# 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 high-skilled 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 show that 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. Finally, we document how these patterns change across the early and latter portions of the period.

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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. 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 a disproportionate 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 these gender patterns, we briefly summarize the predictions of neoclassical theory in Sections 3 and Appendix B.2. Specifically, we consider a general model of occupational choice in the market for high-skilled workers, allowing for gender differences in: (a) the supply and characteristics of workers, (b) discrimination, and (c) labor productivity, both in terms of levels and changes over time. Under minimal assumptions, the facts regarding occupational outcomes and the distribution of wages can be rationalized by three channels. One channel is a greater increase in the demand for female skills relative to male skills—what we refer to as greater *female bias*—in good jobs relative to others.

We explore one potential source of greater female bias in good jobs. Evidence from the psychology and neuroscience literatures indicates 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)). Taking this as given, we consider its implication and study the change in occupational demand for social skills. Rationalizing the divergent gender trends in occupational choice depends on the change in skill demand within occupations,

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

and how this varies across occupations over time.

Specifically, our hypothesis is that the importance of social skills has become 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. In Section 4, following the literature that characterizes occupations as task bundles (Autor, Levy, and Murnane 2003; Gathmann and Schönberg 2010), we use three data sources to measure the importance of social skills within an occupation and, importantly, its change over time. The first two are the Dictionary of Occupational Titles (DOT, hereafter) and its successor the Occupational Information Network (O*NET); the final source is a database of newspaper job advertisements by Atalay et al. (2018). 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 occupational 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 4 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.

**Background** Our work is motivated by the recent innovative and important work of Borghans, Ter Weel, and Weinberg (2014) and Deming (2017). Deming (2017) shows that since 1980, there has been disproportionately strong aggregate employment growth in occupations requiring high *levels* of social interaction, and especially those requiring both math and social skills. While highly related to our work, these findings do not provide direct evidence on factors related to the differential trends in occupational choice between men and women. Specifically, employment growth in jobs requiring high levels of social skills could simply reflect a distributional shift towards such occupations (while low social skill occupations shrank), with no change in the importance of social skill demand within occupations. Indeed, the evidence of Borghans, Ter Weel, and Weinberg (2014) for an increasing importance of "people skills" does just that: holding task measures *constant* at 1977 levels, there has been relative employment growth in high social skill occupations—a *between* occupation shift. But theory states that the increasing sorting of women into certain occupations (while men sort away) depends not on the *level* of skill demand, but the *change* in skill demand *within* occupations, and how those changes vary across jobs. Had there been no differential change in skill demands within occupations, there would have been no change in occupational sorting, all else equal. As we show, however, the rise of women in good jobs is not driven by differential growth of certain occupations, but rather by differential increases in the female share of employment within good jobs.

Our paper contributes to the vast literature that studies gender differences in labor market outcomes. This literature has predominantly focused on the gender pay gap (see, for e.g., Blau and Kahn (2017); Goldin (2014) and the references therein). Instead, we focus on occupational employment outcomes (rather than wage outcomes conditional on employment), with emphasis on the high-skill segment of the labor market. Our approach is related to papers that explore the role of task composition in accounting for the gender pay gap. Borghans, Ter Weel, and Weinberg (2014) show that the trend in social skills importance (again, derived from between occupation shifts in employment, not from changes within occupations) closely mimics the closing of the gender wage gap in the US, 1968-2002.[2] Black and Spitz-Oener (2010) study the West German economy, 1979-1999. When aggregated over all occupations, the performance of "interactive" (and other non-routine) tasks converged between men and women, while the performance of routine tasks diverged. These changes account for about half of the wage gap's narrowing during that time. Interestingly, the convergence in interactive tasks occurred at the lower end of the skill distribution; among the highly educated, there is no significant difference in gender trends of interactive task performance.[3] By contrast, we focus on the high-skilled segment of the labor market, and

[2] Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) also demonstrate that the returns to social skills, at the *individual-level*, has increased over time. This is done in Mincer wage regressions, where individuals' social skills are measured by self-reports of sociability/extroversion and extracurricular participation as youths. By contrast, in Section 6 we discuss the increasing returns to social skills at the *occupational level*.

[3] Accordingly, the narrowing of the gender wage gap in West Germany was driven by changes at the lower end of the education distribution. These results are derived from counterfactuals of a "fixed coefficients" model, holding task prices constant. Our results on the changing relative demand for skills in the US are not consistent with such an assumption; see Section 6. See also Bacolod and Blum (2010) who argue that changing skill/task prices account for 20% of gender gap closing, but do not allow for occupational

on occupational changes in the demand for social skills and its relationship to changing gender representation in employment.

Various papers, including Galor and Weil (1996), Welch (2000), Beaudry and Lewis (2014), Bhalotra, Fernández, and Venkataramani (2015), Yamaguchi (2018), 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 relative demand for physical tasks to the shrinking of the gender wage gap.[4] Ngai and Petrongolo (2017) consider a model of structural transformation, where female relative hours and wage gains are driven by *between industry/sector* changes, away from the goods-producing manufacturing sector, towards the service-producing sector; our work, by contrast, relates female relative employment gains to *within occupation* changes in skill demand.

Finally, our work is most closely related to the small number of papers documenting change in the composition of task demands within occupations. To the best of our knowledge, the first paper to focus on such task changes is Spitz-Oener (2006) for the West German economy, 1979–1999;[5] she finds occupations to have gained in task complexity over time, with the most pronounced changes in those with increased computer usage. More recently, Ross (2017) examines the evolution of the wage return to abstract relative to routine tasks in response to changes in within-occupation task content derived from archived releases of the O*NET database. Hershbein and Kahn (2018) study skill demand using online job advertisements from 2007 onward, and find evidence of persistent "upskilling" in job requirements within occupations in response to the Great Recession. Finally, Atalay et al. (2018) construct a dataset of occupation-level task demands from newspaper job advertisements 1960–2000, and use this to quantify the importance of within occupation task changes to widening earnings inequality; we return to this dataset in our analysis of Section 4 below.

skill measures to change over time. Their analysis is made further problematic by the use of *occupational* measures of social skills in *individual-level* Mincer wage regressions, with no appeal to economic theory and the possibility of changing occupational sorting on comparative advantage.

[4]See also Black and Spitz-Oener (2010) and Burstein, Morales, and Vogel (2015) on the link between computer use and the closing of the gender wage gap; Juhn, Ujhelyi, and Villegas-Sanchez (2014) on the relationship between trade liberalization and gender inequality in labor market outcomes in Mexico; and Olivetti and Petrongolo (2014) on the role of industrial structure in accounting for international differences in gender outcomes.

[5]It is worth noting that Autor, Levy, and Murnane (2003)'s pioneering work on changes in task composition does consider intensive margin changes between the 1977 and the 1991 editions of the DOT.

## 2 Divergence in High-Skilled Labor Market Trends

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. Throughout this paper, we use the terms occupation and job interchangeably.

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, partitioning 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)). *Cognitive* occupations—which include, for example, general managers, physicians, financial analysts, computer software engineers, and economists—are categorized 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.In our second definition, good jobs are defined as those that occupy the top end of the occupational wage distribution; we defer discussion of this categorization to further below.

Our analysis uses the 5% sample of the 1980 Census, and the full sample of the 2016 American Community Survey (ACS), made available by IPUMS (Ruggles et al. 2018). 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.[6] As is well known, this thirty-six year period saw an increase in the high-skilled population: a near tripling, from approximately 21 million to 58 million 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 approximately 60%, as their employment in such jobs also nearly tripled. This constancy masks divergent trends in the COG employment likelihood across genders.

[6] 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 2016.

Table 1: High-Skilled Occupational and Employment Status: 1980–2016

| | 1980 | 2016 | Percentage Point Difference Total | Explained | Unexplained |
|---|---|---|---|---|---|
| **Male** | | | | | |
| *Total (000's)* | *12084* | *26666* | | | |
| Cognitive (%) | 66.2 | 62.1 | −4.1 | −0.9 | −3.2 |
| Other (%) | 26.0 | 26.4 | +0.4 | | |
| Not Working (%) | 7.8 | 11.5 | +3.7 | | |
| **Female** | | | | | |
| *Total (000's)* | *8886* | *31585* | | | |
| Cognitive (%) | 54.2 | 58.8 | +4.6 | −2.1 | +6.7 |
| Other (%) | 18.6 | 20.7 | +2.1 | | |
| Not Working (%) | 27.2 | 20.5 | −6.7 | | |

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 Census and 2016 ACS. Employment categorized by occupational task content. See text for details.

## 2.1 Gender Differences

Table 1 presents the key statistics motivating our analysis. In 1980, 66% of high-skilled men worked in cognitive occupations. Over the next 36 years, this proportion *fell* by 4 percentage points (pp) to 62%.[7] 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 4.5 pp between 1980 and 2016. This improvement in the likelihood of COG employment occurred despite a much larger increase in the number of college-educated women relative to men.[8]

Moreover, this divergence in gender trends is observed throughout the US. When we disaggregate the data by state, we find that the likelihood of working in a good job increases for women relative to men in all 50 states and the District of Columbia. The probability of working in a good job for skilled women increases in absolute terms in all states except Kentucky (where women become less likely to work in good jobs, but the fall for men is larger). The probability of working in a good job falls for skilled men in all states except

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

[8]These gender differences are similar to those noted in Table 3 by Blau and Kahn (2017), who consider managerial occupations and "male" professional occupations. The results we present in this Section document the pervasiveness of this differential gender trend, regardless of the definition of a "good job."

Utah, California, Alaska and DC, where high-skilled men become more likely to work in good jobs, but the propensity increase is greater for skilled women. We provide further discussion regarding the pervasiveness and robustness of this divergence in gender trends below.[9]

In the rightmost columns of Table 1, we study whether the change in COG employment probability can be attributed to changes in demographic characteristics. Denoting $\pi_i$ 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 $t \in \{1980, 2016\}$. 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:

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

As such, the "Total Percentage Point Difference," $\pi_{2000} - \pi_{1980}$, can be decomposed into a component that is explained by changes in the (observable) demographic composition of men/women 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)), or changes in unobservable characteristics. We perform this Oaxaca-Blinder decomposition separately by gender.[10]

Demographic composition change among males accounts for part of the fall; this is due to the increase in young men with college degrees (and the fact that the young have lower tendency to work in COG jobs). However, most of the fall is 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, this fall is particularly acute among men in their prime working ages, 40–54 years old. The decomposition result for females stands in contrast. Demographic change

[9] Note that the gender differences in occupational sorting exist even conditional on working. For instance, consider high-skilled men who experienced a nearly 4 pp fall in employment probability. This was not proportionately distributed across cognitive and other occupations: more than 100% of the fall came from COG, while the probability of other employment actually increased. We return to theories regarding changes in selection on (potentially unobservable) worker characteristics, and the joint determination of non-employment, employment, and occupational choice in Section 3.

