O E_{Ft}). \quad (9)$$

These equate wages (per unit of effective labor) to their (net of wedge) marginal products. Hence, Z_{Mt}^C , Z_{Ft}^C , Z_{Mt}^O and Z_{Ft}^O act as “shifters” to the labor demand curves in wage-employment space.

3.2 Labor Supply

On the supply side, S_{gt} denotes the measure of high-skilled individuals of each gender at date t for $g = \{M, F\}$. Individuals differ in their work ability in the cognitive occupation, a . We allow the distribution of ability to differ by gender and over time: $a \sim \Gamma_{gt}(a)$, where Γ denotes the cumulative distribution function.

For simplicity, all high-skilled workers supply labor (inelastically) to either the cognitive or the other occupation. That is, individuals make a discrete occupational choice. Given the wage per unit of effective labor, w_{gt} , a worker with ability a earns $a \times w_{gt}$ if employed

¹²As an example, consider:

$$G = K^\alpha \left[Z_F^C L_F + Z_M^C L_M \right]^{1-\alpha} + J^\alpha \left[Z_F^O E_F + Z_M^O E_M \right]^{1-\alpha}.$$

Here, males and females are perfect substitutes within the cognitive occupation, and the marginal product of L_M is decreasing in L_F and vice-versa. The same is true of male and female employment in the other occupation. Finally, additivity implies that the cross-products, $G_{12} = G_{21} = 0$.

in the cognitive occupation. Alternatively, the worker earns p_{gt} if employed in the other occupation, independent of a (i.e., all high-skilled workers have equal ability, normalized to 1, in the other job).

Denote by a_{Mt}^* the “cutoff ability level” such that males with $a < a_{Mt}^*$ optimally choose to work in the other occupation, while those with $a \geq a_{Mt}^*$ choose the cognitive occupation. The cutoff is defined by the indifference condition:

$$a_{Mt}^* w_{Mt} = p_{Mt}. \quad (10)$$

Similarly:

$$a_{Ft}^* w_{Ft} = p_{Ft}, \quad (11)$$

defines the female cutoff, a_{Ft}^* . Thus, the fraction of workers of each gender who choose employment in the cognitive occupation, ϕ_{gt} , is simply:

$$\phi_{gt} = 1 - \Gamma_{gt}(a_{gt}^*) \quad (12)$$

with the complementary fraction choosing the other occupation.

Since all high-skilled workers supply labor inelastically, the model abstracts from non-employment and changes in the fraction who choose to work (and their gender differences) over time. In Appendix B, we present an extended version of the model that allows for both an occupational choice and a participation choice, and show that the results we derive in Section 4 are unaltered. That is, our findings are robust to the modeling of gender differences in participation trends.

3.3 Equilibrium

Equilibrium in the high-skilled labor market implies that the demand for labor input in cognitive occupations equals supply:

$$L_{Ft} = S_{Ft} \int_{a_{Ft}^*}^{\infty} a \Gamma'_{Ft}(a) da, \quad (13)$$

$$L_{Mt} = S_{Mt} \int_{a_{Mt}^*}^{\infty} a \Gamma'_{Mt}(a) da. \quad (14)$$

That is, given the number of high-skilled individuals, S_{gt} , effective labor in the cognitive occupation is the weighted ability conditional on being above the endogenous cutoff, a_{gt}^* . Market clearing with respect to the other occupation requires:

$$E_{Mt} = S_{Mt} \Gamma_{Mt}(a_{Mt}^*), \quad (15)$$

$$E_{Ft} = S_{Ft} \Gamma_{Ft}(a_{Ft}^*). \quad (16)$$

Given S_{gt} , employment in the other occupation is the CDF up to a_{gt}^* .

4 Accounting for the “End of Men” and Rise of Women

Here, we investigate the implications of the model as a measurement device. The analysis makes clear what forces are capable of rationalizing the changes in the high-skilled labor market observed between 1980 and 2000.

4.1 No Functional Form Assumption for the Distribution of Ability

In what follows, we assume that (effective) labor inputs of high-skilled men and women are perfect substitutes in both occupations. That is, $f^C(\cdot) = f^C(Z_{Mt}^C L_{Mt} + Z_{Ft}^C L_{Ft})$ and $f^O(\cdot) = f^O(Z_{Mt}^O E_{Mt} + Z_{Ft}^O E_{Ft})$, so that marginal rates of transformation between male and female labor are constant. This assumption is for the sake of exposition and convenience. In Appendix C, we demonstrate that our results are robust to allowing for non-constant marginal rates of transformation in production.

With perfect substitutability, the labor demand equations, (6)–(9), can be simplified as:

$$\frac{w_{Ft}}{w_{Mt}} = \frac{Z_{Ft}^C}{Z_{Mt}^C} \frac{1}{1 + \tau_t^C}, \quad (17)$$

$$\frac{p_{Ft}}{p_{Mt}} = \frac{Z_{Ft}^O}{Z_{Mt}^O} \frac{1}{1 + \tau_t^O}. \quad (18)$$

Using the indifference conditions, (10)–(11), equations (17)–(18) imply:

$$\frac{a_{Mt}^*}{a_{Ft}^*} \frac{Z_{Ft}^O}{Z_{Mt}^O} (1 + \tau_t^C) = \frac{Z_{Ft}^C}{Z_{Mt}^C} (1 + \tau_t^O).$$

Letting Δx_t denote the percentage change in x between any two dates t and t' , we obtain:

$$\Delta a_{Mt}^* - \Delta a_{Ft}^* = \Delta \left(\frac{Z_{Ft}^C}{Z_{Mt}^C} \right) - \Delta \left(\frac{Z_{Ft}^O}{Z_{Mt}^O} \right) + \Delta (1 + \tau_t^O) - \Delta (1 + \tau_t^C). \quad (19)$$

Recall that a_{gt}^* is the minimum cognitive work ability of those who sort into the COG occupation for $g = \{M, F\}$. Hence, the left-hand side of equation (19) is the differential change in selectivity into the cognitive occupation for men versus women, $\Delta a_{Mt}^* - \Delta a_{Ft}^*$.

There are two scenarios under which it is possible to measure the left-hand side from the 1980 and 2000 data, even without making functional form assumptions about the ability distributions, $\Gamma_{gt}(a)$ for $g = \{M, F\}$. The first scenario allows the male distribution, $\Gamma_M(a)$, to differ from the female distribution, $\Gamma_F(a)$, but requires that both have remained constant over time. The second case allows for the support of the distribution to change over time, but requires the male and female distributions to coincide at each point in time.

In either of these cases, the differential gender trends in cognitive work probability discussed in Section 2, $\Delta\phi_{Mt}$ and $\Delta\phi_{Ft}$, would measure the sign of the left-hand side of (19) directly. In the first case, since the probability for men has fallen over time, equation (12) would imply greater selectivity of men in COG employment between 1980 and 2000: $\Delta a_{Mt}^* > 0$. Since the probability for women has fallen, this implies $\Delta a_{Ft}^* < 0$. As a result, $\Delta a_{Mt}^* - \Delta a_{Ft}^* > 0$. In the second case, $\Delta\phi_{Mt}$ and $\Delta\phi_{Ft}$ imply a relative change between men and women, specifically $\Delta a_{Mt}^* - \Delta a_{Ft}^* > 0$. The model identifies two potential channels that account for this change.¹³

The first is if $\Delta(Z_{Ft}^C/Z_{Mt}^C) > \Delta(Z_{Ft}^O/Z_{Mt}^O)$. From (6)–(9), Z_{Mt}^C , Z_{Ft}^C , Z_{Mt}^O and Z_{Ft}^O are “shiffters” to the labor demand curves in wage-employment space. Thus, $\Delta Z_{Ft}^C > \Delta Z_{Mt}^C$ indicates a greater increase in the demand for female labor relative to male labor—what we refer to as a *female bias*—in the cognitive occupation over time. When $\Delta(Z_{Ft}^C/Z_{Mt}^C) > \Delta(Z_{Ft}^O/Z_{Mt}^O)$, production exhibits a *greater* female bias in the *cognitive occupation* relative to the other occupation.

The second channel is if $\Delta(1 + \tau_t^O) > \Delta(1 + \tau_t^C)$. In words, this implies a larger fall in the discrimination wedge in the cognitive occupation relative to the other occupation. We return to the discussion of these two channels in Subsection 4.3.

4.2 Pareto-Distributed Ability

While analytically clean and intuitive, one might not be willing to make the distributional assumptions required above. Here we demonstrate that it is possible to make progress by specifying a functional form for Γ_{gt} .

Given the wage per unit of effective labor, w_{gt} , a high-skilled worker with ability a earns $a \times w_{gt}$ when employed in the cognitive occupation. Since cognitive wages are proportional to ability, Γ_{gt} also describes the distribution of wages in the cognitive occupation. Top earnings (of high-skilled individuals) are characterized by a fat right tail (Piketty and Saez 2003). Hence, we specify ability to be distributed Pareto, with scale parameters a_{Mt}^{min} and a_{Ft}^{min} , and shape parameters κ_{Mt} and κ_{Ft} , for males and females, respectively.

¹³Note that characterizing the forces behind $\Delta a_{Mt}^* > 0$ or $\Delta a_{Ft}^* < 0$ individually would require imposing more structure on the model. To see this, consider for instance (6) and (8):

$$a_{Mt}^* = \frac{Z_{Mt}^O G_2(\cdot) f_1^O(Z_{Mt}^O E_{Mt} + Z_{Ft}^O E_{Ft})}{Z_{Mt}^C G_1(\cdot) f_1^C(Z_{Mt}^C L_{Mt} + Z_{Ft}^C L_{Ft})}.$$

Analyzing changes in a_{Mt}^* requires further restricting the functional forms for $G(\cdot)$, $f^C(\cdot)$, and $f^O(\cdot)$. Hence, our analysis of differential changes can be done under much more general conditions. Moreover, the analytical results we derive in this section regarding the differential female bias across occupations is precisely in line with the specification of the empirical analysis in Section 5.

