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 the deterioration of labor market outcomes for men in the US: Since 1980, the probability that a college-educated man was employed in a cognitive/high-wage occupation fell. This contrasts starkly with the experience of college-educated women: their probability of working in these types of jobs rose, despite a much larger increase in the supply of educated women relative to men during this period. We study a flexible neoclassical model of the labor market that allows us to shed light on the key forces capable of rationalizing these findings. The model indicates that one key channel is a greater increase in the demand for female-oriented skills in cognitive/high-wage occupations relative to other occupations. Using occupational task-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. We find a strong and robust relationship between the change in the female share of employment and the importance of social skills in an occupation over time.

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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, 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) fell. 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. 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 patterns across genders, we study a simple, general model of the market for high-skilled workers in Sections 3 and 4. The model is sufficiently flexible to allow 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 through one of 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. Specifically, 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); Tomova et al. (2014)). As such, we study whether the demand for social skills has changed over time.

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

Specifically, our hypothesis is that the importance of social skills has become greater *within* high-wage/cognitive occupations relative to other occupations, and this is generating the increasing 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 data from the Dictionary of Occupational Titles to measure the importance of social skills within an occupation and its change over time. Our measure 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 (that we define 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.

Finally, in Section 6, we extend our quantitative model analysis to the 2000-2014 period. Recent work by Beaudry, Green, and Sand (2016) provides evidence that, since 2000, there has been a change or reversal in the demand for cognitive skill. 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.

2 Divergence in High-Skilled Labor Market Outcomes

The occupational distribution of employment differs greatly between high- and low-skilled workers. As is well known, 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 in the employment likelihood in these occupations 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 *cogni-*

[2]Our interest in social skills is motivated by the recent work of Borghans, Ter Weel, and Weinberg (2014) and Deming (2015) who emphasize the importance of the *level* of social skills in explaining employment growth. However, our emphasis is on the *change* in social skill importance over time within occupations, a distinction we turn to in Section 5.

tive occupations—which include 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 (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* of the occupational wage distribution, where the mass of each occupational wage is based on its share of aggregate hours.[3] 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.[4] 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. 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%. Interestingly, this fall in the probability of working in a COG job was accompanied by a 3 pp rise in the fraction of college educated men not working (unemployed or out of the labor force).[5] This fall in the probability of working in a

[3]For details on the computation of wages, see Section 4. We note that we 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.

[4]To 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 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.

[5]Note that this does not imply that those who otherwise would have been in COG found themselves not working. This pattern is entirely consistent with men who otherwise would have been in a cognitive job "bumped down" to a routine job, bumping some of those who would have been routine down to manual, and so on. For an explanation of employment dynamics along these lines for the period since 2000, see Beaudry, Green, and Sand (2016).

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

	1980	2000	% Difference Total	% Difference Explained	% Difference Unexplained
Male					
Total (000's)	*12080*	*20340*			
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					
Total (000's)	*8890*	*20470*			
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.

good job was not observed among females. 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.

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:

$$\pi_{it} = X_{it}\beta + \epsilon_{it}, \tag{1}$$

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:

$$\frac{1}{N}\sum_{i}^{N} \pi_{it} = \overline{\pi}_t. \tag{2}$$

As such, the "Total % Difference," $\overline{\pi}_{2000} - \overline{\pi}_{1980}$, 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.[6]

Demographic change predicts that (high-skilled, working age) males should have *increased* their probability of working in the cognitive occupational group 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). 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 overall occupational wage distribution of 1980. The likelihood of a high-skilled, working age man 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.

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 male probability falls while the female probability rises.[7] 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.

[6]We 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.

[7]We have generated the same statistics for the top quintile and top decile occupations, and the nature of results is unchanged. For brevity, we make these available upon request.

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

	1980	2000	% Difference Total	Explained	Unexplained
Male					
Total (000's)	*12080*	*20340*			
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					
Total (000's)	*8890*	*20470*			
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.

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 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:

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

where $\left(F_t^j / E_t^j\right)$ is the female share of employment in a 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

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

	Observed 1980	2000	Between	Within
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 some college education. Data from 1980 and 2000 decennial censuses. See text for details.

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 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* 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

Motivated by the findings of Section 2, we present a simple equilibrium model of the market for high-skilled workers. The model is intentionally flexible, 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 observed changes between 1980 and 2000, and in particular, the falling share of men and the rising share of women working in "good jobs." For the purposes of exposition and quantitative analysis, we label good jobs as cognitive occupations.[8]

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 income, Y_t, via:

$$Y_t = G\left(f^C(Z^C_{Mt}L_{Mt}, Z^C_{Ft}L_{Ft}), f^O(Z^O_{Mt}E_{Mt}, Z^O_{Ft}E_{Ft}), \mathbb{K}_t\right) \tag{4}$$

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, individuals are endowed with different abilities in cognitive work, implying that the amount of effective labor differs from the measure of employed workers. Effective labor is augmented by gender-specific productivity, Z^C_{Ft} and Z^C_{Mt}.