[10] We implement this from a pooled regression over both time periods. Results in which coefficient estimates are obtained for either the 1980 or 2016 period are essentially unchanged.

predicts a 2 pp fall in the fraction of women in COG jobs, again due to the compositional shift towards the young among the college educated. Hence, more than 100% 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 widespread across women from different demographic groups (the main exception being young black women). The largest propensity increases are experienced by young women.[11]

These divergent gender trends imply that there has been a pronounced increase in the female share of employment in good jobs. This can be seen using the occupational employment probabilities and total numbers of high-skilled men and women reported in Table 1. In 1980, the female share of employment in COG jobs was $(8886 \times 0.542) \div (8886 \times 0.542 + 12084 \times 0.662) = 37.6\%$ among college-educated workers. By 2016, this had increased to 52.9% so that among the high-skilled, women represent more than half of those employed in cognitive jobs. This large and important increase in female representation in goods jobs is a point that we return to below.

While the cognitive task content of an occupation is an informative delineation, it is not a particularly stringent definition of a good job: in both 1980 and 2016, over half of the high-skilled population work in COG. To demonstrate robustness of our results, our second definition considers good jobs to be those in only the *top decile* of the occupational wage distribution, where the mass of each occupation is based on its share of aggregate hours.[12]

Table 2 presents the same labor market statistics as Table 1, delineating jobs by their place in the occupational wage distribution of 1980. The likelihood of a high-skilled, working age man being employed in a top decile occupation fell by 6 pp between 1980 and 2016. Changes in demographic composition would have predicted a change in the opposite direction. By contrast, the likelihood for women increased by more than 3 pp.[13]

[11] Appendix Table A.1 contains the analogue of Table 1 for individuals with at least *some* post-secondary education. Again, the results hold (with a sharper increase for women), indicating that these divergent gender trends are robust to the specific definition of high- versus low-skilled.

[12] As is standard, we compute individual-level wages from the Census and the American Community Survey (ACS) as total annual wage and salary income, divided by (weeks worked last year $\times$ usual hours worked per week). Weeks worked last year is only available in intervals for the 2016 ACS; we use the midpoint for each interval. 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 $\geq 250$ 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.

[13] In Appendix Table A.2, we present the analogue of Table 2, this time delineating jobs by their place in the occupational wage distribution of 2000. Based on this ranking, the fall in the male probability is sharper, around 10 pp, while the female probability rises by nearly 2 pp.

Table 2: High-Skilled Occupational and Employment Status: 1980–2016

| | 1980 | 2016 | Percentage Point Difference Total | Explained | Unexplained |
|---|---|---|---|---|---|
| **Male** | | | | | |
| *Total (000's)* | *12084* | *26666* | | | |
| Top 10% | 30.7 | 25.0 | −5.7 | +0.3 | −6.0 |
| Bottom 90% | 61.5 | 63.5 | +2.0 | | |
| Not Working (%) | 7.8 | 11.5 | +3.7 | | |
| **Female** | | | | | |
| *Total (000's)* | *8886* | *31585* | | | |
| Top 10% | 6.5 | 9.9 | +3.3 | −0.0 | +3.3 |
| Bottom 90% | 66.3 | 69.6 | +3.3 | | |
| Not Working (%) | 27.2 | 20.5 | −6.7 | | |

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 Census and 2016 ACS. Employment categorized by ranking in occupational wage distribution of 1980. See text for details.

As before, these divergent trends imply that there has been a pronounced increase in the female share of employment in good jobs—this time, characterizing the quality of jobs by occupational wage ranking. In 1980, the female share of employment in top decile jobs was 13.5% among the high-skilled. At present, this is almost 2.5 times greater, having increased to 31.8% in 2016.[14]

This important increase in the female share of employment in good jobs can be observed at the much finer, 3-digit Census Occupation Code (COC) level. Throughout the paper, to crosswalk successive COC systems, we use the harmonized codes from Autor and Dorn (2013) (hereafter "Dorn codes"). In Figure 1, each circle represents a 3-digit occupation with the size of the circle indicating the occupation's share of aggregate employment in 1980. Occupations are ranked by their place in the 1980 occupational wage distribution along the horizontal axis, and by their change in the female share of high-skilled employment along the vertical axis. This clearly demonstrates that higher paying occupations experienced larger increases in the female proportion of employment, 1980–2016. The positive association, as indicated by the red line, has an estimated slope coefficient that is significant at the 1% level.

[14] We have replicated this analysis for broader definitions of high-paying occupations, looking at the top quintile and top quartile of the distribution. The nature of our results are unchanged, and for brevity, we make them available upon request.

Figure 1: Change in Female Employment Share among College Graduates and Occupational Wage Ranking


Notes: Each circle represents a 3-digit occupation (size indicating its share of aggregate employment in 1980). For visual clarity, the figure excludes five small occupations where the female share of employment increased by more than 45 percentage points. These five occupations combined represent less than 0.2% of aggregate employment in 1980. The fitted regression line is based on all occupations. Data on employment and wages from the Census and the 2016 American Community Survey. See text for details.

Given the findings of Table 1, Table 2, Figure 1, and the discussions of footnotes 11, 13, and 14, the divergence in trends is pervasive, and robust to alternative delineations of occupations and skills. In summary, we find clear evidence that the probability of being employed in a good job has fallen for high-skilled men, while it has risen for women.

## 2.2 Further Accounting Exercises

These divergent gender trends in occupational 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 present simple decomposition exercises that motivate our subsequent analysis.

First, we show that the rising female share of high-skilled employment in good jobs is not simply mechanical, due to the rise in the female share of the college-educated population. That is, the changing equilibrium occupational choice of men and women plays a quantitatively important role. To begin, Figure 1 indicates that the increase is not uniform or random across occupations; it is significantly increasing as a function of its wage ranking.

Taking this furtner, let $\sigma_t$ denote the female share of employment in good jobs at time $t$; let $F_t^{good}$ and $M_t^{good}$ be the number of women and men employed in a good job at time $t$, respectively. Evidently:

$$\sigma_t \equiv \frac{F_t^{good}}{F_t^{good} + M_t^{good}} = \frac{\bar{F}_t \times \pi_t^F}{\bar{F}_t \times \pi_t^F + \bar{M}_t \times \pi_t^M}. \tag{3}$$

Here, $\bar{F}_t$ is the total number of college-educated (i.e., high-skilled) women, $\bar{M}_t$ the total number of high-skilled men, $\pi_t^F \equiv F_t^{good}/\bar{F}_t$ is the fraction of high-skilled women employed in a good job, and $\pi_t^M \equiv M_t^{good}/\bar{M}_t$ is defined similarly for men.

Table 3, Panel A indicates the rise in $\sigma_t$ between 1980 and 2016. The first row shows this increased from approximately 38% to 53% when we consider cognitive occupations; the third row indicates an increase from 14% to 32% when we define good jobs as occupations in the top decile of the wage distribution.

Is this increasing female share of employment in good jobs simply due to the increasing female share of the high-skilled population? To investigate this, we construct a counterfactual by holding $\pi_t^g$ values for $g = \{M, F\}$, at their 1980 values, and allowing only the number of high-skilled men and women, $\bar{M}_t$ and $\bar{F}_t$, to change as observed in the data. This is reported in the third column of Table 3. We discuss only results for the 10%-90% delineation here for brevity; the results for the cognitive-other split are qualitatively similar. On its own, the change in the high-skilled gender composition would have meant a female share of top decile employment in 2016 of 20%; this accounts for just over one-third of the 18.3 pp increase observed in the data.

This is less than the proportion accounted for solely by the divergent gender trends in the likelihood of working in a top decile occupation. The fourth column presents the counterfactual female share in 2016 when holding $\bar{M}_t$ and $\bar{F}_t$ at 1980 values, and allowing only $\pi_t^M$ and $\pi_t^F$ to change. Changes in equilibrium occupational choice alone would have resulted in a female share of top decile employment of 23% in 2016. This difference in the relative roles of change in gender composition and occupational choice is accentuated when we consider the counterfactual results for employment in the bottom 90% of occupations. The increasing female share of the high-skilled population accounts for more of the rise in

Table 3: High-Skilled Female Share (%) of Employment: Decomposition

| | Observed | | Counterfactual | |
|---|---|---|---|---|
| | 1980 | 2016 | 2016 | 2016 |
| *A. Population vs Occupation Choice* | | | Population | Occupation |
| Cognitive | 37.6 | 52.9 | 49.1 | 41.1 |
| Other | 34.5 | 48.1 | 45.9 | 36.5 |
| Top 10% | 13.5 | 31.8 | 20.1 | 22.5 |
| Bottom 90% | 44.2 | 56.5 | 56.1 | 44.6 |
| *B. Between vs Within Occupation* | | | Between | Within |
| Cognitive | 37.6 | 52.9 | 37.0 | 54.4 |
| Top 10% | 13.5 | 31.8 | 12.5 | 34.4 |

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 Census and 2016 ACS. See text for details.

the female share of *low-paying* occupations compared to top decile occupations. That is, increasing the educational attainment of women relative to men does a good job explaining the rising female share of employment irrespective of occupation; but it does a worse job of explaining the increased sorting of women relative to men into high-paying occupations versus lower-paying ones. By contrast, the divergent gender trends in equilibrium occupational choice accounts for more of the rise in *top* decile employment compared to the bottom 90%.

Next, we ask whether this increasing female representation is simply 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. Again, let $F_t^{good}$ denote female employment in all good jobs at time $t$, and let $E_t^{good}\left(= F_t^{good} + M_t^{good}\right)$ denote total employment in these jobs. The female share, $\sigma_t$, is simply:

$$\sigma_t \equiv \frac{F_t^{good}}{E_t^{good}} = \sum_{j \in good} \left(\frac{F_t^j}{E_t^j}\right) \times \left(\frac{E_t^j}{E_t^{good}}\right) \tag{4}$$

where $(F_t^j/E_t^j)$ is the female share of employment in 3-digit occupation $j$, and $(E_t^j/E_t^{good})$ is the 3-digit occupation's share of employment in good jobs at time $t$.

Panel B of Table 3 displays the observed and counterfactual female shares for 1980 and 2016. Again, female representation in COG employment increased from approximately

38% to 53%. By how much would $\sigma_t$ have increased if there were only between-occupation changes? We construct a counterfactual by holding all $(F_t^j/E_t^j)$'s at their 1980 values, and allowing only $(E_t^j/E_t^{good})$ values, the occupational shares, to change as observed in the data. This is reported in the third column of the first row of Panel B: the female share would have actually fallen.

The fourth column presents results for a counterfactual in which $(E_t^j/E_t^{good})$ values are held at 1980 values, and only $(F_t^j/E_t^j)$ values vary as in the data. This over-predicts the increase in $\sigma_t$. 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 86% of 3-digit level COG occupations between 1980 and 2016.

The second row of Panel B presents the decomposition for employment in the top decile occupations of 1980. Again, the increase in $\sigma_t$ is due to "within" occupation changes, with the female share increasing in all top decile occupations at the 3-digit level of aggregation. 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 Summary

Here we summarize the predictions of a simple equilibrium model of the market for high-skilled workers. The goal is to highlight the forces capable of generating the findings of Section 2—namely the increasing likelihood of women, and decreasing likelihood of men, to work in a good job. As discussed, this has resulted in a pronounced increase in female representation in high-paying occupations.