In addition to empirical credibility, the Pareto distribution is analytically attractive. The optimality conditions (10) and (11), imply that ability among workers who choose the COG occupation is truncated from Γ_{gt} at a_{gt}^* . Nonetheless, we are able to derive characteristics of the entire ability distribution. This is because the conditional probability distribution of a Pareto-distributed random variable, truncated from below, is also Pareto with the same shape parameter.

Using this property, we can further decompose the left hand side of equation (19). The fraction of high-skilled individuals who work in the cognitive occupation is given by:

$$\phi_{gt} = \left(\frac{a_{gt}^{min}}{a_{gt}^*} \right)^{\kappa_{gt}}. \quad (20)$$

Taking the total derivative, we obtain:

$$\left(\frac{1}{\kappa_{gt}} \right) \Delta \phi_{gt} = \Delta a_{gt}^{min} - \Delta a_{gt}^* + \log \left(\frac{a_{gt}^{min}}{a_{gt}^*} \right) \Delta \kappa_{gt}.$$

Since $\log(a_{gt}^{min}/a_{gt}^*) = (1/\kappa_{gt}) \log(\phi_{gt})$, this can be rewritten as:

$$\Delta a_{gt}^* = \Delta a_{gt}^{min} + \left(\frac{1}{\kappa_{gt}} \right) \left[\log(\phi_{gt}) \Delta \kappa_{gt} - \Delta \phi_{gt} \right].$$

Subbing this into equation (19) obtains:

$$\begin{aligned} & \left(\frac{1}{\kappa_{Mt}} \right) \left[\log(\phi_{Mt}) \Delta \kappa_{Mt} - \Delta \phi_{Mt} \right] - \left(\frac{1}{\kappa_{Ft}} \right) \left[\log(\phi_{Ft}) \Delta \kappa_{Ft} - \Delta \phi_{Ft} \right] = \\ & \Delta \left(\frac{Z_{Ft}^C}{Z_{Mt}^C} \right) - \Delta \left(\frac{Z_{Ft}^O}{Z_{Mt}^O} \right) + \Delta a_{Ft}^{min} - \Delta a_{Mt}^{min} + \Delta (1 + \tau_t^O) - \Delta (1 + \tau_t^C). \end{aligned} \quad (21)$$

Relative to equation (19), (21) includes changes in both the scale and shape parameters, Δa_{gt}^{min} and $\Delta \kappa_{gt}$. Equation (21) is useful because all of the terms involving ϕ and κ on the left-hand side can be measured in the data, as we show below.

Before proceeding, we discuss the implications of our analysis for the gender wage gap in cognitive jobs. According to the Pareto distribution, the average ability among those who sort into the cognitive occupation (i.e. for $a \geq a_{gt}^*$) is given by $a_{gt}^* \times \kappa_{gt} / (\kappa_{gt} - 1)$. Thus, the mean cognitive wage is given by $w_{gt} \times a_{gt}^* \times \kappa_{gt} / (\kappa_{gt} - 1)$. Combining this with equation (17) implies that the empirically observed ratio of mean cognitive wages of women relative to men among high-skilled workers, $Ratio_t$, is:

$$Ratio_t = \frac{Z_{Ft}^C}{Z_{Mt}^C} \frac{1}{1 + \tau_t^C} \frac{a_{Ft}^* \frac{\kappa_{Ft}}{\kappa_{Ft}-1}}{a_{Mt}^* \frac{\kappa_{Mt}}{\kappa_{Mt}-1}}. \quad (22)$$

Hence, changes in the observed $Ratio_t$ can be decomposed into female bias, $\Delta(Z_{Ft}^C/Z_{Mt}^C)$, changes in the discrimination wedge, $\Delta(1 + \tau_t^C)$, and changes in the average female-to-male ability in the cognitive occupation (which are due to both changes in sorting and changes in the underlying distribution). These are analogous to the factors affecting the gender wage gap more generally, when one is not focused solely on cognitive wages among high-skilled workers (see, for instance, [Blau and Kahn \(2017\)](#) and the references therein).¹⁴

4.2.1 Measuring ϕ

Note that the fractions of high-skilled males and females in the cognitive occupation are reported in [Table 1](#) for both 1980 and 2000. This gives us ϕ_{gt} for $g = \{M, F\}$, and its percentage change over time. Specifically, $\phi_{M,1980} = 0.662$, $\phi_{M,2000} = 0.633$, $\phi_{F,1980} = 0.542$, and $\phi_{F,2000} = 0.588$.

4.2.2 Measuring κ

The shape parameter of the ability distribution, κ_{gt} , and its change over time are pinned down as follows.¹⁵ Using the Pareto functional form, the median wage earned by cognitive workers in the model is given by:

$$\text{med}_{gt} \equiv w_{gt} a_{gt}^* 2^{\frac{1}{\kappa_{gt}}},$$

and the mean wage is:

$$\text{avg}_{gt} \equiv w_{gt} a_{gt}^* \left(\frac{\kappa_{gt}}{\kappa_{gt} - 1} \right).$$

The ratio of the mean to median wage is then:

$$\left(\frac{\kappa_{gt}}{\kappa_{gt} - 1} \right) 2^{-\frac{1}{\kappa_{gt}}}. \tag{23}$$

Thus, data on wages in cognitive occupations allows us to measure κ_{gt} . That is, the ratio of the mean to the median is informative with respect to the degree of skewness in the wage (and, hence, cognitive work ability) distribution. We find that $\kappa_{M,1980} = 2.988$,

¹⁴Note the relationship between the relative deterioration of male versus female employment outcomes (among high-skilled workers) and the empirical literature documenting the decline in the gender wage gap. Though related, we emphasize that these are distinct phenomena. The wage gap literature documents a convergence of earnings, conditional on working. Here, we document divergent trends in the probability of working in high-wage/cognitive occupations.

¹⁵Allowing the shape parameter to change means that our approach is able to accommodate changes in selection into the high-skilled population (i.e. college completion) based on cognitive work ability for both genders. See [Mulligan and Rubinstein \(2008\)](#) for evidence on gender-specific changes in selection into employment based on general labor market ability among all individuals, in response to changing skill prices.

$\kappa_{M,2000} = 2.332$, $\kappa_{F,1980} = 3.753$, and $\kappa_{F,2000} = 3.293$.¹⁶ Hence, the male distribution of cognitive wages has a thicker right tail than does the female distribution, and both genders have experienced an increase in the thickness of the right tail over time.

4.3 The Three Channels

Given the observed changes in occupational outcomes and wage distributions, we measure the left-hand side of equation (21) to be positive:

$$LHS \equiv \left(\frac{1}{\kappa_{Mt}} \right) \left[\log(\phi_{Mt}) \Delta \kappa_{Mt} - \Delta \phi_{Mt} \right] - \left(\frac{1}{\kappa_{Ft}} \right) \left[\log(\phi_{Ft}) \Delta \kappa_{Ft} - \Delta \phi_{Ft} \right] = +4.74\%.$$

As equation (21) makes clear, the model apportions this to the two channels discussed in relation to equation (19), and a new one. Now, the three channels are:

1. $\Delta (Z_{Ft}^C/Z_{Mt}^C) - \Delta (Z_{Ft}^O/Z_{Mt}^O)$: a differential female bias in labor demand across occupations;
2. $\Delta (1 + \tau_t^O) - \Delta (1 + \tau_t^C)$: a differential change in the discrimination wedge across the cognitive and other occupation; and
3. $\Delta a_{Ft}^{min} - \Delta a_{Mt}^{min}$: a differential change in the location parameter of the cognitive ability distribution across genders.

Naturally, all three may have contributed to the divergent employment paths across genders. The data is consistent with greater female bias in the cognitive occupation relative to the other occupation, $\Delta (Z_{Ft}^C/Z_{Mt}^C) > \Delta (Z_{Ft}^O/Z_{Mt}^O)$. There may have been a greater increase in the minimum cognitive work ability of females versus males, $\Delta a_{Ft}^{min} > \Delta a_{Mt}^{min}$. Similarly, the data is consistent with a larger fall in female discrimination in good jobs relative to other jobs, $\Delta (1 + \tau_t^O) > \Delta (1 + \tau_t^C)$.¹⁷ If one were willing to assume that only a single factor was operational then it could be measured. For example, [Hsieh et al. \(2013\)](#) study convergence between male-female and black-white occupational outcomes since 1960 and the implications for allocative efficiency and aggregate output. They provide estimates of the degree of gender/race/occupation-specific discrimination change by making

¹⁶For details on the construction of wages, see footnote 4. We note that the measurement of a distribution's skewness can be disproportionately influenced by outliers at the extremes. Our baseline analysis restricts attention to those who report positive income and worked ≥ 250 annual hours. In analysis not reported here, we verify that our results are robust to: (a) varying the annual hours cutoff between 100 and 500, (b) trimming the top and bottom 1% of wage observations, and (c) using the sum of wage/salary and business income in the computation of wages. Details available upon request.

¹⁷That is, a fall in discrimination implies $\Delta (1 + \tau_t) < 0$, and a larger fall in the cognitive occupation implies $\Delta (1 + \tau_t^C)$ more negative than $\Delta (1 + \tau_t^O)$.

two strong assumptions: that there have been no changes in the distribution of ability, and that changes in labor demand have been identical across race and gender; that is, by ignoring channels (1) and (3) and only allowing channel (2).

In actuality, it is likely that all three factors have been operational since 1980. However, the current literature is largely silent on the empirical plausibility of channels (2) and (3). For instance, [Noonan, Corcoran, and Courant \(2005\)](#) provide evidence for a discrimination effect on the gender wage gap among lawyers that has remained largely constant over time. More generally, [Blau and Kahn \(2017\)](#) discuss the paucity of empirical work documenting a fall in female discrimination, much less differential changes in discrimination across occupations.¹⁸ Similarly, we are unaware of any studies documenting distributional changes in ability in cognitive work relative to other occupations, much less their gender differences. As our analysis makes clear, channel (3) refers specifically to a “horizontal” or location shift of the distribution. Hence, evidence based solely on mean wages or percentile wages would be uninformative; changes in such wage statistics are accounted for in our analysis through measured changes in the shape of the distribution, $\Delta\kappa_{gt}$.