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^O_{Mt} and Z^O_{Ft}.

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 $G_1, G_2 > 0$, $G_{11}, G_{22} < 0$, $f^i_1, f^i_2 > 0$ and $f^i_{11}, f^i_{22} \leq 0$ for $i = C, O$.[9]

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:

$$\max_{\substack{L_{Mt}, L_{Ft}, \\ E_{Mt}, E_{Ft}, \mathbb{K}_t}} Y_t - (1+\tau^C_t)w_{Ft}L_{Ft} - w_{Mt}L_{Mt} - (1+\tau^O_t)p_{Ft}E_{Ft} - p_{Mt}E_{Mt} - \mathbf{r}_t\mathbb{K}_t. \tag{6}$$

For the sake of generality, the discriminatory "wedge" against high-skilled women in the cognitive occupation, $(1+\tau^C_t)$, may differ from that in the other occupation, $(1+\tau^O_t)$.

[8]Our results hold for other definitions explored in Section 2; for brevity, we make these available upon request.

[9]As an example, consider:

$$G = K^\alpha \left[Z^C_F L_F + Z^C_M L_M\right]^{1-\alpha} + J^\alpha \left[Z^O_F E_F + Z^O_M E_M\right]^{1-\alpha}. \tag{5}$$

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, $G_{12} = G_{21} = 0$.

Maximization results in the following labor demand functions for L_{Mt}, L_{Ft}, E_{Mt} and E_{Ft}:

$$w_{Mt} = Z^C_{Mt} G_1(\cdot) f^C_1(Z^C_{Mt} L_{Mt}, Z^C_{Ft} L_{Ft}), \tag{7}$$

$$w_{Ft} = \frac{Z^C_{Ft}}{1+\tau^C_t} G_1(\cdot) f^C_2(Z^C_{Mt} L_{Mt}, Z^C_{Ft} L_{Ft}), \tag{8}$$

$$p_{Mt} = Z^O_{Mt} G_2(\cdot) f^O_1(Z^O_{Mt} E_{Mt}, Z^O_{Ft} E_{Ft}), \tag{9}$$

$$p_{Ft} = \frac{Z^O_{Ft}}{1+\tau^O_t} G_2(\cdot) f^O_2(Z^O_{Mt} E_{Mt}, Z^O_{Ft} E_{Ft}). \tag{10}$$

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

3.2 Labor Supply

On the supply side, denote by S_{gt} 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: $a \sim \Gamma_{gt}(a)$, where Γ denotes the cumulative distribution function.

Individuals make a discrete choice whether to work in the cognitive occupation or other occupation. Given the wage per unit of effective labor, w_{gt}, a worker with ability a earns $a \times w_{gt}$ if employed in the cognitive occupation. Alternatively, the worker earns p_{gt} 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:

$$a^*_{Mt} w_{Mt} = p_{Mt}. \tag{11}$$

Similarly:

$$a^*_{Ft} w_{Ft} = p_{Ft}, \tag{12}$$

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:

$$\phi_{gt} = 1 - \Gamma_{gt}(a^*_{gt}) \tag{13}$$

with complementary fraction choosing the other occupation.

For simplicity, we have assumed that all high-skilled workers supply labor (inelastically) to either the cognitive or other occupation. As a result, we abstract 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:

$$L_{Ft} = S_{Ft} \int_{a^*_{Ft}}^{\infty} a\Gamma'_{Ft}(a)da, \tag{14}$$

$$L_{Mt} = S_{Mt} \int_{a^*_{Mt}}^{\infty} a\Gamma'_{Mt}(a)da. \tag{15}$$

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:

$$E_{Mt} = S_{Mt}\Gamma_{Mt}(a^*_{Mt}), \tag{16}$$

$$E_{Ft} = S_{Ft}\Gamma_{Ft}(a^*_{Ft}). \tag{17}$$

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 Analytics, Part 1

In what follows, we assume that (effective) labor input of men and women are perfect substitutes in both occupations. That is, $f^C(\cdot) = f^C(Z^C_{Mt}L_{Mt} + Z^C_{Ft}L_{Ft})$ and $f^O(\cdot) = f^O(Z^O_{Mt}E_{Mt} + Z^O_{Ft}E_{Ft})$. 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 between male and female labor in production.