The divergent gender trends in employment likelihood are studied in an equilibrium model of occupational choice. The neoclassical framework we consider is intentionally general, allowing for gender differences in the characteristics of supply, demand, and market discrimination for high-skilled workers, and how those factors have changed over time. The details of the equilibrium model are presented in Appendix B. We provide a brief summary of the key components here.

**Labor Demand** High-skilled labor is employed in one of two occupations/jobs: "good" and "other." The key assumption is that male and female workers are distinct labor inputs in both jobs. That is, while they may be perfect substitutes in production (display constant marginal rate of technical substitution), their productivities are gender-specific and may change (differentially) over time.

**Discrimination** There is discrimination against women in the labor market. For simplicity, we model this as a tax representing preference-based discrimination as in the seminal work of Becker (1957). This generates a "wedge" between the wage paid to, and the marginal revenue product of, female labor; this wedge is not present for male labor. The discriminatory wedges may differ between the "good" and "other" job, and may also change over time.

**Labor Supply** Workers make an occupational choice based on comparative advantage. Comparative advantage is idiosyncratic and differs across individuals, and it differs in a distributional sense across males and females. For simplicity, we assume that all individuals are equally productive in the "other" occupation. However, they differ in their ability in the good job. The greater is one's ability, the greater is the return to working in the good job relative to the other job, all else equal. Again, the distribution of ability may differ by gender, and change over time.

Individuals make a discrete participation choice, whether to work or not. Conditional on working, they make an occupational choice based on comparative advantage. As is typical in Roy models of self-selection, workers with ability above a gender-specific threshold choose to work in the good job; all other workers choose the other job. These thresholds may change over time.

Equilibrium simply involves labor demand equalling labor supply in both jobs, for both male and female labor.

### 3.1 Takeaways

Given its analytical generality, the model is useful in illuminating the potential forces behind the changes in the high-skilled labor market observed 1980–2016. Moreover, it makes clear, within a neoclassical setting, what forces *cannot* rationalize the observed changes. For instance, the changes in equilibrium occupational choice—the rising likelihood of women, and falling likelihood of men, to work in a good job—cannot be due simply to the rising female share of the college-educated population.

Perhaps less obvious is the fact that the divergent trends in occupational choice cannot be attributed simply to a fall in female discrimination, without reference to occupation-level differences. Suppose the discriminatory wedge had fallen equally in the "good" and "other" job. While this might account for rising female participation, it would *not* account for the change in occupational choice among women—away from the other job, in favor of the good job. Similarly, these trends cannot be attributed to a general increase in the demand for female labor, e.g. due to gender-biased technological change, as in Heathcote, Storesletten, and Violante (2010), without differential change across occupations.

Our model analysis indicates that the "end of men" and rise of women documented in Section 2 is potentially attributable to the following three factors.

1. The first relates to change in the demand for female labor relative to male labor within occupations, and how this varies across occupations. We refer to an increase in the relative demand for female labor over time as a *female bias*. Given this, the findings of Section 2 can be attributed to labor demand featuring a *greater* female bias in the *good job* compared to the other job.

2. The second channel relates to discrimination change that differs across occupations. As discussed above, rationalizing the data would require a greater reduction of discrimination in the good job relative to the other occupation.

3. Finally, the divergent trends in occupational choice can be due to gender differences in comparative advantage change. For brevity, we do not discuss the gender-specific ability distributions in detail here, but refer interested readers to Appendix B.2 for detail. There, we provide characterizations of how the distributions may have changed over time—ranging from analytical, paper-and-pencil examples to quantitatively realistic (yet numerically tractable) cases—so as to be consistent with the data.

Naturally, all three factors may have contributed to the divergent occupational employment changes across genders. If one were willing to assume that only a single factor was operational, then the magnitude of the change could be measured.[15]

Our approach differs in that we do not preclude any of the three factors as having been operational since 1980. Indeed, we believe it is likely that all three may have played roles.

[15] 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 make 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. These are made absent appeal to, or evidence of, empirical support. By assuming away channels (1) and (3), they are able to provide estimates of channel (2) and quantify the degree of gender/race/occupation-specific discrimination change.

However, we note 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 changes in discrimination that differ across occupations.[16] Similarly, we are unaware of any studies documenting distributional changes in comparative advantage in good jobs relative to other occupations, much less their gender differences.

By contrast, we provide empirical evidence in favor of channel (1). We find an increase in the demand for female labor (relative to male labor) in good jobs that is larger than in other occupations. 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, allowing for greater temporal flexibility and largely eliminating the part-time work penalty (see also Goldin (2014)); these changes can be interpreted as changes enhancing the relative productivity of women as pharmacists. In Sections 4 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.

## 4 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. We note that the idea that there is comparative advantage in labor market tasks across genders, in a distributional sense, is not new to our work (see, for instance, Galor and Weil (1996), Goldin (2006), and the subsequent literature). 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);

[16] 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.

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.[17] These occupational task requirements are measured at a point in time—from the 1977 Dictionary of Occupational Titles (DOT) by Borghans, Ter Weel, and Weinberg (2014), and the 1998 O*NET by Deming (2017). While related to our work, these findings speak to "between" occupation changes in the composition of aggregate employment. On their own, the findings of Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) would be indicative of a relative increase in female labor demand due to disproportionate growth in female-dominated occupations with high levels of social skill requirement. But as noted in Sections 2 and 3, the divergent gender trends have been due to changes "within" occupation, increasing the demand for female-oriented skills in good jobs relative to other occupations.[18]

By contrast, we study whether the demand for social skills within occupations has changed over time. 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 women versus men in these occupations.[19, 20]

To measure the change in the importance of social skills within occupations we combine information from the DOT and its successor, O*NET. We also use information from newspaper job advertisements (from Atalay et al. 2018) in Subsection 5.2.

The DOT and the O*NET provide detailed measures of skills and aptitudes that are required to perform the tasks associated with specific occupations, as well as information on the main work activities performed by job incumbents. A growing literature pioneered by

[17] 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.

[18] 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.

[19] See 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.

[20] Note 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 C.3 shows how this alternative view can, in fact, be written as a model isomorphic to that of Section 3.

Autor, Levy, and Murnane (2003) (ALM hereafter) uses information from these sources to characterize occupations along various task dimensions. This literature almost exclusively uses task information recorded at a point in time and assumes that the task content of occupations is fixed over time. A major challenge in analyzing within-occupation task change over long time horizons is that the way in which occupational information is elicited and recorded was changed between the DOT—which was conducted in 1977 and 1991—and the O*NET—which has been available in a consistent format since 2002, with major updates being released roughly at an annual frequency.

However, as indicated in Section 3, our analysis is concerned solely with the *relative ranking* of occupations in terms of social skill demand within each period, and how that has changed over time. Our hypothesis is that over time, good jobs have become *relatively* more social skill intensive than others, and that this is a factor in the increasing representation of women in such occupations. Even though the *levels* of task intensity measures from DOT and O*NET are not directly comparable, we can use them to rank occupations at a given time period along the relevant task dimension, and then compute changes in the relative ranking of occupations over time.

To construct a measure of the importance of social skills from the DOT, we focus on the data regarding occupational "temperaments," defined as "adaptability requirements made on the worker by specific types of job-worker situations" (see ICPSR 1981). These 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 measures used by Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) in the DOT and O*NET, respectively, to identify social skill intensity.[21]

In the O*NET dataset, we use the same four measures used by Deming (2017), namely the "level" measures for the following four items from the Skills questionnaire:

A. Social Perceptiveness: being aware of others' reactions and understanding why they react as they do (Question 11; item 2.B.1.a);

B. Coordination: adjusting actions in relation to others' actions (Question 12; item 2.B.1.b);

C. Persuasion: persuading others to change their minds or behavior (Question 13; item 2.B.1.c);

D. Negotiation: bringing others together and trying to reconcile differences (Question 14; item 2.B.1.d).

We create a single *social skill index* for each occupation at a point in time by combining the occupation's scores for the four items, 1–4 in the DOT and A-D in the O*NET, listed above.

We also construct measures of the importance of cognitive, routine, and manual tasks within each occupation from the DOT and O*NET. Following ALM, we measure cognitive tasks in the DOT 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 task intensity is based on the importance of "eye-hand-foot coordination." In the O*NET, Deming (2017) defines analytical task intensity as the average of: (i) the extent to which an occupation requires mathematical reasoning (question 12 in the Abilities questionnaire; item 1.A.1.c.1), (ii) whether the occupation requires using mathematics to solve problems (question 5 in the Skills questionnaire; item 2.A.1.e), and (iii) whether the occupation requires knowledge of mathematics (question 14 in the Knowledge questionnaire; item 2.C.4.a). In keeping with the definition of cognitive tasks from ALM, our measure of O*NET cognitive tasks averages the three mathematical measures of Deming (2017) with three measures that capture direction, control and planning responsibilities, namely the "level" ratings for three measures

[21] In particular, Borghans, Ter Weel, and Weinberg (2014) use items 1, 2 and 4, plus two measures from the "interests" module of the DOT: preference for activities involving business contact with people, and preference for working for the presumed good of people. Our choice differs because the latter two questions better measure worker aspirations of occupational outcomes, as compared to skills required to perform in a job. In addition, our choice allows for greater consistency with the O*NET measures used by Deming (2017).

from the Skills questionnaire: (i) "Management of Financial Resources" (question 33; item 2.B.5.b), (ii) "Management of Material Resources" (question 34; item 2.B.5.c), and (iii) "Management of Personnel Resources" (question 35; item 2.B.5.d). O*NET Routine tasks, as in Deming (2017), are measured as the average of two measures from the Work Context questionnaire: (i) "how automated is the job?" (question 49; item 4.C.3.b.2) and (ii) "how important is repeating the same physical activities (e.g. key entry) or mental activities (e.g. checking entries in a ledger) over and over, without stopping, to performing this job?" (question 51; item 4.C.3.b.7). Finally, we develop a measure of manual task intensity in O*NET based on the average of the "level" ratings for two measures from the Abilities questionnaire (i) "Multilimb Coordination" (question 26; item 1.A.2.b.2), and (ii) "Gross Body Coordination" (question 39; item 1.A.3.c.3).

The DOT and O*NET information is provided at a very detailed occupational code level. In order to aggregate the 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 weighted averages of task measures at the level of the harmonized codes from Autor and Dorn (2013) ("Dorn codes"). In order to capture the relative ranking of each occupation, we normalize each of the task indices in each period to have mean zero and unit standard deviation across the sample-weighted employment distribution from the 1980 Census. Hence, a one unit increase 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. Full details of how we assign a relative ranking to each occupation are described in Appendix D.

In what follows, we attach task demand data from the 1977 DOT (4th edition) to the employment outcomes for the year 1980, and task data from the August 2016 release of O*NET (version 21.0) to the 2016 employment outcomes.

### 4.1 Social Skills and Female Shares: Levels

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 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.