By contrast, we provide empirical evidence in favor of channel (1). We find an “outward shift” of the demand curve for female labor (relative to male labor) in the cognitive occupation, $\Delta(Z_{Ft}^C/Z_{Mt}^C)$, that is larger than in other occupations, $\Delta(Z_{Ft}^O/Z_{Mt}^O)$. That is, there has been greater female bias in labor demand in good jobs relative to other jobs. Naturally, there are many factors that may have contributed to such changes in labor demand. For example, [Goldin and Katz \(2016\)](#) demonstrate how technological and institutional change in the pharmacy occupation allowed the profession to circumvent “indivisibility” of labor/hours worked, allowing for greater temporal flexibility and largely eliminating the part-time work penalty (see also [Goldin \(2014\)](#)). In Sections 5 and 6, we use data on occupational tasks to demonstrate another, complementary channel generating an increase in relative demand, that is measurable for all occupations.

Before proceeding, we note that recent work by [Beaudry, Green, and Sand \(2016\)](#) provides evidence that, since 2000, there has been a slowdown or reversal in the demand for high-skilled, cognitive tasks. To consider the implications of this, we extend our quantitative model analysis to the 2000-2014 period. For brevity, this is in Appendix E. Interestingly, we find an analogous change in gender trends in the high-skilled labor market, a change consistent with a reduction in female bias in cognitive occupations.

¹⁸See [Gayle and Golan \(2012\)](#) for an estimated structural model of the labor market with adverse selection. They find that increased female labor market experience explains nearly all of the fall in the gender wage gap. This is driven by a fall in the fixed cost of hiring and increases in productivity in “professional” occupations, which interacts with beliefs to reduce the extent of gender-based statistical discrimination.

5 Changes in the Demand for Social Skills

In this section we explore whether the increased relative demand for female labor in high-wage/cognitive occupations (compared to other jobs) is related to changes in the types of tasks performed and, therefore, skills required in these occupations. Evidence from psychology and neuroscience research indicates that women have a comparative advantage in tasks requiring social skills such as empathy, communication, emotion recognition, and verbal expression (see, for instance, [Hall \(1978\)](#); [Feingold \(1994\)](#); [Baron-Cohen, Knickmeyer, and Belmonte \(2005\)](#); [Chapman et al. \(2006\)](#); [Woolley et al. \(2010\)](#); [Koenig et al. \(2011\)](#)).

We are motivated by recent innovative work in economics by [Borghans, Ter Weel, and Weinberg \(2014\)](#) and [Deming \(2017\)](#). They show that since 1980, employment and wage growth in the U.S. has been strongest in occupations that involve high *levels* of social skills, and especially those combining social and cognitive skills.¹⁹ While related to our work, these findings are indicative of a relative increase in female labor demand due to composition change “between” occupations, with disproportionately large gains in employment in occupations with high levels of social skill requirement. However, as noted in Sections 2 and 4, the rising female share of employment in the US has been due to changes “within” occupation, increasing the demand for female-oriented skills in cognitive occupations relative to other occupations.²⁰

We study whether the demand for social skills *within occupations* has grown over time. That is, our hypothesis is that the *change* in the importance of social skills has been greater in good jobs, and is thus related to the increasing demand for females versus males in these occupations.^{21, 22}

To measure the change in the importance of social skills within occupations we use two data sources. The first is the Dictionary of Occupational Titles (DOT), which we discuss here. We defer discussion of the second, based on the work of [Atalay et al. \(2017\)](#) using

¹⁹[Deming and Kahn \(2017\)](#) provide evidence on the correlation between wages and firms’ demand for cognitive and social skill using evidence from online job ads. At the worker level, [Weinberger \(2014\)](#) documents increasing returns to cognitive skills to be concentrated in individuals with strong social skills.

²⁰[Deming \(2017\)](#) also finds a positive relationship between changes in the female share of occupational employment and the occupation’s level of social skills. Again, this does not speak to changes in social skill importance within occupation.

²¹See [Eagly and Carli \(2003\)](#), for example, for work in psychology making a similar point with respect to managerial and leadership positions, without explicit empirical evidence on skill or task content within occupations, or labor market data.

²²Note that the model of Section 3 views male and female labor as distinct factors of production. In the empirical analysis here, we view social skills and “other/non-social” skills as the factors of production—factors that can be supplied by either men or women, with women having the comparative advantage in social skills. While subtly different, Appendix D shows how this alternative view can, in fact, be written as a model isomorphic to that of Section 3.

newspaper job advertisements to Subsection 5.2.

The DOT provides detailed measures of skills and “temperaments” that are required to perform the tasks associated with occupations, as well as information on work activities performed by job incumbents. A growing literature pioneered by [Autor, Levy, and Murnane \(2003\)](#) (ALM hereafter) uses information from the DOT in order to characterize occupations along these dimensions. The data is available at two points in time: 1977 and 1991.

We focus on the data regarding occupational temperaments, which are defined as “adaptability requirements made on the worker by specific types of job-worker situations” (see [ICPSR 1981](#)). These factors are assessed by analysts from the US Department of Labor based on their importance with respect to successful job performance (see, for example, [U.S. Department of Labor \(1991\)](#)). The DOT indicates the presence or absence of a given temperament (rather than the level or degree required) for a large set of detailed occupation codes. Out of a total of ten temperaments, we identify four as relating to the importance of social skills:

1. Adaptability to situations involving the interpretation of feelings, ideas or facts in terms of personal viewpoint;
2. Adaptability to influencing people in their opinions, attitudes, or judgments about ideas or things;
3. Adaptability to making generalizations, evaluations, or decisions based on sensory or judgmental criteria;
4. Adaptability to dealing with people beyond giving and receiving instructions.

These are motivated by and, hence, very similar to the four measures in the O*NET used by [Deming \(2017\)](#) to identify social skill intensity. Crucially, the measures for each occupation were updated between DOT-77 and DOT-91. This allows us to measure the *change* in the importance of social skills within different occupations over time, between 1977 and 1991. While this does not overlap perfectly with the 1980-2000 time period considered above, there exists no other official national-level dataset in the U.S. measuring change in tasks and skills at the occupational level over this exact time period.²³

The DOT information is provided at a very detailed occupational code level. In order to aggregate DOT data to the Census Occupation Code 3-digit level at which we have information on employment and wages, we follow an approach similar to ALM and compute

²³The O*NET (the successor to the DOT) provides occupational measures for the time period after 2000; however, the way in which occupational information is elicited and recorded was changed dramatically between the DOT and the O*NET. Hence, it is not possible to link task measures across the two datasets.

weighted averages of DOT task measures at the level of the harmonized codes from [Autor and Dorn \(2013\)](#) (hereafter “Dorn codes”). Details are provided in Appendix [F](#).

Once aggregated to the Dorn code level, we create a single *social skill index* for each occupation by adding the occupation’s scores for the four temperaments listed above. For ease of interpretation, we normalize the social skill index in each period (as well as all other occupational measures used below) to have mean zero and unit standard deviation across the sample-weighted employment distribution from the 1980 Census. Hence, a one unit increase between the two DOT waves in any of our normalized task measures for a given occupation can be interpreted as a one standard deviation increase in the *relative* position of that occupation within the employment-weighted distribution of that task. This conforms with our model-based analysis of Section [4](#), that there has been a differential, or relative, change in the demand for certain skills in good jobs relative to other occupations.

5.1 Results

Before studying the *change* in the importance of social skills and its relationship to *changing* relative demand of females in good jobs, we first verify that occupational employment outcomes are consistent with female comparative advantage in jobs requiring social skills. To do so we first regress the *level* of the female share of employment within each 3-digit level occupation in 1980 on its social skill index in 1977. As the first column of Table [4](#) reports, occupations with higher social skill requirements have a larger proportion of female workers. This is clearly significant at the 1% level.

One might be concerned that the social skill index could be proxying for other occupational task characteristics. Column (2) in Table [4](#) illustrates that this correlation is robust to controlling for other task intensities considered in the job polarization literature, available in the DOT. Specifically, following ALM, we measure cognitive tasks within each occupation as the average of “adaptability to accepting responsibility for the direction, control or planning of an activity” and “GED-mathematical development.” Routine tasks are measured as the average of “adaptability to situations requiring the precise attainment of set limits, tolerances or standards” and “finger dexterity,” and manual tasks based on the importance of “eye-hand-foot coordination.” Column (2) indicates that the point estimate on the level of social skill importance actually increases, with essentially unchanged standard error, after controlling for the ALM characteristics.

In Columns (3) and (4) of Table [4](#), we repeat the analysis using the female share of employment in 2000 and occupational characteristics in 1991. The cross sectional results of Columns (1) and (2) hold with respect to 2000 occupational gender composition as well.

Table 4: Female Share of Occupational Employment, 1980 and 2000

	1980	1980	2000	2000
	(1)	(2)	(3)	(4)
Social	0.065 (0.018)***	0.118 (0.017)***	0.062 (0.017)***	0.092 (0.021)***
Cognitive		-.142 (0.019)***		-.109 (0.021)***
Routine		0.086 (0.018)***		0.017 (0.019)
Manual		-.120 (0.016)***		-.132 (0.015)***
Obs.	323	323	323	323
R^2	0.041	0.325	0.042	0.256

Notes: Data on employment shares from 1980 and 2000 decennial censuses. Data on social skills and other occupational task characteristics from 1977 and 1991 Dictionary of Occupational Titles. See text for details.

We find this particularly informative given our hypothesis that occupations where social skill importance has increased over time are those that have experienced greater female bias in labor demand.