With perfect substitutability, the labor demand equations, (7)–(10), can be rearranged and simplified as:

$$\frac{w_{Ft}}{w_{Mt}} = \frac{Z_{Ft}^C}{Z_{Mt}^C} \frac{1}{1+\tau_t^C}, \tag{18}$$

$$\frac{p_{Ft}}{p_{Mt}} = \frac{Z_{Ft}^O}{Z_{Mt}^O} \frac{1}{1+\tau_t^O}. \tag{19}$$

Using the indifference conditions, (11)–(12), equations (18)–(19) imply:

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

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

$$\Delta a_{Mt}^* - \Delta a_{Ft}^* = \Delta \left(\frac{Z_{Ft}^C}{Z_{Mt}^C}\right) - \Delta \left(\frac{Z_{Ft}^O}{Z_{Mt}^O}\right) + \Delta \left(1+\tau_t^O\right) - \Delta \left(1+\tau_t^C\right). \tag{20}$$

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 (20) is the differential change in selectivity into the cognitive occupation for men versus women, $\Delta a_{Mt}^* - \Delta a_{Ft}^*$.

The left-hand side can be measured from the 1980 and 2000 data, even without making functional form assumptions about the ability distributions, $\Gamma_{gt}(a)$ for $g = \{M, F\}$; this is true under two scenarios. 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 distributional change over time, but requires the male and female distributions to coincide at each point in time.

In either case, the differential gender trends in cognitive work probability discussed in Section 2, $\Delta\phi_{Mt}$ and $\Delta\phi_{Ft}$, would measure the left-hand side of (20) directly. Since the probability for men has fallen over time, equation (13) 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 this case, the model identifies two channels that account for this change.

The first channel is if $\Delta\left(Z_{Ft}^C/Z_{Mt}^C\right) > \Delta\left(Z_{Ft}^O/Z_{Mt}^O\right)$. From (7)–(10), 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. 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

$\Delta(Z^C_{Ft}/Z^C_{Mt}) > \Delta(Z^O_{Ft}/Z^O_{Mt})$, production exhibits a *greater female bias in the cognitive occupation* relative to the other occupation.

The second channel is if $\Delta\left(1+\tau^O_t\right) > \Delta\left(1+\tau^C_t\right)$. 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 Section 4.2.3.[10]

4.2 Analytics, Part 2

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}.

Recall that given the wage per unit of effective labor, w_{gt}, a 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. Hence, we specify ability to be distributed Pareto, with scale parameters a^{min}_{Mt} and a^{min}_{Ft}, and shape parameters κ_{Mt} and κ_{Ft}, for males and females, respectively.

In addition to empirical plausibility, the Pareto distribution is analytically attractive. Occupational choice determined by the labor supply conditions, (11) and (12), imply that ability among COG workers is truncated from Γ_{gt} at a^*_{gt}. Nonetheless, we are able to derive characteristics of the entire ability distribution since the the conditional probability distribution of a Pareto-distributed random variable truncated from below is also Pareto distributed with the same shape parameter. We use this property in our analysis below.

Given the Pareto functional form, we can further decompose the left hand side of equation (20). The fraction of high-skilled individuals who work in the cognitive occupation is given by:

$$\phi_t = \left(\frac{a^{min}_t}{a^*_t}\right)^{\kappa_t}. \tag{21}$$

[10] Finally, we note that it is the empirical differential gender trend in COG employment likelihood—the end of men and rise of women—that allows us to identify the model's differential change in selectivity, $\Delta a^*_{Mt} - \Delta a^*_{Ft}$. 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 (7) and (9):

$$a^*_{Mt} = \frac{Z^O_{Mt}}{Z^C_{Mt}} \frac{G_2(\cdot)}{G_1(\cdot)} \frac{f^O_1(Z^O_{Mt}E_{Mt} + Z^O_{Ft}E_{Ft})}{f^C_1(Z^C_{Mt}L_{Mt} + Z^C_{Ft}L_{Ft})}.$$

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.