Table 4: Female Share of Occupational Employment and Occupational Tasks

| | 1980 | 1980 | 2016 | 2016 |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Social | 0.06 | 0.115 | 0.042 | 0.121 |
| | (0.016)*** | (0.016)*** | (0.014)*** | (0.02)*** |
| Cognitive | | -.107 | | -.174 |
| | | (0.015)*** | | (0.018)*** |
| Routine | | 0.079 | | 0.035 |
| | | (0.015)*** | | (0.014)** |
| Manual | | -.082 | | -.130 |
| | | (0.015)*** | | (0.015)*** |
| Obs. | 312 | 312 | 312 | 312 |
| $R^2$ | 0.044 | 0.285 | 0.026 | 0.391 |

Notes: Data on employment shares from the 1980 decennial census and the 2016 American Community Survey. Data on social skills and other occupational task characteristics from the 1977 Dictionary of Occupational Titles and from the 2016 O*NET. Each occupation is weighted by its share of aggregate employment in the corresponding year. See text for details.

One might be concerned that the social skill index is proxying for other occupational task characteristics. Column (2) in Table 4 indicates that this correlation is robust to controlling for other task intensities considered in the job polarization literature. The point estimate on the level of social skill importance actually increases, with essentially unchanged standard error, after controlling for the ALM characteristics.

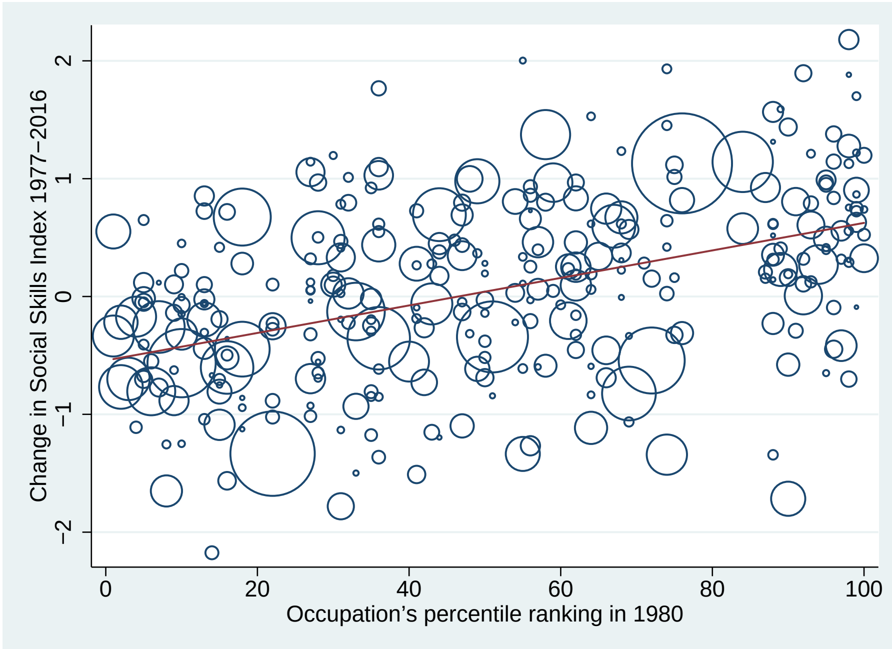
In Columns (3) and (4) of Table 4, we repeat the analysis using the female share of employment and occupational characteristics in 2016. The cross sectional results for 1980 hold with respect to 2016 occupational gender composition as well.

## 4.2 Social Skills and Female Shares: Changes

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?

Figure 1, presented in Section 2, confirms that higher paying occupations experienced larger increases in the female proportion of employment. Again, each circle represents a 3-digit occupation (with the size of the circle indicating the occupation's share of aggregate

Figure 2: Change in Demand for Social Skills and Occupational Wage Ranking



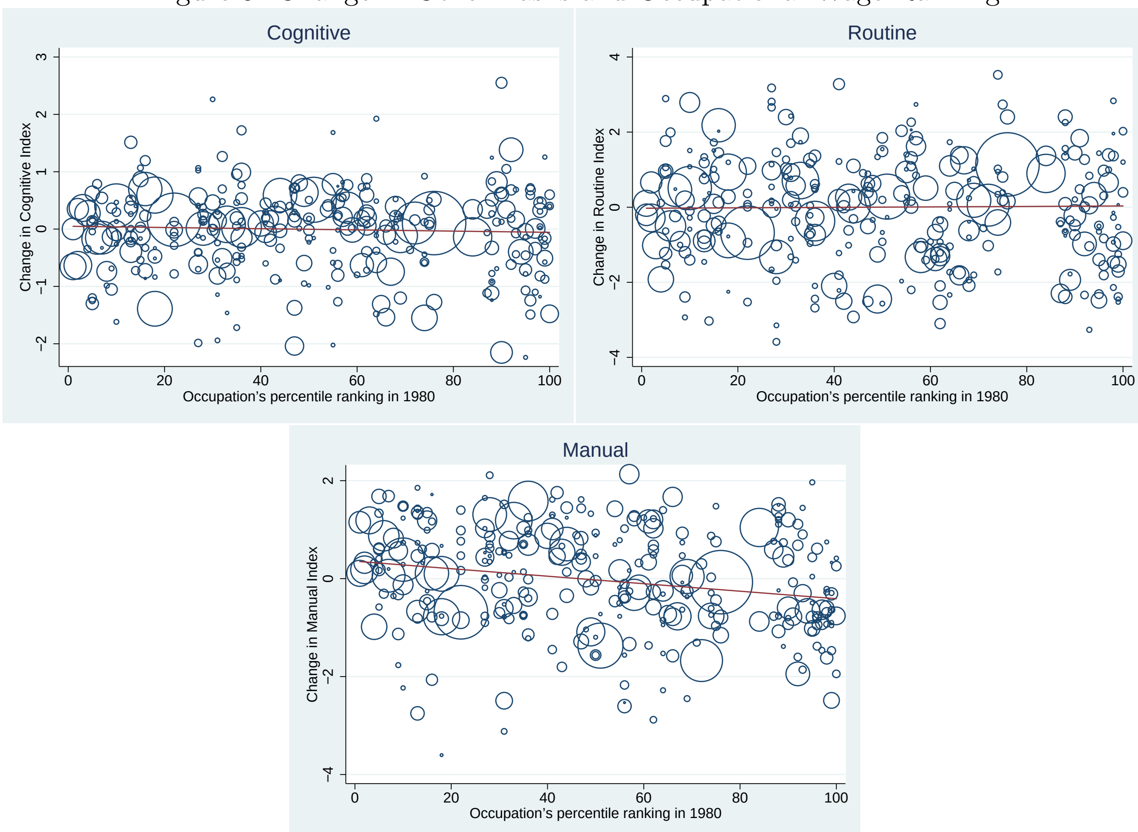

Notes: Each circle represents a 3-digit occupation (size indicating its share of aggregate employment in 1980). Data on employment and wages from the 1980 decennial census. Data on social skills from the 1977 DOT and the 2016 O*NET. See text for details.

employment in 1980). An occupation's ranking in the 1980 wage distribution is positively associated with the change in its female share, 1980–2016.

Figure 2 illustrates that an occupation's position in the wage distribution is systematically related to the relative change in demand for social skills: higher paying occupations experienced larger increases in the importance of social skills compared to lower paying ones. This relationship is significant at the 1% level. Figure 3, meanwhile, shows that there is no systematic relationship between an occupation's wage ranking and the relative change it experienced in the importance of either cognitive or routine tasks, 1977–2016. The bottom panel of Figure 3 shows that higher paying occupations tended to experience a decline in manual task intensity relative to lower paying occupations, and this relationship is significant at the 1% level; we return to this relationship below.

Our key relationship of interest is between the within-occupation changes in the female share of employment and the within-occupation changes in the importance of social skills, the vertical-axis variables of Figures 1 and 2. This is analyzed in Table 5. Column (1) shows that, at the 3-digit occupation level, an increase in the importance of social skills is

Figure 3: Change in Other Tasks and Occupational Wage Ranking




Notes: Each circle represents a 3-digit occupation (size indicating its share of aggregate employment in 1980). Data on employment and wages from the 1980 decennial census. Data on occupational task characteristics from the 1977 DOT and the 2016 O*NET. See text for details.

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 3.4 pp increase in the female share. This relationship is clearly significant at the 1% level. Column (2) of Table 5 illustrates that our key result is robust to controlling for changes in other task intensity measures. The point estimate on the change in social skill importance, and its standard error, remain essentially unchanged after controlling for cognitive, routine, and manual task changes within occupations.

Interestingly, the coefficient estimates of Column (2) indicate that the female share of employment also tends to increase (decrease) in occupations that saw an increase in the importance of routine (cognitive) tasks. However, as shown in Figure 3, changes in the importance of these two tasks are not concentrated within good jobs—in fact, they are not systematically related to job quality in any statistically significant way. Hence, the increase

Table 5: Change in Female Share of Occupational Employment, 1980-2016

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Social | 0.034 | 0.039 | 0.035 | 0.043 |
| | (0.008)*** | (0.007)*** | (0.007)*** | (0.007)*** |
| Δ Cognitive | | -.041 | | -.033 |
| | | (0.009)*** | | (0.008)*** |
| Δ Routine | | 0.041 | | 0.040 |
| | | (0.005)*** | | (0.006)*** |
| Δ Manual | | 0.004 | | 0.012 |
| | | (0.006) | | (0.008) |
| Obs. | 312 | 312 | 312 | 312 |
| $R^2$ | 0.054 | 0.273 | 0.073 | 0.226 |

Notes: The dependent variable is the change in the female share of occupational employment among college graduates based on 1980 Census and 2016 American Community Survey data. Data on social skills and other occupational task characteristics from the 1977 Dictionary of Occupational Titles and the 2016 O*NET. In Columns (1) and (2), occupations are weighted according to their share of aggregate employment in 1980. In Columns (3) and (4), occupations are weighted according to their share of aggregate *college* employment in 1980.

(decrease) in the female share observed in jobs that are becoming more routine (cognitive) intensive (conditional on other task changes) does not help us in understanding the "end of men" and rise of women in good jobs.

Finally, note that the estimated coefficient on the change in manual tasks is small and statistically insignificant; changes in manual tasks (conditional on other task changes) are not systematically related to changes in female share. So while good jobs are becoming less intensive in manual tasks relative to other jobs (see Figure 3), the increasing female share in good jobs is *not* driven by the decrease in their manual task intensity. In fact, the positive sign on the coefficient estimate would go against an explanation for the rise of women in good jobs: it implies that the female share tends to increase in jobs that become *more* manual-intensive; these are the low-paying, not the high-paying, occupations.

Columns (1) and (2) weight occupations in the regression according to their share of aggregate employment. Given that we are focusing on outcomes for college-educated workers, Columns (3) and (4) repeat the analysis, but weighting occupations according to their share of total *college* employment. The nature of our results are very similar and, indeed, quantitatively stronger. Occupations that experienced an increase in the social skill index of one standard deviation above the average saw a 4.3 pp increase in the female share, after controlling for other task changes.

We view this as 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.