Returning to our original hypothesis, we ask: Has the importance of social skills increased in good jobs relative to other occupations? Moreover, have occupations in which social skill importance increased more also experienced larger increases in the demand for female (versus male) labor?

Table 5 shows the relationship between the change in the importance of social skills and the change in the female share of employment for the three broad occupation groups considered above. Cognitive occupations—those that we consider to be good jobs—have seen the largest increase in the proportion of employment by women (9.2 pp), and also the largest positive change in the social skills index (i.e., largest relative increase in the importance of such skills). Routine occupations (which tend to occupy the middle of the wage distribution) experience a more modest increase in both their female share and the importance of social skills. Meanwhile, manual occupations (at the bottom of the distribution) experience a decline over time in both their female share and the social skills index.

Next, we show that this pattern for broad occupational groups also holds when considering occupations at the much finer, 3-digit level. To do so, we first confirm that higher paying occupations—our other definition of good jobs—experience larger increases in the female proportion of employment. This is demonstrated in Figure 1. Each circle represents

Table 5: Social Skills and Female Bias: Cognitive vs Other Occupations

	Change in female share of employment 1980-2000	Change in importance of social skills 1977-1991
Cognitive	+0.0924	+0.2723
Routine	+0.0217	+0.1038
Manual	-0.0225	-0.2963

Notes: Data on employment shares from 1980 and 2000 decennial censuses. Data on social skills from 1977 and 1991 Dictionary of Occupational Titles. See text for details.

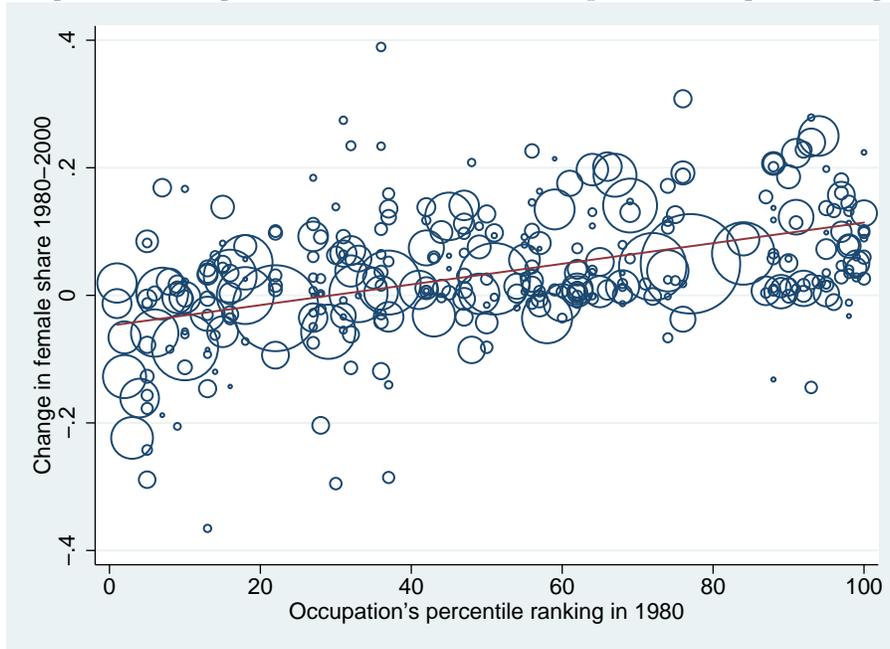
a 3-digit occupation with the size of the circle representing the occupation’s share of total employment in 1980. An occupation’s ranking in the 1980 wage distribution is clearly associated with the change in its female share between 1980 and 2000. Figure 2 further illustrates that high-wage occupations experienced greater increase in the importance of social skills compared to lower paying occupations.

The first column of Table 6 presents our key relationship of interest at the 3-digit occupation level: an increase in the importance of social skills is associated with an increase in the occupation’s female share of employment. Occupations that experienced an increase in the social skill index of one standard deviation above the average saw a 4.0 pp increase in the female share. This relationship is clearly significant at the 1% level.

Column (2) of Table 6 illustrates that our key result is robust to controlling for changes in ALM task intensity measures. The point estimate on the change in social skill importance, and its standard error, remain essentially unchanged even after including changes in cognitive, routine, and manual task intensity within occupations in the regression. And interestingly, none of the estimates on the job polarization measures are significant at standard levels. Column (3) illustrates robustness when we include three additional DOT variables in the measures of cognitive, routine, and manual task change, respectively: “numerical aptitude,” “adaptability to performing repetitive work, or to continuously performing the same work, according to set procedures,” and “motor coordination.” Though not reported for brevity, this is also true when we consider these three additional variables as independent regressors. Again, the results for the importance of social skill remain.

We view this as strongly indicative of an increased demand for female labor in good jobs due to an increase in the importance of social skills in these occupations relative to other occupations. In Appendix G we perform a back-of-the-envelope calculation of the extent to which the change in social skill importance can account for the rise of women in good jobs.

Figure 1: Change in Female Share and Occupational Wage Ranking



Notes: Each circle represents a 3-digit occupation (size indicating its share of total employment in 1980). Data on employment and wages from the 1980 and 2000 decennial censuses. See text for details.

Figure 2: Change in Social Skills and Occupational Wage Ranking



Notes: Each circle represents a 3-digit occupation (size indicating its share of total employment in 1980). Data on employment and wages from the 1980 decennial census. Data on social skills from the 1977 and 1991 DOT. See text for details.

Table 6: Change in Female Share of Occupational Employment, 1980-2000

	(1)	(2)	(3)
Δ Social	0.038 (0.011)***	0.044 (0.011)***	0.042 (0.012)***
Δ Cognitive		-.0007 (0.017)	0.0004 (0.017)
Δ Routine		-.006 (0.015)	-.004 (0.015)
Δ Manual		0.024 (0.016)	0.022 (0.017)
Obs.	323	323	323
R^2	0.039	0.048	0.068

Notes: The dependent variable is the change in the female share of occupational employment between 1980 and 2000 based on decennial census data. Data on social skills and other occupational task characteristics from 1977 and 1991 Dictionary of Occupational Titles. Column (3) includes additional controls for cognitive, routine and manual task change. See text for details.

We find that the increasing importance of social skills accounts for approximately 57% of the increase.

5.2 Evidence based on newspaper job advertisement data

One concern with the above results is the possibility of reverse causality. In constructing the DOT, the U.S. Department of Labor explicitly instructs analysts to assign temperaments based on the activities that are important for successful job performance, rather than incidental work activities (see [U.S. Department of Labor 1991](#)). However, it is possible that when DOT experts analyze an occupation, they may spuriously infer that social skills have become more important when they see that the proportion of women employed in the occupation has risen. To address this concern we use an alternative, and potentially more accurate, measure of the tasks employers demand and its change over time.²⁴

Here we exploit data based on over 9 million job advertisements constructed by [Atalay et al. \(2017\)](#). Using newspaper ads published in the *New York Times*, *Wall Street Journal*, and *Boston Globe* between 1940 and 2000, [Atalay et al. \(2017\)](#) construct a dataset of occupation-level job requirements. This is done by translating job ad titles to Standard Occupational Classification (SOC) codes, then grouping keywords in the job ad according

²⁴In Section 6, we use wage data to further rule out reverse causality, and to provide additional evidence of an increase in the demand for social skills.

to their meaning. By doing so, [Atalay et al. \(2017\)](#) generate measures of advertised task demands and requirements, by occupation.²⁵ One such measure is analogous to the social skill measure used by [Deming and Kahn \(2017\)](#), based on the (average) frequency with which the following words are mentioned (per year) in an occupation’s job ads: communication, teamwork, collaboration, negotiation, presentation, and social. A major advantage of this data is that it reflects the attributes that employers explicitly desire for a specific job, and hence can be considered a more accurate reflection of labor demand.²⁶ Moreover, since the data is available at an annual frequency until the year 2000, we are able to generate changes in task requirements by occupation over the same time period that we consider for employment changes.

We convert the data from [Atalay et al. \(2017\)](#) from SOC 2010 occupation codes to 2010 Census codes, and then to the Dorn code level used above. When multiple SOC 2010 codes map to a single Dorn code, we generate a weighted average of the task data using the number of job ads as weights. We generate a social skill index for 1980 and 2000 using five year averages (1976-1980 and 1996-2000, respectively), and construct the change in the importance of social skills across the two periods.²⁷

Table 7 displays results analogous to those presented in Table 6, but replacing the social skills measure from DOT with the one from the newspaper data.²⁸ Column (1) shows that changes in the demand for social skills within an occupation are again positively and statistically significantly associated with changes in the female share of employment in the occupation.

In Column (2), we add the ALM measures from the DOT as discussed above, and confirm the relationship between changes in social skills and female shares. Column (3) replaces the ALM measures with the skill requirement measures from [Spitz-Oener \(2006\)](#), as constructed in the [Atalay et al. \(2017\)](#) dataset. Once again, our relationship of interest is robust.

Overall, the estimates across the first three columns are similar. These coefficients imply that a one standard deviation increase in the usage of a Deming-Kahn “social word” (approximately 0.05 additional words per job ad, per year) is associated with slightly more

²⁵For full details, we refer the reader to the [Atalay et al. \(2017\)](#) paper. The data is available from https://ssc.wisc.edu/~eatalay/occupation_data.html.

²⁶There are obviously potential downsides as well, if for instance (changes in) the frequency of word use does not reflect (changes in) firm demand; or if (changes in) these newspaper advertisements are not representative of (changes in) the aggregate.

²⁷Results are qualitatively similar when using three year averages (1978-1980 and 1998-2000, respectively) or when directly using the annual measures for 1980 and 2000.

²⁸Note, however, that the magnitude of the coefficient estimates cannot be compared across tables since the construction of the right-hand side variable differs.