Taking the total derivative, we obtain:

$$\left(\frac{1}{\kappa_t}\right)\Delta\phi_t = \Delta a_t^{min} - \Delta a_t^* + \log\left(\frac{a_t^{min}}{a_t^*}\right)\Delta\kappa_t.$$

Since $\log\left(\frac{a_t^{min}}{a_t^*}\right) = \left(\frac{1}{\kappa_t}\right)\log(\phi_t)$, this can be rewritten as:

$$\Delta a_t^* = \Delta a_t^{min} + \left(\frac{1}{\kappa_t}\right)\Big[\log(\phi_t)\,\Delta\kappa_t - \Delta\phi_t\Big].$$

Subbing this into equation (20) obtains:

$$\left(\frac{1}{\kappa_{Mt}}\right)\Big[\log(\phi_{Mt})\,\Delta\kappa_{Mt} - \Delta\phi_{Mt}\Big] - \left(\frac{1}{\kappa_{Ft}}\right)\Big[\log(\phi_{Ft})\,\Delta\kappa_{Ft} - \Delta\phi_{Ft}\Big] =$$
$$\Delta\left(\frac{Z_{Ft}^C}{Z_{Mt}^C}\right) - \Delta\left(\frac{Z_{Ft}^O}{Z_{Mt}^O}\right) + \Delta a_{Ft}^{min} - \Delta a_{Mt}^{min} + \Delta\left(1+\tau_t^O\right) - \Delta\left(1+\tau_t^C\right). \quad (22)$$

Relative to equation (20), (22) includes changes in both the scale and shape parameters, Δa_{gt}^{min} and $\Delta\kappa_{gt}$. Equation (22) is useful because all the ϕ and κ terms 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 $a_{gt}^* \times \kappa_{gt}/\left(\kappa_{gt}-1\right)$. Thus, the mean cognitive wage is given by $w_{gt} \times a_{gt}^* \times \kappa_{gt}/\left(\kappa_{gt}-1\right)$. Combining this with equation (18) implies that the empirically observed ratio of mean cognitive wages among high-skilled workers, Ratio_t, is:

$$\text{Ratio}_t = \frac{Z_{Ft}^C}{Z_{Mt}^C}\frac{1}{1+\tau_t^C}\frac{a_{Ft}^*\frac{\kappa_{Ft}}{\kappa_{Ft}-1}}{a_{Mt}^*\frac{\kappa_{Mt}}{\kappa_{Mt}-1}}. \quad (23)$$

Hence, changes in the observed Ratio_t can be decomposed into female bias, $\Delta\left(Z_{Ft}^C/Z_{Mt}^C\right)$, 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 (2016) and the references therein).[11]

[11] Note 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. Finally, we refer the reader to Black and Spitz-Oener (2010), Beaudry and Lewis (2014), and Burstein, Morales, and Vogel (2015) who study the decline of the gender wage gap and its relationship to changes in the skill/task content of work and computerization.

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.[12] 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 average 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:

$$\left(\frac{\kappa_{gt}}{\kappa_{gt} - 1} \right) 2^{-\frac{1}{\kappa_{gt}}}. \tag{24}$$

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 $\kappa_{M,1980} = 2.988$, $\kappa_{M,2000} = 2.332$, $\kappa_{F,1980} = 3.753$, and $\kappa_{F,2000} = 3.293$.[13] 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.

[12] Allowing the shape parameter to change means that our approach is able to accommodate changes in selection into the high-skilled population (i.e. college degree 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.

[13] As is standard, we compute wages from the census as total annual wage and salary income, divided by the product of weeks worked last year and usual hours worked per week. Annual income in 1980 is multiplied by 1.4 for those who are top-coded (see, Firpo, Fortin, and Lemieux (2011)). We note that the measurement of a distribution's skewness can be disproportionately influenced by outliers at the extremes. As such, we restrict attention to those who report positive income and worked at least 250 annual hours. In analysis not reported here, we verify that our results derived below 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.

4.2.3 The three channels

Given the observed changes in occupational outcomes and wage distributions, we measure the left-hand side of equation (22) 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 (22) makes clear, the model apportions this to the two factors discussed with relation to equation (20), and a new one. The three factors are:

1. $\Delta\left(Z^C_{Ft}/Z^C_{Mt}\right) - \Delta\left(Z^O_{Ft}/Z^O_{Mt}\right)$: a differential female bias in labor demand across occupations;

2. $\Delta\left(1+\tau^O_t\right) - \Delta\left(1+\tau^C_t\right)$: a differential change in the discrimination wedge across the cognitive and other occupation; and

3. $\Delta a^{min}_{Ft} - \Delta a^{min}_{Mt}$: a differential change in the location parameter of the cognitive ability distribution across genders

Thus, if one were willing to assume the change in discrimination was the same across occupations, i.e. $\Delta\left(1+\tau^O_t\right) = \Delta\left(1+\tau^C_t\right)$, and the scale shift in ability distributions was the same across genders, i.e. $\Delta a^{min}_{Ft} = \Delta a^{min}_{Mt}$, then equation (22) implies that the only way to rationalize the observed changes in occupational outcomes and wages is a larger "outward shift" of the demand curve for female labor (relative to male labor) in the cognitive occupation, i.e. $\Delta\left(Z^C_{Ft}/Z^C_{Mt}\right) > \Delta\left(Z^O_{Ft}/Z^O_{Mt}\right)$.