# 5 The Pace of Change across Sub-Periods

The period of 1980–2000 is viewed as a period of unambiguously increasing demand for skilled labor and cognitive tasks. These labor market changes, most notably the increasing skill premium, were the catalysts for the literature on skill-biased technical change (see Violante (2008) and the references therein) and subsequent job polarization literature (see, for instance, Acemoglu and Autor (2011)). But recent work by Beaudry, Green, and Sand (2016) indicates that since 2000, this trend has slowed or even reversed. Given this evidence, we analyze the past 35 years broken into sub-periods, before and after the turn of the millennium, to determine whether there has been a concomitant change in the demand for social skills.

## 5.1 1980–2000, Part I

We begin by analyzing the patterns over the 1980–2000 period. We construct our employment-related measures for the year 2000 using data from the 2000 Census 5% sample, made available through IPUMS (see Ruggles et al. (2010)). Occupational task-related measures for the year 2000 are constructed using the June 2002 release of O*NET (version 4.0), the initial release of the "analyst database" with a revised structure.

Columns (1) and (2) of Table 6 are analogous to Columns (1) and (2) of Table 5, but using changes in the female share of employment within occupations during 1980–2000 as the dependent variable, and changes in relative task intensity measures between the 1977 DOT and the 2002 O*NET as regressors. Similar to what we find for the entire 1980–2016 period, increases in the relative demand for social skills within an occupation imply increases in the female share of employment. This relationship is statistically significant, and holds both unconditionally and controlling for other task intensity changes within occupations.

As a check on robustness, we construct measures of changes in occupational task importance for this sub-period using the 1977 (4th edition) and 1991 (revised 4th edition) of the DOT (ICPSR 1991). While this does not overlap perfectly with the 1980–2000 sub-period that we consider in terms of employment changes, this allows us to use Department of Labor analyst ratings of skill requirements that are consistently measured over time,

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Social | 0.029 | 0.033 | 0.025 | 0.025 |
| | (0.006)*** | (0.006)*** | (0.011)** | (0.012)** |
| Δ Cognitive | | -.023 | | -.012 |
| | | (0.009)*** | | (0.014) |
| Δ Routine | | 0.005 | | 0.022 |
| | | (0.004) | | (0.011)** |
| Δ Manual | | -.003 | | 0.022 |
| | | (0.005) | | (0.016) |
| Obs. | 312 | 312 | 312 | 312 |
| $R^2$ | 0.071 | 0.095 | 0.016 | 0.047 |

Notes: The dependent variable is the change in the female share of occupational employment among college graduates based on 1980 and 2000 Census data. Occupations are weighted according to their share of aggregate employment in 1980. Columns (1) and (2) use data on social skills and other occupational task characteristics from the 1977 Dictionary of Occupational Titles and the 2002 O*NET. Columns (3) and (4) use data on social skills and other occupational task characteristics from the 1977 and the 1991 Dictionary of Occupational Titles.

within the DOT. The regression results are reported in Columns (3) and (4). Comparing Column (1) versus (3), and Column (2) versus (4), the findings are remarkably consistent, especially considering that task variables are measured very differently across the DOT and the O*NET.

Hence, the increased demand for female labor in good jobs due to the relative increase in the importance of social skills in these jobs observed overall, 1980–2016, is clearly evident during the sub-period most closely associated with skill-biased technical change and the increasing demand for high-skilled labor, prior to 2000.

### 5.2 1980–2000, Part II

One concern with the results presented so far 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—performance of tasks that employers demand—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.[22]

Here we exploit data based on over 9 million job advertisements constructed by Atalay et al. (2018). Using newspaper ads published in the *New York Times*, *Wall Street Journal*, and *Boston Globe* between 1940 and 2000, Atalay et al. (2018) 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 to their meaning. By doing so, Atalay et al. (2018) generate measures of advertised task demands and requirements, at the occupational level.[23]

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 is a more accurate reflection of labor demand.[24] 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 for which we observe a significant correlation between task changes and female shares using DOT and O*NET data.

We convert the data from Atalay et al. (2018) 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 construct a social skill index for 1980 and 2000 using five year averages (1976-1980 and 1996-2000, respectively), and generate the change in the importance of social skills across the two periods.[25]

Table 7 displays results analogous to those in Table 6, but replacing the social skills measure with the one from the newspaper data.[26] Column (1) shows that changes in the

[22] In 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 over the 1980–2000 period.

[23] For full details, we refer the reader to the Atalay et al. (2018) paper. The data is available from `https://ssc.wisc.edu/~eatalay/occupation_data.html`.

[24] There 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.

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

[26] Note, however, that the magnitude of the coefficient estimates cannot be compared across tables since the construction of the explanatory variable differs.

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

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Δ Social (DK) | 0.333 | 0.344 | 0.353 | | | |
| | (0.1)*** | (0.1)*** | (0.111)*** | | | |
| Δ Social (Extended) | | | | 0.219 | 0.229 | 0.262 |
| | | | | (0.063)*** | (0.063)*** | (0.077)*** |
| Δ Cognitive | | -.011 | | | -.013 | |
| | | (0.009) | | | (0.009) | |
| Δ Routine | | 0.007 | | | 0.008 | |
| | | (0.005) | | | (0.005)* | |
| Δ Manual | | -.005 | | | -.004 | |
| | | (0.005) | | | (0.005) | |
| Δ NR Analytic | | | -.038 | | | -.069 |
| | | | (0.055) | | | (0.057) |
| Δ NR Interactive | | | 0.035 | | | -.002 |
| | | | (0.088) | | | (0.091) |
| Δ R Cognitive | | | -.590 | | | -.573 |
| | | | (0.431) | | | (0.430) |
| Δ R Manual | | | -.061 | | | -.024 |
| | | | (0.331) | | | (0.332) |
| Δ NR Manual | | | 0.042 | | | 0.034 |
| | | | (0.08) | | | (0.079) |
| Obs. | 305 | 305 | 305 | 305 | 305 | 305 |
| $R^2$ | 0.036 | 0.050 | 0.046 | 0.038 | 0.054 | 0.050 |

Notes: The dependent variable is the change in the female share of occupational employment among college graduates based on 1980 and 2000 Census data. Occupations are weighted according to their share of aggregate employment in 1980. Social (DK) is based on the benchmark Deming-Kahn social skill measure computed by Atalay et al. (2018). Social (Extended) is based on the alternative "bag of words" measure of word frequency from Atalay et al. (2018). Cognitive, Routine and Manual are from the 1977 DOT and the 2002 O*NET. NR Analytic, NR Interactive, R Cognitive, R Manual and NR Manual are based on the Spitz-Oener task measures computed by Atalay et al. (2018). See text for details.

demand for social skills within an occupation are again positively associated with changes in the occupation's female share of employment, statistically significantly at the 1% level. In Column (2), we add the ALM measures based on the 1977 DOT and the 2002 O*NET, and confirm the relationship between changes in social skills demand and female share remains. Column (3) replaces the ALM measures with the skill requirement measures from Spitz-Oener (2006), as constructed in the Atalay et al. (2018) dataset. Once again, our relationship of interest is robust.

The coefficient estimate of interest is remarkably consistent across Columns (1)-(3). These estimates 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 than a 2 pp increase in the occupation's female share of employment. Again, 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. (2018). 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 remains: an increase in the importance of social skills is associated with an increase in an occupation's female share of employment.

Hence, we find clear evidence that prior to 2000, the increased demand for female labor in good jobs was due to an increase in the demand for social skills in these jobs relative to other occupations.

### 5.3 2000-2016

The work of Beaudry, Green, and Sand (2016) indicates that since about the turn of the century, the increasing demand for high-skilled labor is no longer keeping pace with the increasing supply of such workers, driven by rising educational attainment rates. This "great reversal" is evident in our analysis of occupational employment and, more relevant for the purposes of this paper, is experienced differently for high-skilled men and women. For instance, reconsider the likelihood of employment in a cognitive occupation, displayed in Table 1. In 2000, the probability of COG employment was 0.633 for men, and 0.588 for women. Therefore, the divergence in gender trends between 1980 and 2000 was driven by both a decrease for men and an increase for women; but since 2000, the tendency to work in a good job has continued to fall for men, and stopped growing for women.

Table 8: Change in Female Share of Occupational Employment, 2000-2016

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Social | -.003 | -.005 | 0.002 | 0.003 |
| | (0.007) | (0.009) | (0.006) | (0.007) |
| Δ Cognitive | | 0.0004 | | -.002 |
| | | (0.009) | | (0.007) |
| Δ Routine | | 0.013 | | 0.010 |
| | | (0.003)*** | | (0.002)*** |
| Δ Manual | | 0.0001 | | -.002 |
| | | (0.004) | | (0.003) |
| Obs. | 312 | 312 | 433 | 433 |
| $R^2$ | 0.0007 | 0.069 | 0.0003 | 0.041 |

Notes: The dependent variable is the change in the female share of occupational employment among college graduates based on 2000 Census and 2016 American Community Survey data. Occupations are weighted according to their share of aggregate employment in 2000. Data on social skills and other occupational task characteristics from the 2002 and the 2016 O*NET datasets. The observations in columns (1) and (2) are occupations at the occ1990dd level. The observations in columns (3) and (4) are occupations at the 2000 Census code level.

In Appendix B.2, we interpret this change across sub-periods within the context of our neoclassical occupational choice model. We illustrate how this change can be quantified if minimal additional structure is imposed on the distributions of male and female cognitive work ability. Quantitative analysis of the model indicates a break at the turn of the century.

Table 8 presents regression results for the key relationship of interest for the 2000-2016 sub-period. The dependent variable, the within-occupation change in the female share of employment, is constructed based on 2000 Census and 2016 ACS data; the explanatory variables, within-occupation changes in the importance of social skills and other job tasks, uses data from the 2002 and 2016 O*NET. Columns (1) and (2) present results analogous to the first two columns of Table 5 for the entire period, and Table 6 for 1980–2000. Interestingly, and consistent with the notion that there was a trend break around the year 2000, there is no longer a relationship between the change in female share and the change in relative social skill intensity across occupations.

As with the previous regressions, occupations in Columns (1) and (2) are cross-walked and categorized at the 3-digit Dorn code level. But when focusing on the period after 2000, we are also able to consistently categorize occupations using the somewhat more disaggregated 2000 Census Occupation Codes. We adopt this in Columns (3) and (4) of Table 8. Again, there is no significant relationship between changes in the relative demand for social skills and changes in female shares within occupations, 2000–2016.

This mirrors our finding regarding the trend break in the female probability of cognitive employment in 2000. Moreover, as we show in the following section, the "wage return" to social skills increased 1980–2000 and, while remaining high, shows no further increase since 2000. Overall, we conclude that the findings for the entire 1980–2016 period are driven by the changes that occurred prior to about the year 2000.

## 6 Wage Evidence

Here we analyze 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 above. But chiefly, we use the wage data to indicate the primacy of an increase in the demand for social skills 1980–2000, and contrast to the period 2000–2016.