Table 7: Change in Female Share of Occupational Employment, 1980-2000

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Social (DK)	0.378 (0.098)***	0.381 (0.098)***	0.402 (0.109)***			
Δ Social (Extended)				0.238 (0.062)***	0.241 (0.063)***	0.286 (0.074)***
Δ Cognitive		0.005 (0.017)			0.003 (0.017)	
Δ Routine		0.013 (0.015)			0.015 (0.015)	
Δ Manual		0.011 (0.016)			0.009 (0.016)	
Δ NR Analytic			-0.073 (0.053)			-0.102 (0.055)*
Δ NR Interactive			0.068 (0.084)			0.036 (0.086)
Δ R Cognitive			0.252 (0.417)			0.265 (0.416)
Δ R Manual			-0.163 (0.3)			-0.122 (0.301)
Δ NR Manual			-0.020 (0.079)			-0.035 (0.078)
Obs.	313	313	313	313	313	313
R^2	0.046	0.049	0.054	0.045	0.049	0.057

Notes: The dependent variable is the change in the female share of occupational employment between 1980 and 2000 based on decennial census data. Social (DK) is based on the benchmark Deming-Kahn social skill measure computed by [Atalay et al. \(2017\)](#). Social (Extended) is based on the alternative “bag of words” measure of word frequency from [Atalay et al. \(2017\)](#). Cognitive, Routine and Manual are from the 1977 and the 1991 Dictionary of Occupational Titles. NR Analytic, NR Interactive, R Cognitive, R Manual and NR Manual are based on the Spitz-Oener task measures computed by [Atalay et al. \(2017\)](#). See text for details.

than a 2 pp increase in the occupation’s female share. In all specifications this is significant at the 1% level.

Finally, Columns (4)-(6) use the alternative “bag of words” measure of word frequency from [Atalay et al. \(2017\)](#). This adds additional words to the measurement of social skill requirements, where the additional words are deemed to be related to the original [Deming and Kahn \(2017\)](#) set of words through a machine learning algorithm. Using this alternative measure, our key result—that an increase in the importance of social skills in an occupation is associated with an increase in the female share of employment—remains.

Taken together with the results of subsection 5.1, this indicates an increased demand for female labor in high-wage/cognitive occupations associated with an increase in the importance of social skills in these jobs relative to other occupations.

6 Wage Evidence

Here we provide analysis of occupational wages, and their change over time, in relation to our findings. We first provide further evidence against the possibility of reverse causality in our findings of Subsection 5.1. But chiefly, we use the wage data to indicate the primacy of an increase in the demand for social skills between 1980 and 2000.

For both purposes, the Census data are used to estimate wage premia for each 3-digit occupation. We measure variation in occupational wages by regressing log hourly real wages at the individual level on age (five year bins), education (four categories), race (white, black, hispanic, other), nativity, and a full set of 3-digit occupation dummies. These regressions are run separately by gender for each year, 1980 and 2000. The coefficients on the occupation dummies are thus estimates of occupational wage premia that are gender- and time-specific.²⁹

First, suppose the change in the social skill index of an occupation derived from the DOT, does not reflect a change in the demand for social skill. Instead, it merely reflects a change in the female employment share in that occupation relative to others. All else equal, this would imply that changes in female occupational wage premia would be *negatively correlated* with changes in the social skill index. To test this, we regress the change in the female occupational wage premium on the within-occupation change in the social skill index between 1980 and 2000. Rather than being negative, the coefficient estimate is positive at 0.015 though not statistically different from zero (standard error of 0.011). Changes in the

²⁹See footnote 4 for details on the construction of the wage variable. The wage regressions are weighted using person weights from the Census.

social skill index may be proxying for other changes, such as changes in an occupation’s task content. To address this, we run the same regression controlling for changes in the cognitive, routine, and manual task measures of ALM. The point estimate on social skill change increases to 0.053 with standard error 0.012, statistically significant at the 1% level. Hence, at a first pass, increases in the relative importance of social skills are associated with *increases* in relative female wages between 1980 and 2000. As such, we do not find evidence that the increase in the social skill index, as measured in the DOT, merely reflects an increase in the relative employment of women.

Next, we provide further evidence that the patterns are driven by an increase in the demand for social skills. We ask whether the importance of social skills explains the variation in occupational wages, and whether this relationship has changed over time. In Panel A of Table 8, we regress the occupational wage premium for women on the social skill index and other characteristics of the occupation. Columns (1) and (2) show that there is a positive and significant relationship between the importance of social skills and the female wage premium, both in 1980 and 2000. More importantly, the magnitude of the coefficient estimate doubles over time. Given the standard errors, this change is clearly statistically significant. In addition, the increase in the R^2 indicates that while social skill importance explains less than 10% of the variation in occupational wages in 1980, it accounts for over one-quarter of this variation in 2000.

Columns (3) and (4) of Table 8 indicate that the result is robust to controlling for changes in ALM task intensities within occupation. The estimate on the importance of social skills is positive but insignificant at the 5% level in 1980. But it is much larger and significant at the 1% level in 2000. This again implies that the wage return to social skills increased for women between 1980 and 2000.³⁰ Finally, Columns (5) and (6) include the occupation’s female share of employment as a regressor. As documented in Table 4, occupations with higher social skill importance have a larger female share, and the literature indicates that more female-dominated occupations pay less.³¹ As such, changes in the return to social skills could be driven by changes in the female share of high social skill occupations and/or changes in the wage penalty to more female-dominated occupations (due, for instance, to changes in discrimination). Including the female share allows us to control for these effects. Columns (5) and (6) indicate that variation in social skill importance that is orthogonal

³⁰Note that this analysis is related to the literature that aims to estimate the return to tasks across occupations (e.g. Gottschalk, Green, and Sand 2015; Cortes 2016; Böhm 2016; Fortin and Lemieux 2016). Papers in this literature focus on addressing issues related to sorting into occupations based on unobservable skills. To the extent that this sorting is driven by other task characteristics of the occupation, such as the importance of cognitive skills, these are controlled for in the regressions in Columns (3) and (4).

³¹See, for instance, Levanon, England, and Allison (2009).

Table 8: Relationship between Occupational Wage Premia and Social Skill Importance

Panel A: Female Occupational Wage Premia

	1980	2000	1980	2000	1980	2000
	(1)	(2)	(3)	(4)	(5)	(6)
Social	0.058 (0.011)***	0.118 (0.011)***	0.017 (0.01)*	0.046 (0.013)***	0.025 (0.01)**	0.056 (0.013)***
Cognitive			0.153 (0.012)***	0.159 (0.014)***	0.14 (0.013)***	0.145 (0.014)***
Routine			0.042 (0.009)***	0.064 (0.012)***	0.054 (0.01)***	0.076 (0.012)***
Manual			0.037 (0.013)***	0.037 (0.013)***	0.037 (0.013)***	0.029 (0.013)**
Female Share					-.100 (0.039)***	-.137 (0.04)***
Obs.	323	323	323	323	323	323
R^2	0.081	0.251	0.396	0.513	0.408	0.53

Panel B: Male Occupational Wage Premia

	1980	2000	1980	2000	1980	2000
	(1)	(2)	(3)	(4)	(5)	(6)
Social	0.013 (0.01)	0.115 (0.012)***	-.027 (0.01)***	0.032 (0.014)**	-.016 (0.01)	0.045 (0.014)***
Cognitive			0.127 (0.01)***	0.164 (0.014)***	0.114 (0.009)***	0.152 (0.014)***
Routine			0.013 (0.011)	0.027 (0.012)**	0.008 (0.011)	0.011 (0.012)
Manual			0.027 (0.007)***	0.029 (0.009)***	0.006 (0.008)	0.001 (0.01)
Female Share					-.227 (0.039)***	-.269 (0.047)***
Obs.	323	323	323	323	323	323
R^2	0.006	0.229	0.38	0.49	0.44	0.538

Notes: The dependent variable is the occupation's wage premium. Occupations are weighted by their share of aggregate employment. Data on occupational wage premia based on wage regressions using Census data. Data on social skills and other occupational task characteristics from the Dictionary of Occupational Titles. See text for details.

to female share still accounts for differences in female occupational wages in both years. More importantly, the effect is at least twice as large in 2000 relative to 1980, indicating an overall increase in the return to social skills.

The results in Panel A could potentially be attributed to differential changes in female discrimination. In order for this to be the case, it would require discrimination to have fallen more in high social skill index occupations. To rule this out, we repeat our analysis using occupational wage premia for men in Panel B. Our underlying assumptions are that male wages are not affected by gender discrimination (as in Section 3), and that men—despite not having a comparative advantage relative to women—also supply social skills, so that variation in social skill importance is reflected in male occupational wages.

In Panel B, the change in the return to social skills for male wages is even more striking. As Columns (1) and (2) show, the effect of social skills is small and statistically insignificant in 1980, but positive and significant in 2000. Moreover, the increase is nearly a factor of 9. The social skill index accounts for a much larger share of the variation in occupational wage premia over time as well, as evidenced by the increase in the R^2 . The nature of the results are unchanged after conditioning on other occupational characteristics in Columns (3)–(4) and (5)–(6).

In all cases considered in Table 8, the results indicate a clear increase in the return to social skills over time. This further supports our hypothesis that the U.S. economy has experienced an overall increase in the demand for such skills between 1980 and 2000. Given the literature’s finding that women hold a comparative advantage in social skills relative to men, we view this as evidence for an increase in the demand for female skills.

6.1 Linking the Increased Demand for Social Skills and College Attainment

The results from Table 8 show robust evidence of an increase in the return to social skills over time. A natural question that arises is: what factors are driving or contributing to the change in the demand for social skills? To shed some light on this question, we exploit variation across geographic areas in these returns, and determine whether certain regional labor market characteristics are associated with varying returns to social skills.