Naturally, all three factors may have contributed to the divergent employment paths across the genders. For instance, the data is consistent with a greater increase in the minimum cognitive work ability of females versus males, $\Delta a^{min}_{Ft} > \Delta a^{min}_{Mt}$. Similarly, the data is consistent with a larger fall in female discrimination in good jobs relative to other jobs, $\Delta\left(1+\tau^O_t\right) > \Delta\left(1+\tau^C_t\right)$.[14] If one were willing to assume that only one 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. By assuming that there has been no changes in the distribution of ability and that changes in labor demand do not differ by race and gender, they provide quantitative estimates of the degree of gender/race/occupation-specific discrimination change.

[14] That is, a fall in discrimination implies $\Delta\left(1+\tau_t\right) < 0$, and a larger fall in the cognitive occupation implies $\Delta\left(1+\tau^C_t\right)$ more negative than $\Delta\left(1+\tau^O_t\right)$.

However, we note that the current literature is largely silent on the empirical plausibility of factors (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 constant over time. More generally, Blau and Kahn (2016) discuss the paucity of empirical work documenting a fall in female discrimination, much less differential changes in discrimination across occupations.[15] 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, factor (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, $\Delta\kappa_{gt}$.

Nonetheless, while all three factors may have contributed to the divergence in gender outcomes, use data on occupational tasks in the next section to provide evidence for factor (1), greater female bias in good jobs.

5 Changes in the Demand for Social Skills

In this section we explore whether the increased demand for female (relative to male) labor in high-wage/cognitive occupations is related to changes in the types of tasks performed and 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); Tomova et al. (2014)). In economics, recent innovative work by Borghans, Ter Weel, and Weinberg (2014) and Deming (2015) show that since 1980, employment and wage growth have been strongest in occupations that involve high levels of social skills, and especially those combining social and cognitive skills.[16] While related to our work, these findings are consistent with a relative increase in female labor demand due to composition change "between" occupations, for e.g., disproportionately large gains in employment in occupations with high levels of social skill requirement. However, as

[15] See 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.

[16] Deming and Kahn (2016) provide evidence on the correlation between wages and firms' demand for cognitive and social skill using evidence from online job vacancy postings. At the worker level, Weinberger (2014) documents increasing returns to cognitive skills to be concentrated in individuals with strong social skills.

noted in Sections 2 and 4, the rising female share of employment in the US has been due to changes "within" occupation, increasing the relative demand for female-oriented skills in cognitive occupations relative to others.[17]

Motivated by this research 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 relative demand of females versus males in these occupations.

To measure the change in the importance of social skills within occupations we use data from the Dictionary of Occupational Titles (DOT). The DOT provides detailed measures of abilities and "temperaments" that are required to perform the tasks associated with different occupations, as well as information on a number of work activities performed by job incumbents. A growing literature pioneered by Autor, Levy, and Murnane (2003) 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). 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:[18]

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.

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

[17] Deming (2015) 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.

[18] These are very similar to the four measures in the O*NET used by Deming (2015) to identify social skill intensity. We study the DOT (as opposed to its successor, the O*NET) since this allows us to measure changes in importance over time.

occupations between 1977 and 1991. While this does not overlap perfectly with the 1980-2000 time period considered above, there exists no other U.S. dataset measuring tasks and skills at the occupational level.

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 Autor, Levy, and Murnane (2003) and compute 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 D.

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.[19] 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.

5.1 Results

Before studying the change in the importance of social skills and its relationship to increasing 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 Autor, Levy, and Murnane (2003) (hereafter, 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 as the average of "adaptability to situations requiring the precise attainment of set limits, tolerances or standards" and "finger dexterity," and manual

[19] All of our results are robust to the exclusion of any one of the four chosen temperaments.

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

	1980		2000	
	(1)	(2)	(3)	(4)
Social	0.066	0.119	0.062	0.094
	(0.018)	(0.017)	(0.017)	(0.022)
Cognitive		-0.145		-0.106
		(0.019)		(0.022)
Routine		0.087		0.013
		(0.018)		(0.019)
Manual		-0.114		-0.119
		(0.016)		(0.015)
Observations	323	323	323	323
R^2	0.042	0.310	0.041	0.226

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.

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. Evidently, the cross sectional results of Columns (1) and (2) hold with respect to 2000 occupational gender composition as well. This is perhaps even more 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.

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 (8.9 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

Table 5: Interpersonal 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	+0.0888	+0.2712
Routine	+0.0196	+0.1031
Manual	−0.0275	−0.2929

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.