For both purposes, the Census and ACS 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. The coefficients on the occupation dummies are thus estimates of occupational wage premia that are gender- and time-specific.[27]

First, suppose the change in the social skill index of an occupation, as derived from the task datasets, 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, if this were driven simply by an increase in the supply of women to that occupation, 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 0.021 and statistically significant at the 1% level (standard error of 0.006). Changes in the 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

[27] See footnote 12 for details on the construction of the wage variable. The wage regressions are weighted using person weights from the Census.

increases slightly to 0.025 with standard error 0.006, remaining statistically significant at the 1% level. Hence, 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 and O*NET, 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 9, 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 nearly triples 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 two-fifths of this variation in 2000.

Columns (3) and (4) of Table 9 indicate that the result is robust to controlling for ALM task intensities within occupation. The estimate on the importance of social skills is positive and significant at the 5% level in 1980, but much larger and significant at the 1% level in 2000. Finally, we 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 (see, for instance, Levanon, England, and Allison (2009)). 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 to female share still accounts for differences in female occupational wages in both years. More importantly, the effect is five times as large in 2000 relative to 1980. Again, this implies that the wage return to social skills increased for women between 1980 and 2000, alongside largely stable or decreasing returns to other occupational task characteristics.[28]

[28] Note 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).

Table 9: Relationship between Occupational Wage Premia and Social Skill Importance, 1980 and 2000

*Panel A: Female Occupational Wage Premia*

| | 1980 | 2000 | 1980 | 2000 | 1980 | 2000 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Social | 0.056 | 0.162 | 0.023 | 0.145 | 0.032 | 0.160 |
| | (0.012)*** | (0.011)*** | (0.011)** | (0.017)*** | (0.011)*** | (0.018)*** |
| Cognitive | | | 0.133 | 0.074 | 0.118 | 0.052 |
| | | | (0.011)*** | (0.015)*** | (0.012)*** | (0.016)*** |
| Routine | | | 0.05 | 0.078 | 0.061 | 0.089 |
| | | | (0.009)*** | (0.011)*** | (0.009)*** | (0.011)*** |
| Manual | | | 0.035 | 0.009 | 0.035 | -.003 |
| | | | (0.014)** | (0.011) | (0.014)** | (0.012) |
| Female Share | | | | | -.114 | -.138 |
| | | | | | (0.04)*** | (0.039)*** |
| Obs. | 312 | 312 | 312 | 312 | 312 | 312 |
| $R^2$ | 0.071 | 0.410 | 0.384 | 0.584 | 0.400 | 0.601 |

*Panel B: Male Occupational Wage Premia*

| | 1980 | 2000 | 1980 | 2000 | 1980 | 2000 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Social | 0.012 | 0.138 | -.023 | 0.089 | -.014 | 0.110 |
| | (0.010) | (0.009)*** | (0.01)** | (0.016)*** | (0.010) | (0.015)*** |
| Cognitive | | | 0.113 | 0.097 | 0.103 | 0.066 |
| | | | (0.009)*** | (0.015)*** | (0.008)*** | (0.014)*** |
| Routine | | | 0.017 | 0.049 | 0.009 | 0.058 |
| | | | (0.010)* | (0.011)*** | (0.010) | (0.010)*** |
| Manual | | | 0.027 | 0.023 | 0.006 | -.024 |
| | | | (0.008)*** | (0.011)** | (0.008) | (0.012)** |
| Female Share | | | | | -.237 | -.327 |
| | | | | | (0.040)*** | (0.043)*** |
| Obs. | 312 | 312 | 312 | 312 | 312 | 312 |
| $R^2$ | 0.005 | 0.413 | 0.372 | 0.548 | 0.436 | 0.619 |

Notes: The dependent variable is the occupation's wage premium. Occupations are at the occ1990dd level and are weighted by their share of aggregate (gender-specific) employment. Data on occupational wage premia based on wage regressions using Census data. Data on social skills and other occupational task characteristics from the 1977 Dictionary of Occupational Titles and the 2002 O*NET. See text for details.

The results in Panel A could potentially be attributed to differential changes in female discrimination. This would be the case if discrimination had 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 at least as 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; the increase is nearly a factor of 12. 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)–(6).

In all cases considered in Table 9, 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.

In Table 10 we replicate our analysis for the years 2000 and 2016 at the 2000 Census Occupation Code level. The results for 2000 are in line with those displayed in Table 9 and only differ slightly because of the finer level of aggregation (2000 Census codes instead of Dorn codes). The results for 2016 are broadly similar to the results for the year 2000. The return to social skills remains essentially stable over this period. Importantly, the returns remain high—at least as high as the return to cognitive skills.

Consistent with our earlier findings, and with other findings in the literature, these results suggest a change in labor market trends emerging around the year 2000. Our results suggest that, alongside the slowdown in the demand for skilled workers that occurs around this time period, the increasing trend in the demand for social skills also reaches a halt. However, it is important to emphasize that even in 2016, demand for social skills remains high, with a steep gradient across occupations in the wage return to these skills.

Table 10: Relationship between Occupational Wage Premia and Social Skill Importance, 2000 and 2016

*Panel A: Female Occupational Wage Premia*

| | 2000 | 2016 | 2000 | 2016 | 2000 | 2016 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Social | 0.173 | 0.216 | 0.147 | 0.129 | 0.159 | 0.142 |
| | (0.010)*** | (0.012)*** | (0.017)*** | (0.018)*** | (0.017)*** | (0.018)*** |
| Cognitive | | | 0.081 | 0.104 | 0.061 | 0.08 |
| | | | (0.015)*** | (0.017)*** | (0.016)*** | (0.019)*** |
| Routine | | | 0.072 | 0.04 | 0.081 | 0.045 |
| | | | (0.010)*** | (0.011)*** | (0.010)*** | (0.011)*** |
| Manual | | | 0.007 | -.049 | -.002 | -.058 |
| | | | (0.010) | (0.013)*** | (0.011) | (0.013)*** |
| Female Share | | | | | -.127 | -.147 |
| | | | | | (0.035)*** | (0.048)*** |
| Obs. | 433 | 433 | 433 | 433 | 433 | 433 |
| $R^2$ | 0.405 | 0.446 | 0.561 | 0.576 | 0.574 | 0.585 |

*Panel B: Male Occupational Wage Premia*

| | 2000 | 2016 | 2000 | 2016 | 2000 | 2016 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Social | 0.144 | 0.19 | 0.082 | 0.049 | 0.100 | 0.106 |
| | (0.008)*** | (0.011)*** | (0.015)*** | (0.018)*** | (0.014)*** | (0.017)*** |
| Cognitive | | | 0.103 | 0.128 | 0.075 | 0.048 |
| | | | (0.015)*** | (0.016)*** | (0.014)*** | (0.016)*** |
| Routine | | | 0.045 | 0.021 | 0.054 | 0.046 |
| | | | (0.010)*** | (0.013) | (0.009)*** | (0.012)*** |
| Manual | | | 0.014 | -.061 | -.030 | -.136 |
| | | | (0.010) | (0.013)*** | (0.010)*** | (0.014)*** |
| Female Share | | | | | -.319 | -.552 |
| | | | | | (0.038)*** | (0.050)*** |
| Obs. | 433 | 433 | 433 | 433 | 433 | 433 |
| $R^2$ | 0.404 | 0.429 | 0.519 | 0.542 | 0.587 | 0.644 |

Notes: The dependent variable is the occupation's wage premium. Occupations are at the 2000 Census code level and are weighted by their share of aggregate (gender-specific) employment. Data on occupational wage premia based on wage regressions using Census data for 2000 and American Community Survey data for 2016. Data on social skills and other occupational task characteristics from O*NET. See text for details.

### 6.1 Linking the Increased Demand for Social Skills and College Attainment

The results from Table 9 show robust evidence of an increase in the return to social skills between 1980 and 2000. 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 9, 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.

Columns (1) to (3) of Table 11 present 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 9 regarding the strong increase over time in this correlation, now estimated using within-state variation.[29]

Column (2) adds a control for the state's college share, computed as the fraction of 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 0.219; this indicates that the wage return to social skills is much stronger in states with higher college shares.[30] 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 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 nearly doubling; the estimated positive correlation between the return to social skills and a state's

[29]Columns (1) and (2) in Table 9 imply a point estimate for the coefficient on social skills in 1980 of 0.056 and a point estimate for the change over time in this coefficient of 0.106. These magnitudes are quite similar to the ones obtained using within-state variation in Table 11.

[30]The 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.

Table 11: 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 | 0.019 | -.043 | 0.013 | -.041 | -.092 |
| | (0.003)*** | (0.008)** | (0.010)*** | (0.003)*** | (0.012)*** | (0.014)*** |
| Social x y2000 | 0.094 | 0.076 | 0.054 | 0.110 | 0.086 | 0.05 |
| | (0.002)*** | (0.004)*** | (0.004)*** | (0.003)*** | (0.005)*** | (0.005)*** |
| College | | 0.442 | 0.391 | | -1.350 | -1.376 |
| | | (0.462) | (0.451) | | (0.614)** | (0.599)** |
| Social x College | | 0.219 | 0.426 | | 0.321 | 0.447 |
| | | (0.043)*** | (0.054)*** | | (0.061)*** | (0.072)*** |
| Cognitive | | | 0.170 | | | 0.126 |
| | | | (0.007)*** | | | (0.009)*** |
| Cognitive x College | | | -.318 | | | -.086 |
| | | | (0.037)*** | | | (0.043)** |
| Routine | | | 0.025 | | | 0.014 |
| | | | (0.004)*** | | | (0.008)* |
| Routine x College | | | 0.149 | | | 0.104 |
| | | | (0.022)*** | | | (0.034)*** |
| Manual | | | 0.088 | | | 0.025 |
| | | | (0.009)*** | | | (0.007)*** |
| Manual x College | | | -.260 | | | 0.009 |
| | | | (0.038)*** | | | (0.035) |
| Obs. | 27606 | 27606 | 27606 | 30535 | 30535 | 30535 |
| $R^2$ | 0.230 | 0.232 | 0.404 | 0.212 | 0.220 | 0.382 |

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 (gender-specific) 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 1977 Dictionary of Occupational Titles and the 2002 O*NET. See text for details.

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 further. This indicates that an important fraction 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 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: 1980–2016

| | 1980 | 2016 | Percentage Point Difference Total | Explained | Unexplained |
|---|---|---|---|---|---|
| **Male** | | | | | |
| *Total (000's)* | *25592* | *54705* | | | |
| Cognitive (%) | 45.0 | 40.8 | −4.2 | +0.2 | −4.5 |
| Other (%) | 42.1 | 42.6 | +0.5 | | |
| Not Working (%) | 12.9 | 16.6 | +3.7 | | |
| **Female** | | | | | |
| *Total (000's)* | *23419* | *63751* | | | |
| Cognitive (%) | 33.0 | 40.6 | +7.6 | −0.7 | +8.3 |
| Other (%) | 33.9 | 34.3 | +0.4 | | |
| Not Working (%) | 33.1 | 25.1 | −8.0 | | |

Notes: Labor Force statistics, 20-64 year olds with at least some post-secondary education. Data from 1980 Census and 2016 ACS. Employment categorized by occupational task content.