Specifically, we explore whether the increasing availability of college-educated workers is associated with an increase in the demand for social skills. For instance, increases in the supply of college-educated workers may increase the demand for social skills due to an increase in the prevalence of teamwork in high-paying occupations (see, for example, [Deming](#)

(2017)). If college workers (those with the requisite skill and training) are scarce, it may be more efficient to perform tasks in cognitive occupations in relative isolation; if college workers are abundant, the same work may be more efficiently done in collaborative and interactive settings, increasing the importance of social skills. Alternatively, the increased availability of college graduates may induce a change in the skills that firms prioritize in their recruitment process, or that consumers prioritize when demanding cognitive services: If college workers are scarce, firms and consumers may be more likely to prioritize technical knowledge, whereas when college workers are relatively abundant, firms and consumers may begin to emphasize other dimensions of skill in these jobs, such as social skills. Although we cannot explicitly investigate the channels through which this operates (e.g. changes in production processes or changes in demand due to a lexicographic ordering of job tasks), we explore whether rising educational attainment in the population can account for at least some of the increase in the return to social skills observed between 1980 and 2000.

Our analysis exploits variation across states, both in the share of college-educated individuals in the population, and in the return to social skills. Following the same approach as in Section 6, we construct wage premia for each occupation by regressing individual-level wages on a full set of 3-digit occupation dummies plus demographic controls. We now run the regressions separately for each state, which provides us with a set of occupation wage premia that are gender, time, and state specific. We then run a set of regressions similar to the ones in Table 8, with the occupation wage premium as the dependent variable, but with observations now being at the occupation-state-year level. We add the college share of the population in each state as an additional regressor, both on its own and interacted with the task characteristics of the occupation. We present results with data pooled across years (1980 and 2000), and include a year dummy as well as a full set of state fixed effects. Identification in this setting is obtained from variation in within-state wage premia across occupations. Observations are weighted by each occupation’s gender-specific share of employment in each state; standard errors are clustered at the state level.

Table 9 presents the results using occupational wage premia for women. The first column confirms the existence of a positive correlation between an occupation’s social skill importance and its wage premium among women. The coefficient on the interaction of social skill importance and time confirms the result from Table 8 regarding the strong increase over time in this correlation, now estimated using within-state variation.³²

Column (2) adds a control for the state’s college share, computed as the fraction of

³²Columns (1) and (2) in Table 8 imply a point estimate for the coefficient on social skills in 1980 of 0.058 and a point estimate for the change over time in this coefficient of 0.060. These magnitudes are quite similar to the ones obtained using within-state variation in Table 9.

Table 9: Relationship between State-Specific Occupational Wage Premia and Social Skill Importance

	Women	Women	Women	Men	Men	Men
	(1)	(2)	(3)	(4)	(5)	(6)
Social	0.056 (0.003)***	0.023 (0.009)**	-0.020 (0.009)**	0.013 (0.003)***	-0.043 (0.012)***	-0.072 (0.014)***
Social x y2000	0.055 (0.002)***	0.039 (0.004)***	0.004 (0.004)	0.09 (0.003)***	0.065 (0.005)***	0.033 (0.005)***
College		0.578 (0.467)	0.508 (0.461)		-1.169 (0.612)*	-1.243 (0.603)**
Social x College		0.195 (0.054)***	0.222 (0.049)***		0.331 (0.066)***	0.28 (0.076)***
Cognitive			0.14 (0.006)***			0.096 (0.009)***
Cognitive x College			0.063 (0.032)**			0.216 (0.044)***
Routine			0.026 (0.005)***			0.022 (0.007)***
Routine x College			0.141 (0.028)***			0.023 (0.032)
Manual			0.07 (0.011)***			0.018 (0.006)***
Manual x College			-0.118 (0.051)**			0.052 (0.029)*
Obs.	28217	28217	28217	31463	31463	31463
R^2	0.161	0.163	0.398	0.142	0.149	0.365

Notes: Observations are at the occupation-state-year level. The dependent variable is the occupation's state-specific wage premium. Regressions use pooled data for 1980 and 2000 and include time and state fixed effects. Occupations are weighted by their share of aggregate employment in the corresponding year and state. Standard errors are clustered at the state level. Data on occupational wage premia based on wage regressions using Census data. Data on social skills and other occupational task characteristics from the Dictionary of Occupational Titles (1977 data used for 1980; 1991 data used for 2000). See text for details.

the population aged 20-64 who has at least a college degree, and its interaction with the occupation's social skill index. This allows us to determine whether the return to social skills is heterogeneous across states with different shares of college workers. The coefficient on the interaction term is 0.195; this indicates that the wage return to social skills is much stronger in states with higher college shares.³³ In other words, states where college graduates are more abundant feature a stronger wage premium for high social skill occupations (a stronger gradient in the wage profile with respect to social skills).

This result also implies that as the college share increases over time, the rewards to social skills will also increase. This is reflected in the results from Column (2) in that the coefficient on the interaction of social skills and the year 2000 dummy is significantly reduced. Hence, another interesting result from this analysis is that at least some of the estimated change over time in the importance of social skills can be accounted for by the increasing availability of college workers.

Column (3) adds controls for the ALM tasks and their interaction with the state's college share. Two results are particularly relevant. First, the coefficient on the interaction between social skills and college share remains statistically significant, with its magnitude increasing slightly; the estimated positive correlation between the return to social skills and a state's college share remains and is not driven by differential returns to other ALM tasks. Also note that the coefficient on this interaction is larger than the coefficients on the interactions of the college share with the other ALM tasks: increases in the college share increase the return to social tasks more than they do the return to other tasks.

Second, the estimated coefficient on the interaction between social skills and the time dummy is reduced even closer to zero. This indicates that the vast majority of the estimated increase over time in the return to social skills can be accounted for by the increase in the college share. This evidence suggests that increasing educational attainment has induced changes in the nature of labor demand, with associated changes in the returns to different skills and tasks.

Columns (4) to (6) show similar results for the occupational wage premia for men. The return to social skills is also greater in states with higher college shares (and hence increasing when states' college shares increase over time). Increases in the college share also raise the return to social tasks more than they do the return to other tasks. Finally, changes in the

³³The coefficient on the (non-interacted) college share is not of particular interest. The coefficient would reflect whether the mean of the dependent variable (the occupation wage premium) varies systematically with a state's college share, after controlling for state and time fixed effects. Given that the occupation wage premia are estimated separately for each state in each year, the dependent variable is normalized relative to a base occupation in each state-year, so it would only vary due to differential changes in the occupational composition relative to the base occupation, which are not of particular interest.

college share and the associated changes in the return to social and other tasks also account for a substantial fraction of the positive time trend in the return to social skills.

To summarize, these findings uncover evidence regarding mechanisms that can account for an important fraction of the increase over time in the return to social skills. Variation in the college share is associated with variation in the returns to various tasks. In particular, the return to social skills is strongly increasing in the educational attainment of the population. Hence, an important fraction of the increase in the return to social skills between 1980 and 2000 can be accounted for by the increase in the college share. Without identifying specific channels, this evidence indicates that these two variables are inextricably linked. The increase in educational attainment may have induced some of the increase in the demand for social skills (via directed technical change or re-organization of production processes) that we have documented as accounting for the rise of women in high-paying occupations. Exploring the specific mechanisms through which this relationship operates is an interesting avenue for future research.

7 Conclusions

The demand for high-skilled workers who perform cognitive tasks is widely considered to have increased dramatically between 1980 and 2000. In this paper we show that improvements in labor market outcomes were not experienced equally by both genders. Despite the rapid growth in employment in high-paying/cognitive occupations, the probability that a college-educated male was employed in one of these jobs fell over this period. This contrasts with the increase in probability experienced by college-educated women, in spite of the larger increase in skilled labor supply among women. We develop a general model that allows us to study the driving forces that can account for this rise of women in the high-skilled labor market. The model implies that a greater increase in the demand for female (versus male) skills in good jobs relative to other occupations can account for the empirical patterns. Motivated by this prediction, we explore the relationship between changes in female employment shares within occupations and changes in occupational skill requirements. We find a robust link between the change in an occupation's female share and the change in the importance of social skills in the occupation. This evidence is consistent with findings in the psychology and neuroscience literatures that indicate that women have a comparative advantage in performing tasks that require social skills. Evidence based on wage data also indicates that the U.S. economy has experienced an increase in the demand for social skills.

Appendix

A Additional Tables, Section 2

Table A.1: High-Skilled Occupational and Employment Status: 1980–2000

	1980	2000	% Difference		
			Total	Explained	Unexplained
Male					
<i>Total (000's)</i>	<i>12080</i>	<i>20340</i>			
Top 25%	61.3	58.5	−2.8	+0.1	−2.9
Bottom 75%	30.9	30.8	−0.1		
Not Working (%)	7.8	10.7	+2.9		
Female					
<i>Total (000's)</i>	<i>8890</i>	<i>20470</i>			
Top 25%	44.0	47.1	+3.1	−0.2	+3.3
Bottom 75%	28.8	31.4	+2.6		
Not Working (%)	27.2	21.5	−5.7		

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 and 2000 decennial censuses. Employment categorized by ranking in occupational wage distribution of 2000. See text for details.

Table A.2: High-Skilled Occupational and Employment Status: 1980–2000

	1980	2000	% Difference		
			Total	Explained	Unexplained
Male					
<i>Total (000's)</i>	<i>25590</i>	<i>43610</i>			
Cognitive (%)	45.0	41.6	−3.4	+0.8	−4.2
Routine (%)	36.3	36.2	−0.1		
Manual (%)	5.8	7.6	+1.8		
Not Working (%)	12.9	14.6	+1.7		
Female					
<i>Total (000's)</i>	<i>23420</i>	<i>47640</i>			
Cognitive (%)	33.0	38.8	+5.8	+2.3	+3.5
Routine (%)	27.8	27.8	+0.0		
Manual (%)	6.1	8.2	+2.1		
Not Working (%)	33.1	25.2	−7.9		

Notes: Labor Force statistics, 20-64 year olds with at least some post-secondary education. Data from 1980 and 2000 decennial censuses. Employment categorized by occupational task content. See text for details.