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 wage 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 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: an occupation's ranking in the 1980 wage distribution is clearly associated with a larger increase in the female share. 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." Again, the results for

Figure 1: Change in Female Share and Occupational Wage Ranking

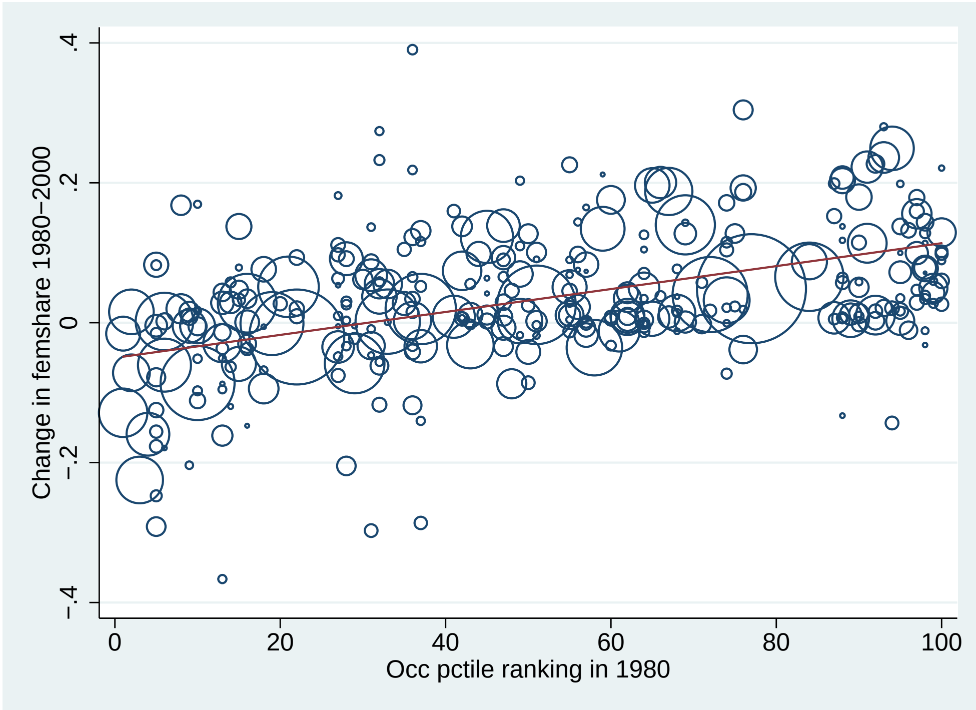


Figure 2: Change in Social Skills and Occupational Wage Ranking

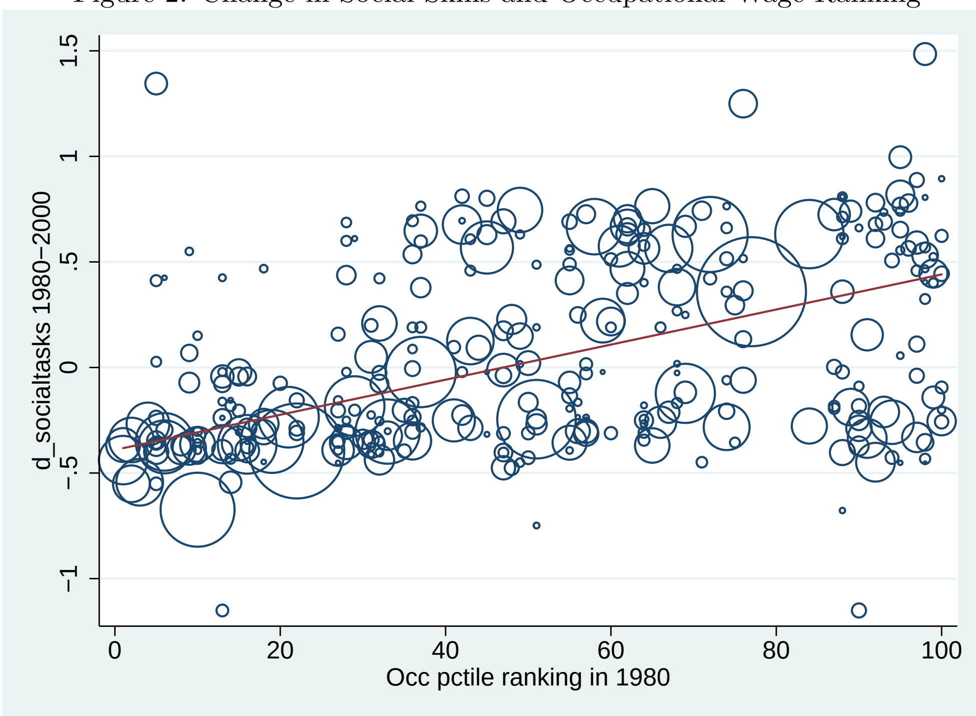


Table 6: Change in Female Share of Occupational Employment, 1980-2000

	(1)	(2)	(3)	(4)
Δ Social	0.040	0.044	0.045	0.044
	(0.011)	(0.011)	(0.011)	(0.011)
Δ Cognitive		-0.002	-0.014	-0.008
		(0.017)	(0.021)	(0.017)
Δ Routine		0.005	-0.022	-0.004
		(0.014)	(0.017)	(0.014)
Δ Manual		0.023	0.022	0.016
		(0.017)	(0.022)	(0.017)
Additional controls			x	
Δ Under stress				0.030
				(0.011)
Observations	323	323	323	323
R^2	0.042	0.051	0.052	0.073

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.

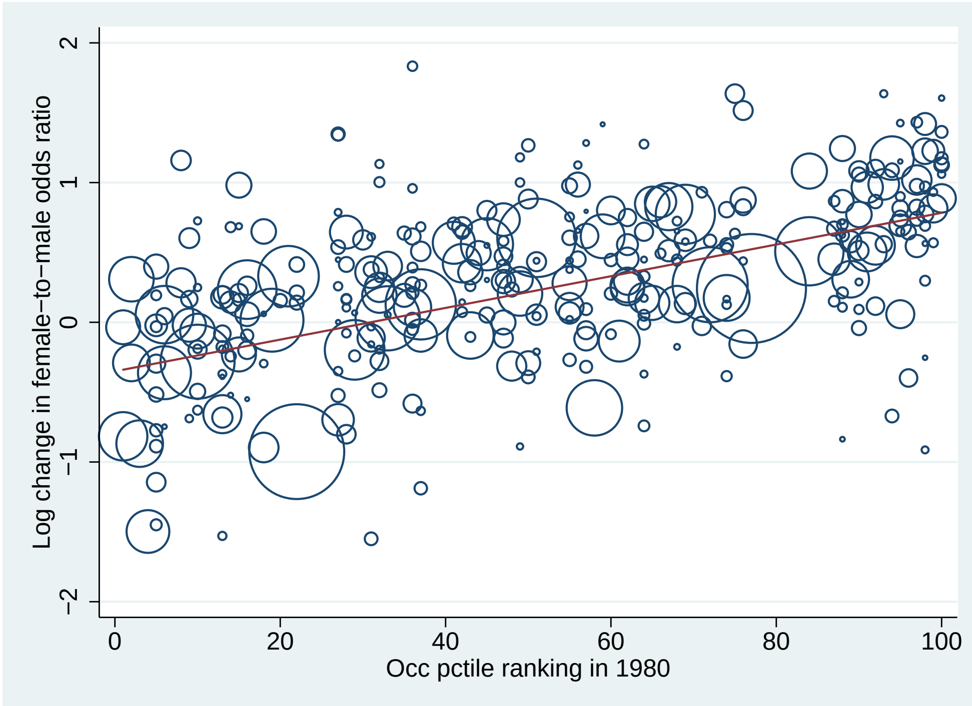
the importance of social skill remain.[20]

In psychology and neuroscience, recent research indicates that men and women make different decisions and perform differently in stressful situations (see, for instance, Preston et al. (2007); van den Bos et al. (2014); Tomova et al. (2014)). In Column (4), we add the change in the DOT measure "adaptability to performing under stress when confronted with emergency, critical, unusual, or dangerous situations." We find that occupations in which the importance of performing under stress increased were associated with increases in the female share of employment. Nonetheless, the strong and significant positive effect of changes in the importance of social skills on female share remain.

Taken together, we view this as convincing evidence that the increased demand for female labor in good jobs is due to an increase in the importance of social skills in these occupations relative to other occupations.

[20] This is also true when we consider the three additional variables as independent regressors.

Figure 3: Log Change in Female-to-Male Odds Ratio and Occupational Wage Ranking



5.2 Social Skills and Divergent Gender Trends

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 3, 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 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 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 57.9% of the increase.

6 Accounting for Labor Market Outcomes to 2014

To this point, our analysis has focused 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 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, $\Delta a^*_{Mt} - \Delta a^*_{Ft} > 0$.[21] From equation (20), this implies greater female bias and/or a greater reduction in discrimination in cognitive occupations relative to other occupations.