Table A.2: High-Skilled Occupational and Employment Status: 1980–2016

| | 1980 | 2016 | Percentage Point Difference Total | Explained | Unexplained |
|---|---|---|---|---|---|
| **Male** | | | | | |
| *Total (000's)* | *12084* | *26666* | | | |
| Top 10% | 25.1 | 14.9 | −10.2 | −0.1 | −10.1 |
| Bottom 90% | 67.1 | 73.6 | +6.5 | | |
| Not Working (%) | 7.8 | 11.5 | +3.7 | | |
| **Female** | | | | | |
| *Total (000's)* | *8886* | *31585* | | | |
| Top 10% | 6.3 | 8.0 | +1.7 | +0.1 | +1.6 |
| Bottom 90% | 66.5 | 71.5 | +5.0 | | |
| Not Working (%) | 27.2 | 20.5 | −6.7 | | |

Notes: Labor Force statistics, 20-64 year olds with at least college degree. Data from 1980 Census and 2016 ACS. Employment categorized by ranking in occupational wage distribution of 2000.

# B Simple Model with Occupation Choice

## B.1 Model

**Labor Demand** Our theoretical results can be derived from a very general specification of the demand for labor in "good jobs" relative to other occupations. Here, we will label the good job as a cognitive occupation for the purposes of exposition, though any other definition (e.g. top decile job in the occupational wage distribution) would be fine. We assume that high-skilled (college-educated) labor is combined with other inputs to produce real output, $Y_t$, via:

$$Y_t = G\left(f^C(Z^C_{Mt}L_{Mt}, Z^C_{Ft}L_{Ft}), f^O(Z^O_{Mt}E_{Mt}, Z^O_{Ft}E_{Ft}), \mathbb{K}_t\right). \tag{A.1}$$

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, $Z^C_{Ft}$ and $Z^C_{Mt}$.

High-skilled males and females who work in the non-cognitive or *other* occupation, $E_{Mt}$ and $E_{Ft}$, produce "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 $f^i_{11}, f^i_{22} \le 0$ for $i = C, O$.[31]

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:

$$\max_{\substack{L_{Mt}, L_{Ft},\\ E_{Mt}, E_{Ft}, \mathbb{K}_t}} Y_t - (1+\tau^C_t)w_{Ft}L_{Ft} - w_{Mt}L_{Mt} - (1+\tau^O_t)p_{Ft}E_{Ft} - p_{Mt}E_{Mt} - \mathbf{r}_t\mathbb{K}_t. \tag{A.2}$$

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

[31] As an example, consider:

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

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

standard labor demand functions for $L_{Mt}$, $L_{Ft}$, $E_{Mt}$ and $E_{Ft}$:

$$w_{Mt} = Z^C_{Mt} G_1(\cdot) f^C_1 (Z^C_{Mt} L_{Mt}, Z^C_{Ft} L_{Ft}), \tag{A.3}$$

$$w_{Ft} = \frac{Z^C_{Ft}}{1+\tau^C_t} G_1(\cdot) f^C_2 (Z^C_{Mt} L_{Mt}, Z^C_{Ft} L_{Ft}), \tag{A.4}$$

$$p_{Mt} = Z^O_{Mt} G_2(\cdot) f^O_1 (Z^O_{Mt} E_{Mt}, Z^O_{Ft} E_{Ft}), \tag{A.5}$$

$$p_{Ft} = \frac{Z^O_{Ft}}{1+\tau^O_t} G_2(\cdot) f^O_2 (Z^O_{Mt} E_{Mt}, Z^O_{Ft} E_{Ft}). \tag{A.6}$$

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.

**Labor Supply** On the supply side, $S_{gt}$ denotes the measure of high-skilled individuals of each gender at date $t$ for $g = \{M, F\}$. For exposition here, all high-skilled workers supply labor (inelastically) to either the cognitive or the other occupation (and we relax this assumption in the following Appendix). Individuals make a discrete occupational choice based on comparative advantage.

To model this, 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 $\Gamma$ denotes the cumulative distribution function. 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 $p_{gt}$ 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:

$$a^*_{Mt} w_{Mt} = p_{Mt}. \tag{A.7}$$

Similarly:

$$a^*_{Ft} w_{Ft} = p_{Ft}, \tag{A.8}$$

defines the female cutoff, $a^*_{Ft}$. Thus, the fraction of workers of each gender who choose employment in the cognitive occupation, $\phi_{gt}$, is simply:

$$\phi_{gt} = 1 - \Gamma_{gt}(a^*_{gt}) \tag{A.9}$$

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 C.1, we consider an extended version of the model that allows for both an occupational choice and a participation choice, and show that the results we derive here are unaltered. That is, our findings are robust to the modeling of gender differences in participation trends.

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

$$L_{Ft} = S_{Ft} \int_{a^*_{Ft}}^{\infty} a\Gamma'_{Ft}(a)da, \tag{A.10}$$

$$L_{Mt} = S_{Mt} \int_{a^*_{Mt}}^{\infty} a\Gamma'_{Mt}(a)da. \tag{A.11}$$

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:

$$E_{Mt} = S_{Mt}\Gamma_{Mt}(a^*_{Mt}), \tag{A.12}$$

$$E_{Ft} = S_{Ft}\Gamma_{Ft}(a^*_{Ft}). \tag{A.13}$$

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

## B.2 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 2016.

In what follows, we assume that (effective) labor inputs of high-skilled men and women are perfect substitutes in both occupations. That is, $f^C(\cdot) = f^C(Z^C_{Mt}L_{Mt} + Z^C_{Ft}L_{Ft})$ and $f^O(\cdot) = f^O(Z^O_{Mt}E_{Mt} + Z^O_{Ft}E_{Ft})$, 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.2, 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, (A.3)–(A.6), can be simplified as:

$$\frac{w_{Ft}}{w_{Mt}} = \frac{Z^C_{Ft}}{Z^C_{Mt}} \frac{1}{1+\tau^C_t}, \tag{A.14}$$

$$\frac{p_{Ft}}{p_{Mt}} = \frac{Z^O_{Ft}}{Z^O_{Mt}} \frac{1}{1+\tau^O_t}. \tag{A.15}$$

Using the indifference conditions, (A.7)–(A.8), equations (A.14)–(A.15) imply:

$$\frac{a^*_{Mt}}{a^*_{Ft}} \frac{Z^O_{Ft}}{Z^O_{Mt}} \left(1+\tau^C_t\right) = \frac{Z^C_{Ft}}{Z^C_{Mt}} \left(1+\tau^O_t\right).$$

Letting $\Delta x_t$ denote the percentage change in $x$ between any two dates $t$ and $t'$, we obtain:

$$\Delta a^*_{Mt} - \Delta a^*_{Ft} = \Delta\left(\frac{Z^C_{Ft}}{Z^C_{Mt}}\right) - \Delta\left(\frac{Z^O_{Ft}}{Z^O_{Mt}}\right) + \Delta\left(1+\tau^O_t\right) - \Delta\left(1+\tau^C_t\right). \tag{A.16}$$

### B.2.1 No Functional Form Assumption for the Distribution of Ability

Recall that $a^*_{gt}$ is the minimum cognitive work ability (i.e., comparative advantage) of those who sort into the COG occupation for $g = \{M, F\}$. Hence, the left-hand side of equation (A.16) 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 2016 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 (A.16) directly. In the first case, since the probability for men has fallen over time, equation (A.9) would imply greater selectivity of men in COG employment between 1980 and 2016: $\Delta a^*_{Mt} > 0$. 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.[32]

The first is if $\Delta\left(Z^C_{Ft}/Z^C_{Mt}\right) > \Delta\left(Z^O_{Ft}/Z^O_{Mt}\right)$. From (A.3)–(A.6), $Z^C_{Mt}$, $Z^C_{Ft}$, $Z^O_{Mt}$ and $Z^O_{Ft}$ are "shifters" to the labor demand curves in wage-employment space. Thus, $\Delta Z^C_{Ft} > \Delta Z^C_{Mt}$ 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 below.

### B.2.2 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

[32] Note 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 (A.3) and (A.5):

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

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 4.

specifying a functional form for $\Gamma_{gt}$.

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, $\Gamma_{gt}$ 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 $\kappa_{Mt}$ and $\kappa_{Ft}$, for males and females, respectively.

In addition to empirical credibility, the Pareto distribution is analytically attractive. The optimality conditions (A.7) and (A.8), imply that ability among workers who choose the COG occupation is truncated from $\Gamma_{gt}$ at $a_{gt}^*$. Nonetheless, we are able to derive characteristics of the entire ability distribution: 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 (A.16). The fraction of high-skilled individuals who work in the cognitive occupation is given by:

$$\phi_{gt} = \left( \frac{a_{gt}^{min}}{a_{gt}^*} \right)^{\kappa_{gt}}. \tag{A.17}$$

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

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

Subbing this into equation (A.16) obtains:

$$\begin{aligned} \left( \frac{1}{\kappa_{Mt}} \right) \Big[ \log(\phi_{Mt}) \, \Delta \kappa_{Mt} - \Delta \phi_{Mt} \Big] - \left( \frac{1}{\kappa_{Ft}} \right) \Big[ \log(\phi_{Ft}) \, \Delta \kappa_{Ft} - \Delta \phi_{Ft} \Big] = \\ \Delta \left( \frac{Z_{Ft}^C}{Z_{Mt}^C} \right) - \Delta \left( \frac{Z_{Ft}^O}{Z_{Mt}^O} \right) + \Delta a_{Ft}^{min} - \Delta a_{Mt}^{min} + \Delta \left( 1 + \tau_t^O \right) - \Delta \left( 1 + \tau_t^C \right). \end{aligned} \tag{A.18}$$

Relative to equation (A.16), (A.18) includes changes in both the scale and shape parameters, $\Delta a_{gt}^{min}$ and $\Delta \kappa_{gt}$. Equation (A.18) is useful because all of the terms involving $\phi$ and $\kappa$ 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 (A.14) implies that the empirically observed ratio of mean cognitive wages of women relative to men among high-skilled workers, $Ratio_t$, is:

$$Ratio_t = \frac{Z^C_{Ft}}{Z^C_{Mt}} \frac{1}{1+\tau^C_t} \frac{a^*_{Ft} \frac{\kappa_{Ft}}{\kappa_{Ft}-1}}{a^*_{Mt} \frac{\kappa_{Mt}}{\kappa_{Mt}-1}}. \tag{A.19}$$

Hence, changes in the observed $Ratio_t$ can be decomposed into female bias, $\Delta\left(Z^C_{Ft}/Z^C_{Mt}\right)$, changes in the discrimination wedge, $\Delta(1+\tau^C_t)$, 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).[33]

**Measuring $\phi$:** Note that the fractions of high-skilled males and females in the cognitive occupation are reported in Table 1 for both 1980 and 2016. This gives us $\phi_{gt}$ for $g = \{M, F\}$, and its percentage change over time. Specifically, $\phi_{M,1980} = 0.662$, $\phi_{M,2016} = 0.621$, $\phi_{F,1980} = 0.542$, and $\phi_{F,2016} = 0.588$.