B Extended Model with Participation Choice

Here, we present a simple extension to the model of Section 3 that allows for a labor force participation decision among high-skilled workers. The purpose is to show that the key results from Section 4 are unaltered by this modification.

To begin, we note that the setup of production technology and, therefore, the labor demand equations, (6)–(9), are identical. Modeling a participation margin affects only the specification of labor supply. A high-skilled individual now chooses between not working, working in the cognitive occupation, or working in the other occupation.

This choice has two stages. First, an individual draws a disutility of labor (or alternatively, a utility value of home production/leisure), b , from a gender-specific distribution, $\Omega_{gt}(b)$, for $g = \{M, F\}$. Based on this draw, individuals choose whether to work prior to observing their cognitive work ability, a , knowing only that it is drawn from $\Gamma_{gt}(a)$.

As such, the expected return to working is given by:

$$\bar{w}_{gt} = p_{gt}\Gamma_{gt}(a_{gt}^*) + w_{gt} \int_{a_{gt}^*}^{\infty} a\Gamma'_{gt}(a)da.$$

This anticipates the result that *ex post*, conditional on choosing to work, workers sort into the cognitive and other occupation according to the cutoff rules (10) and (11) as before.

Ex ante, individuals with disutility $b < b_{gt}^*$ choose to work, while those with $b \geq b_{gt}^*$ optimally choose not to participate. This disutility cutoff is defined by:

$$b_{gt}^* = \bar{w}_{gt}, \quad \text{for } g = \{M, F\}.$$

The labor market equilibrium conditions become:

$$\begin{aligned} L_{gt} &= S_{gt} \Omega_{gt}(b_{gt}^*) \int_{a_{gt}^*}^{\infty} a \Gamma'_{gt}(a) da, \\ E_{gt} &= S_{gt} \Omega_{gt}(b_{gt}^*) \Gamma_{gt}(a_{gt}^*), \end{aligned}$$

and the fraction of high-skilled individuals who do not work is $1 - \Omega_{gt}(b_{gt}^*)$, for $g = \{M, F\}$.

Note that the key equations that we use in analyzing the benchmark model of Section 3—namely equations (6)–(9), (10), and (11)—are identical in this extended model. Hence, the key equation under consideration, equation (19), is unchanged.

The only change comes in the quantification of the model. With endogenous participation, equation (20) describing the fraction of individuals who work in the cognitive occupation becomes:

$$\phi_{gt} = \Omega_{gt}(b_{gt}^*) \times \left(\frac{a_{gt}^{min}}{a_{gt}^*} \right)^{\kappa_{gt}}.$$

As a result, the left-hand side of (21) becomes:

$$\begin{aligned} LHS &= \left(\frac{1}{\kappa_{Mt}} \right) \left[\Delta \Omega_{Mt}(b_{Mt}^*) + \log(\phi_{Mt}) \Delta \kappa_{Mt} - \Delta \phi_{Mt} \right] \\ &\quad - \left(\frac{1}{\kappa_{Ft}} \right) \left[\Delta \Omega_{Ft}(b_{Ft}^*) + \log(\phi_{Ft}) \Delta \kappa_{Ft} - \Delta \phi_{Ft} \right]. \end{aligned}$$

Critically, each of these terms can be measured in the data. Relative to the analysis of Section 4, the extended model adds only the term $\Delta \Omega_{gt}(b_{gt}^*)$, the change in the fraction of working men and women, which is directly observed in Table 1. Including this, we find that $LHS = +1.60\%$ remains positive. Thus, if the change in discrimination was the same across occupations, i.e. $\Delta(1 + \tau_t^O) = \Delta(1 + \tau_t^C)$, and the scale shift in ability distributions was the same across genders, i.e. $\Delta a_{Ft}^{min} = \Delta a_{Mt}^{min}$, then the changes in occupational outcomes and wages are rationalized by greater female bias in cognitive occupations relative to other occupations.

C Accounting with Non-Constant Marginal Rates of Transformation

Here, we extend our analysis of Section 4 to the case in which the labor inputs of men and women are not perfect substitutes. We assume a constant elasticity of substitution between

labor inputs: $f^C(\cdot) = f^C\left([Z_{Mt}^C L_{Mt}^\rho + Z_{Ft}^C L_{Ft}^\rho]^{\frac{1}{\rho}}\right)$ and $f^O(\cdot) = f^O\left([Z_{Mt}^O E_{Mt}^\rho + Z_{Ft}^O E_{Ft}^\rho]^{\frac{1}{\rho}}\right)$, with $\rho < 1$.³⁴

The labor demand equations, (6)–(9), can be rearranged and simplified as:

$$\frac{w_{Ft}}{w_{Mt}} = \frac{Z_{Ft}^C}{Z_{Mt}^C} \frac{1}{1 + \tau_t^C} \frac{L_{Ft}^{\rho-1}}{L_{Mt}^{\rho-1}}, \quad (\text{A.1})$$

$$\frac{p_{Ft}}{p_{Mt}} = \frac{Z_{Ft}^O}{Z_{Mt}^O} \frac{1}{1 + \tau_t^O} \frac{E_{Ft}^{\rho-1}}{E_{Mt}^{\rho-1}}. \quad (\text{A.2})$$

Using the indifference conditions, (10)–(11), and the Pareto functional form on the distribution of cognitive work ability, these conditions can be combined as:

$$\begin{aligned} & \left(\frac{1}{\kappa_{Mt}}\right) \left[\log(\phi_{Mt}) \Delta \kappa_{Mt} - \Delta \phi_{Mt} \right] - \\ & \left(\frac{1}{\kappa_{Ft}}\right) \left[\log(\phi_{Ft}) \Delta \kappa_{Ft} - \Delta \phi_{Ft} \right] + (1 - \rho) \left[\Delta \left(\frac{L_{Ft}}{L_{Mt}}\right) - \Delta \left(\frac{E_{Ft}}{E_{Mt}}\right) \right] = \\ & \Delta \left(\frac{Z_{Ft}^C}{Z_{Mt}^C}\right) - \Delta \left(\frac{Z_{Ft}^O}{Z_{Mt}^O}\right) + \Delta a_{Ft}^{min} - \Delta a_{Mt}^{min} + \Delta(1 + \tau_t^O) - \Delta(1 + \tau_t^C). \quad (\text{A.3}) \end{aligned}$$

The first two terms on the left-hand side are unaltered relative to Section 4 and remain positive. Effective labor in the cognitive occupation, L_{gt} , and employment in the other occupation, E_{gt} , for $g = \{M, F\}$ are given in expressions (13)–(16). Hence, as before, all terms on the left-hand side of (A.3) can be measured given values for the number of high-skilled men and women in 1980 and 2000. These are given in Table 1: normalizing $S_{M,1980} = 1$, we have $S_{F,1980} = 0.736$, $S_{M,2000} = 1.684$, and $S_{F,2000} = 1.695$. Using these we find $\Delta\left(\frac{L_{Ft}}{L_{Mt}}\right) > 0$ and $\Delta\left(\frac{E_{Ft}}{E_{Mt}}\right) < 0$. Since $\rho < 1$, this implies that $(1 - \rho) \left[\Delta\left(\frac{L_{Ft}}{L_{Mt}}\right) - \Delta\left(\frac{E_{Ft}}{E_{Mt}}\right) \right] > 0$. Thus, if the change in discrimination was the same across occupations, i.e. $\Delta(1 + \tau_t^O) = \Delta(1 + \tau_t^C)$, and the scale shift in ability distributions was the same across genders, i.e. $\Delta a_{Ft}^{min} = \Delta a_{Mt}^{min}$, then the changes in occupational outcomes and wages are rationalized by greater female bias in cognitive occupations relative to other occupations.

D Social Skills Model

Here, we show how a model with “social” skills and “non-social” skills as factor inputs, in which women have a comparative advantage at social skills, can be formulated to be isomorphic to the model of Section 3.

Let S denote social skills and N denote non-social skills, both of which are used as labor input in production. To make the mapping as simple as possible, assume a female

³⁴We have also studied the case where the elasticity of substitution differs between the cognitive and other occupation. For brevity, these results are not presented here and are available upon request.

worker possesses only S skills, distributed $a \sim \Gamma_{Ft}(a)$, and zero N skills. Analogously, male workers possess only N skills, distributed $a \sim \Gamma_{Mt}(a)$, and zero S skills. Clearly, women have the comparative advantage in social skills, since men have none.

For the production function, the analogue to equation (4) is:

$$Y_t = G(f^C(Z_{Nt}^C L_{Nt}, Z_{St}^C L_{St}), f^O(Z_{Nt}^O E_{Nt}, Z_{St}^O E_{St}), \mathbb{K}_t),$$

where L_N is the input of effective N skills, and L_S is the input of effective S skills, into the cognitive occupation. Again for simplicity, assume that in the other occupation, an individual's ability does not matter; if a man chooses to work in the other occupation, he provides one unit of N skills (irrespective of his a draw), and a female worker provides one unit of S skills (independent of her a) in the other occupation. And Z_N^C (Z_N^O) is the productivity of N skills, and Z_S^C (Z_S^O) is the productivity of S skills, in the cognitive (other) occupation.

In this labeling of the model, the analogue to the $\Delta(Z_{Ft}^C/Z_{Mt}^C) > \Delta(Z_{Ft}^O/Z_{Mt}^O)$ condition is clear: $\Delta(Z_{St}^C/Z_{Nt}^C) > \Delta(Z_{St}^O/Z_{Nt}^O)$, that the data is consistent with a greater increase in the demand for social skills (relative to non-social skills) in the cognitive occupation than in the other occupation.

E Accounting for Labor Market Outcomes to 2014

In the main body of the paper, our analysis focuses on 1980-2000, the period of unambiguously rising demand for skilled labor and cognitive tasks. However, recent work by [Beaudry, Green, and Sand \(2016\)](#) provides evidence that since 2000, this trend has slowed or even reversed. To study the implications of this, we extend our quantitative model analysis of Section 4 to 2014 by using the most recent American Community Survey (ACS) sample available from IPUMS.