Finally, we investigate equation (22) which decomposes forces when we assume the ability distribution to be Pareto, gender specific, and allow those distributions to change

[21] Unlike 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.

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).[22] 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 $\kappa_{F,2014} = 3.006$.[23] 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 (22) 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 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).

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 improve-

[22] As discussed in Section 4, 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.

[23] Relative 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 (22) to be positive, as before. Details are available upon request.

ments 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 end of men and 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.

Appendix

A Additional Tables, Section 2

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

	1980	2000	% Difference Total	% Difference Explained	% Difference Unexplained
Male					
Total (000's)	*12080*	*20340*			
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					
Total (000's)	*8890*	*20470*			
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					
Total (000's)	*25590*	*43610*			
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					
Total (000's)	*23420*	*47640*			
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, (7)–(10), 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:

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

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 (11) and (12) 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:

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

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 high-skilled individuals who do not work is $1 - \Omega_{gt}(b^*_{gt})$, for $g = \{M, F\}$.

Note that the characterizing equations that we use in analyzing the benchmark model of Section 3—namely equations (7)–(10), (11), and (12)—are identical in this extended model. Hence, the key equation under consideration, equation (20), is unchanged.

The only change comes in quantification of the model. With endogenous participation, equation (21) describing the fraction of individuals who work in the cognitive occupation becomes:

$$\phi_t = \Omega_t(b^*_t) \times \left(\frac{a^{min}_t}{a^*_t}\right)^{\kappa_t}.$$

As a result, the left-hand side of (22) becomes:

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

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. $\Delta\left(1 + \tau^O_t\right) = \Delta\left(1 + \tau^C_t\right)$, and the scale shift in ability distributions was the same across genders, i.e. $\Delta a^{min}_{Ft} = \Delta a^{min}_{Mt}$, 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 input of men and women are perfect substitutes. We assume a constant elasticity of substitution between labor inputs: $f^C(\cdot) = f^C\left(\left[Z^C_{Mt}L^\rho_{Mt} + Z^C_{Ft}L^\rho_{Ft}\right]^{\frac{1}{\rho}}\right)$ and $f^O(\cdot) = f^O\left(\left[Z^O_{Mt}E^\rho_{Mt} + Z^O_{Ft}E^\rho_{Ft}\right]^{\frac{1}{\rho}}\right)$, with $\rho < 1$.[24]

The labor demand equations, (7)–(10), can be rearranged and simplified as:

$$\frac{w_{Ft}}{w_{Mt}} = \frac{Z^C_{Ft}}{Z^C_{Mt}} \frac{1}{1+\tau^C_t} \frac{L^{\rho-1}_{Ft}}{L^{\rho-1}_{Mt}}, \tag{A.1}$$

$$\frac{p_{Ft}}{p_{Mt}} = \frac{Z^O_{Ft}}{Z^O_{Mt}} \frac{1}{1+\tau^O_t} \frac{E^{\rho-1}_{Ft}}{E^{\rho-1}_{Mt}}. \tag{A.2}$$

Using the indifference conditions, (11)–(12), and the Pareto functional form on the distribution of cognitive work ability, these conditions can be combined as:

$$\begin{aligned}\left(\frac{1}{\kappa_{Mt}}\right)\Big[\log(\phi_{Mt})\,\Delta\kappa_{Mt} - \Delta\phi_{Mt}\Big] - \\ \left(\frac{1}{\kappa_{Ft}}\right)\Big[\log(\phi_{Ft})\,\Delta\kappa_{Ft} - \Delta\phi_{Ft}\Big] + (1-\rho)\left[\Delta\left(\frac{L_{Ft}}{L_{Mt}}\right) - \Delta\left(\frac{E_{Ft}}{E_{Mt}}\right)\right] = \\ \Delta\left(\frac{Z^C_{Ft}}{Z^C_{Mt}}\right) - \Delta\left(\frac{Z^O_{Ft}}{Z^O_{Mt}}\right) + \Delta a^{min}_{Ft} - \Delta a^{min}_{Mt} + \Delta\left(1+\tau^O_t\right) - \Delta\left(1+\tau^C_t\right).\end{aligned} \tag{A.3}$$

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 (14)-(17). 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 $\Delta\left(\frac{E_{Ft}}{E_{Mt}}\right)$. 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. $\Delta\left(1+\tau^O_t\right) = \Delta\left(1+\tau^C_t\right)$, and the scale shift in ability distributions was the same across genders, i.e. $\Delta a^{min}_{Ft} = \Delta a^{min}_{Mt}$, then the changes in occupational outcomes and wages are rationalized by greater female bias in cognitive occupations relative to other occupations.

D 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 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,

[24] We 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.

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 calculated 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.

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