The “great reversal” in the demand for cognitive tasks is evident in the probabilities of employment in a COG occupation. In contrast to 1980-2000 when the likelihood of a high-skilled female working in a cognitive job rose, the likelihood has fallen slightly since 2000, from $\phi_{F,2000} = 0.588$ to $\phi_{F,2014} = 0.578$. The fall was even greater for males, from $\phi_{M,2000} = 0.633$ to $\phi_{M,2014} = 0.614$, continuing the downward trend from the end of the 20th century.

Proceeding as in Subsection 4.1, it is possible to infer the source of these changes without restricting the functional form of the distribution of cognitive work ability, $\Gamma_{gt}(a)$. This is possible if the male and female distributions coincide, even if the support of that distribution has changed over time. The fact that the cognitive work probability fell implies greater selectivity into COG for both genders. But the fact that it fell proportionately more for men implies that the differential change in selectivity, $\Delta a_{Mt}^* - \Delta a_{Ft}^* > 0$.³⁵ From equation (19),

³⁵Unlike Subsection 4.1, we are unable to sign $\Delta a_{Mt}^* - \Delta a_{Ft}^*$ for the case where ability distributions differ by gender, but remain constant over time. This is because selectivity has moved in the same direction for both genders between 2000 and 2014.

this implies greater female bias and/or a greater reduction in discrimination in cognitive occupations relative to other occupations.

Finally, we investigate equation (21) which decomposes forces when we assume the ability distribution to be Pareto, gender specific, and allow those distributions to change over time. As discussed in Subsection 4.2, doing so requires data on the distribution of cognitive wages in 2000 and 2014. Since it is not possible to measure hourly wages in the ACS, we do so using the March supplement of the Current Population Survey (CPS).³⁶ While use of the CPS allows us to study wage changes between 2000-2014, it comes with an important tradeoff: a much smaller sample size relative to the 5% Census samples and ACS.

With this caveat in mind, we use the ratio of the mean to median wage in cognitive occupations in the CPS to compute the Pareto shape parameter. We find that $\kappa_{M,2000} = 2.917$, $\kappa_{M,2014} = 2.321$, $\kappa_{F,2000} = 3.889$, and $\kappa_{F,2014} = 3.006$.³⁷ Using these and the probabilities of employment in cognitive occupations from above, we find that between 2000 and 2014:

$$LHS \equiv \left(\frac{1}{\kappa_{Mt}} \right) \left[\log(\phi_{Mt}) \Delta \kappa_{Mt} - \Delta \phi_{Mt} \right] - \left(\frac{1}{\kappa_{Ft}} \right) \left[\log(\phi_{Ft}) \Delta \kappa_{Ft} - \Delta \phi_{Ft} \right] = +0.87\%.$$

Hence, if the change in discrimination was the same across occupations, and the scale shift in ability distributions was the same across genders, then equation (21) implies greater female bias in cognitive occupations compared to other occupations.

Note, however, that the magnitude is substantially smaller than the +4.74% change computed for 1980-2000. Moreover, the result is somewhat sensitive to details regarding data restrictions, likely due to the small CPS sample size. For instance, trimming the top and bottom 1% of wage observations to remove outliers, we find that $LHS = -0.03\%$. This indicates that the change in the relative demand for female versus male labor in cognitive jobs was roughly the same as the change in other occupations. This contrasts sharply with the robustness of the result derived in Section 4 to details regarding treatment of the data. Hence, we conclude that the evidence points to a reduction or slowdown in female bias in cognitive occupations since 2000. This mirrors the reduction in the demand for cognitive skills documented in [Beaudry, Green, and Sand \(2016\)](#).

F Task Data Details

To generate our task measures, we use the 4th Edition, published in 1977, and the revised 4th Edition, published in 1991, of the Dictionary of Occupational Titles (DOT) made available

³⁶As discussed in Section 2, wages are computed as total annual income divided by the product of weeks worked last year and usual hours worked per week. In the ACS, the weeks worked variable is intervalled (e.g., 14-26 weeks, 27-39 weeks) preventing accurate calculation of wages.

³⁷Relative to the decennial Census data, wage distributions in the CPS display thinner right tails; this is true for both 1980 and 2000. We have re-done the analysis of Section 4.2 using the κ 's derived from the CPS, and the nature of our results are unchanged. Specifically, we compute the left-hand side of equation (21) to be positive, as before. Details are available upon request.

through the Interuniversity Consortium for Political and Social Research (ICPSR 1981; ICPSR 1991).

DOT-77 and DOT-91 have their own occupational coding schemes, which are much more disaggregated than the Census Occupation Code (COC) classification (for example, DOT-91 has over 12,700 occupation codes). We match DOT-91 and DOT-77 occupation codes based on the DOT-91 codebook (ICPSR 1991). In results not reported here, we also consider an alternative mapping for DOT-91 to DOT-77 by matching on the first 3 digits of the DOT code, which correspond to occupation group categorizations. When doing the mapping at this level, we can decide whether to include or exclude the roughly 5% of detailed DOT-91 codes that did not exist in DOT-77. With either choice, results are very similar to those presented in the paper.

In order to aggregate the information to the COC level, we follow an approach similar to Autor, Levy, and Murnane (2003). Specifically, we use the April 1971 CPS Monthly File, in which experts assigned both 1970-COC and DOT-77 codes to respondents. We augment the dataset by attaching the harmonized codes from Autor and Dorn (2013) (hereafter “Dorn codes”) corresponding to each 1970 COC. We use the sampling weights from the augmented April 1971 CPS Monthly File to calculate means of each DOT temperament in 1977 and 1991 at the Dorn code level. Once aggregated to the Dorn code level, we create a social task index for each occupation by adding the scores for the four temperaments listed in Section 5.

All of the Dorn code level occupational measures are added to the Census data on employment and wages for 1980 and 2000 used in Section 2. In a small number of instances, we slightly aggregate the Dorn codes to avoid cases that do not have a corresponding 1970-COC and would otherwise have missing task data.

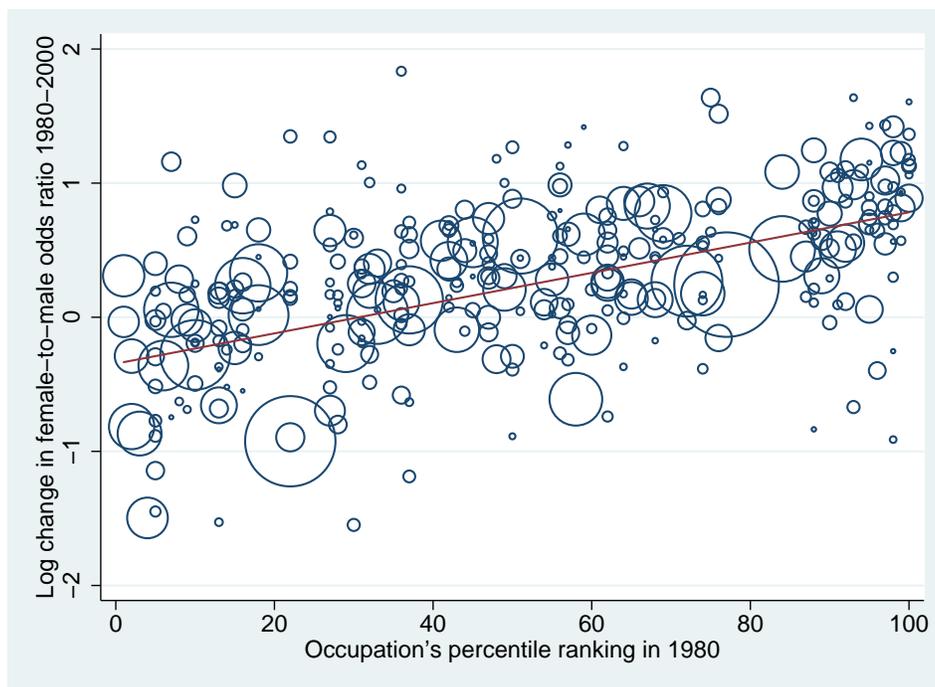
G Quantifying the Importance of the Change in Social Skills

As indicated in Table 2, the probability of working in a top quartile occupation for a woman relative to the probability for a man was $39.7/59.9 = 0.663$ in 1980. By 2000, the relative probability was $40.7/55.9 = 0.728$, representing a 9.4 log point increase. In this subsection, we try to determine how much of this can be accounted for by the increasing importance of social skills in good jobs relative to other occupations.

To do so, we measure the ratio of the female-to-male probability of working in each of the 3-digit level occupations, and compute the log change between 1980 and 2000. In Figure A.1, we plot this against the occupation’s ranking in the 1980 wage distribution. In a similar manner to Figure 1, this confirms that higher paying occupations experienced a larger increase in employment probability for women relative to men.

We regress this occupation-specific change in female-to-male probability on the change in the social skill index between 1977 and 1991. In doing so, we find that a change in social skill importance that is one standard deviation above the mean is associated with a 28.6 log

Figure A.1: Change in Female-Male Employment Probability and Occupational Wage Ranking



Notes: Each circle represents a 3-digit occupation (size indicating its share of total employment in 1980). Data on employment and wages from the 1980 and 2000 decennial censuses. See text for details.

point increase in the relative employment probability (with standard error of 6.78). When we control for changes in the ALM measures of cognitive, routine, and manual task change, the point estimate becomes 22.3 (with standard error of 7.02).

We use this latter estimate to infer the role of increasing social skill importance as follows. Within the top quartile occupations, the average change in the social skill index is 0.244 standard deviations above the (employment-weighted) mean. This change is associated with a $0.244 \times 22.3 = 5.4$ log point increase in the female-to-male employment probability in a top quartile occupation. Thus, based on this regression analysis, the increasing importance of social skills accounts for approximately 57% of the increase.

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