**Measuring $\kappa$:** The shape parameter of the ability distribution, $\kappa_{gt}$, and its change over time are pinned down as follows.[34] 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:

$$\left(\frac{\kappa_{gt}}{\kappa_{gt}-1}\right) 2^{-\frac{1}{\kappa_{gt}}}. \tag{A.20}$$

Thus, data on wages in cognitive occupations allows us to measure $\kappa_{gt}$. 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 $\kappa_{M,1980} = 2.988$,

[33] 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.

[34] 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 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.

$\kappa_{M,2016} = 2.339$, $\kappa_{F,1980} = 3.753$, and $\kappa_{F,2016} = 2.812$.[35] 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.

**The Three Channels**: Given the observed changes in occupational outcomes and wage distributions, we measure the left-hand side of equation (A.18) to be positive:

$$LHS \equiv \left(\frac{1}{\kappa_{Mt}}\right)\left[\log(\phi_{Mt})\,\Delta\kappa_{Mt} - \Delta\phi_{Mt}\right] - \left(\frac{1}{\kappa_{Ft}}\right)\left[\log(\phi_{Ft})\,\Delta\kappa_{Ft} - \Delta\phi_{Ft}\right] = +3.23\%.$$

As equation (A.18) makes clear, the model apportions this to the two channels discussed in relation to equation (A.16), and a new one. Now, the three channels 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.

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, $\Delta\left(Z^C_{Ft}/Z^C_{Mt}\right) > \Delta\left(Z^O_{Ft}/Z^O_{Mt}\right)$. This is what we investigate in Section 4.

### B.2.3 Sub-Period Analysis

As discussed in Section 5, the extent of female bias in good jobs relative to other occupations stops growing after 2000. This is evident in our model accounting as well.

Again, without making functional form assumptions about $\Gamma_{gt}(a)$, assume either that: $\Gamma_M(a)$ differs from $\Gamma_F(a)$, but that both have remained constant over time; or the support of the distribution has changed, but the male and female distributions coincide at each point in time. In the year 2000, $\phi_{M,2000} = 0.633$, $\phi_{F,2000} = 0.588$. Hence, from equation (A.16), $\Delta a^*_{Mt} - \Delta a^*_{Ft} > 0$ in both sub-periods, 1980–2000 and 2000–2016; however, the magnitude was much larger in the early compared to the late sub-period. That is, the data is consistent with greater female bias in the cognitive (versus other) occupation overall, but more so 1980–2000.

[35] For details on the construction of wages, see footnote 12. 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 $\geq 250$ 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 0.5% of wage observations, and (c) using the sum of wage/salary and business income in the computation of wages. Details available upon request.

Finally, if we are willing to assume $\Gamma_{gt}$ is Pareto we can further decompose equation (A.16). Using wage data as above, $\kappa_{M,2000} = 2.332$, $\kappa_{F,2000} = 3.293$. As a result, the left-hand side of equation (A.18) is positive (+4.74%) during 1980–2000, and negative (−1.58%) for 2000–2016. This change across sub-periods mirrors our findings in Section 5.

# C Model Extensions

## C.1 Participation Choice

Here, we present a simple extension to the model of Appendix B that allows for a labor force participation decision among high-skilled workers. The purpose is to show that the key results from Section B.2 are unaltered by this modification.

To begin, we note that the setup of production technology and, therefore, the labor demand equations, (A.3)–(A.6), 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 (A.7) and (A.8) 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:

$$L_{gt} = S_{gt}\Omega_{gt}(b^*_{gt})\int_{a^*_{gt}}^{\infty} a\Gamma'_{gt}(a)da,$$
$$E_{gt} = S_{gt}\Omega_{gt}(b^*_{gt})\Gamma_{gt}(a^*_{gt}),$$

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 Appendix B—namely equations (A.3)–(A.6), (A.7), and (A.8)—are identical in this extended model. Hence, the key equation under consideration, equation (A.16), is unchanged.

The only change comes in the quantification of the model. With endogenous participation, equation (A.17) describing the fraction of individuals who work in the cognitive occupation becomes:

$$\phi_{gt} = \Omega_{gt}(b^*_{gt}) \times \left(\frac{a^{min}_{gt}}{a^*_{gt}}\right)^{\kappa_{gt}}.$$

As a result, the left-hand side of (A.18) becomes:

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

Critically, each of these terms can be measured in the data. Relative to the analysis of Section B.2, 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 $LHS = +0.94\%$ remains positive.

## C.2 Non-Constant Marginal Rates of Transformation

Here, we extend our analysis of Section B.2 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: $f^C(\cdot) = f^C\left(\left[Z^C_{Mt}L^\rho_{Mt} + Z^C_{Ft}L^\rho_{Ft}\right]^{\frac{1}{\rho}}\right)$ 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 $\rho < 1$.[36]

The labor demand equations, (A.3)–(A.6), can be rearranged and simplified as:

$$\frac{w_{Ft}}{w_{Mt}} = \frac{Z^C_{Ft}}{Z^C_{Mt}}\frac{1}{1+\tau^C_t}\frac{L^{\rho-1}_{Ft}}{L^{\rho-1}_{Mt}}, \tag{A.21}$$

$$\frac{p_{Ft}}{p_{Mt}} = \frac{Z^O_{Ft}}{Z^O_{Mt}}\frac{1}{1+\tau^O_t}\frac{E^{\rho-1}_{Ft}}{E^{\rho-1}_{Mt}}. \tag{A.22}$$

Using the indifference conditions, (A.7)–(A.8), and the Pareto functional form on the distribution of cognitive work ability, these conditions can be combined as:

$$\left(\frac{1}{\kappa_{Mt}}\right)\Big[\log(\phi_{Mt})\,\Delta\kappa_{Mt} - \Delta\phi_{Mt}\Big] - \left(\frac{1}{\kappa_{Ft}}\right)\Big[\log(\phi_{Ft})\,\Delta\kappa_{Ft} - \Delta\phi_{Ft}\Big] + (1-\rho)\left[\Delta\left(\frac{L_{Ft}}{L_{Mt}}\right) - \Delta\left(\frac{E_{Ft}}{E_{Mt}}\right)\right] = \Delta\left(\frac{Z^C_{Ft}}{Z^C_{Mt}}\right) - \Delta\left(\frac{Z^O_{Ft}}{Z^O_{Mt}}\right) + \Delta a^{min}_{Ft} - \Delta a^{min}_{Mt} + \Delta\left(1+\tau^O_t\right) - \Delta\left(1+\tau^C_t\right). \tag{A.23}$$

[36] 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.

The first two terms on the left-hand side are unaltered relative to Section B.2 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 (A.10)-(A.13). Hence, as before, all terms on the left-hand side of (A.23) can be measured in 1980 and 2016. Given that women are increasingly sorting into the cognitive occupation (away from the other occupation) relative to men, and given that the thickness of the Pareto right tail has increased more for women relative to men, and 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, the left-hand side of (A.23) remains positive. So, for example, if the change in discrimination was the same across occupations, i.e. $\Delta\left(1+\tau_t^O\right) = \Delta\left(1+\tau_t^C\right)$, 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.3 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 Appendix B.

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 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 (A.1) is:

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

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 $\Delta\left(Z_{Ft}^C/Z_{Mt}^C\right) > \Delta\left(Z_{Ft}^O/Z_{Mt}^O\right)$ condition is clear: $\Delta\left(Z_{St}^C/Z_{Nt}^C\right) > \Delta\left(Z_{St}^O/Z_{Nt}^O\right)$, 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.

# D Task Data Details

Our task measures are derived from the Dictionary of Occupational Titles (DOT), and its successor, O*NET. We use information from the 4th Edition of the DOT, published in 1977, and the revised 4th Edition, published in 1991. These are made available through the Interuniversity Consortium for Political and Social Research (ICPSR 1981; ICPSR 1991). Regarding O*NET, we rely on information from the June 2002 release (O*NET version 4.0) and the August 2016 release (O*NET version 21.0). These are available at `https://www.onetcenter.org/db_releases.html`.

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.

There are some Dorn codes that do not have a corresponding 1970-COC code. For these occupations, we have employment and earnings information from the Census and ACS, but no direct measures of tasks from DOT, so we impute the task information using a closely related occupation for which we do have task data. The details are in Table A.3

Following Deming (2017), we rescale all of the task variables from DOT so that they range from 0 to 10. We then construct our composite task measures. The social skill measure is generated by adding the (rescaled) scores for the four temperaments listed in Section 4. Other task measures are generated as in ALM. These composite measures are then rescaled to range from 0 to 10, and then normalized to have mean zero and standard deviation one across the employment-weighted occupational distribution in the 1980 Census.

O*NET data is available at the O*NET-SOC Code level, a more disaggregated version of the Standard Occupational Classification (SOC) coding system. We also need to aggregate these measures to the Dorn code level. To do so, we proceed as follows:

1. We generate task measures at the SOC code level by computing simple averages across all of the O*NET-SOC occupations that fall within the same SOC code.

2. We merge in information from the Bureau of Labor Statistics' Occupational Employ-

Table A.3: Imputation of DOT task data for occ1990dd codes without a corresponding 1970 Census code

| occ1990dd codes with no 1970 code | occ1990dd codes used for imputation | occ1990dd codes with no 1970 code | occ1990dd codes used for imputation |
|---|---|---|---|
| 4, 8, 37 | 22 | 461 | 462 |
| 24, 25, 26 | 23 | 470 | 469 |
| 27 | 13 | 503, 507, 509 | 505 |
| 34 | 256 | 518 | 516 |
| 83 | 78 | 536 | 535 |
| 98, 99, 103, 104 | 105 | 539, 543 | 549 |
| 106 | 84 | 558 | 35 |
| 158 | 156 | 614 | 598 |
| 184 | 183 | 617 | 616 |
| 234 | 313 | 684 | 637 |
| 243 | 258 | 688 | 687 |
| 317, 326, 379 | 319 | 694 | 695 |
| 336, 356 | 335 | 699 | 696 |
| 377 | 375 | 729, 733 | 727 |
| 415 | 423 | 743, 747 | 749 |
| 427 | 426 | 753, 755, 757, 763, 765 | 779 |
| 433 | 436 | 803, 834 | 804 |
| 439 | 444 | 853 | 594 |
| 448 | 453 | 865 | 869 |
| 450, 455 | 451 | 873, 878 | 889 |

ment Statistics (OES) dataset, which provides data on employment by occupation at the SOC code level.[37]

3. We use crosswalks from the Census Bureau and from O*NET to map SOC codes to Census Occupation Codes; specifically, we map SOC-2000 codes to 2000 Census Occupation Codes in the case of the 2002 O*NET, and SOC-2010 codes to 2010 Census Occupation codes in the case of the 2016 O*NET.

4. We compute weighted averages of all of the task measures at the corresponding Census Occupation Code level using OES employment levels by SOC code as weights.

5. We map the Census Occupation Codes to Dorn codes, and we compute weighted averages of the task measures at the Dorn Code level using employment levels by Census Occupation Code as weights.

We match our employment data from the Census and the ACS to the O*NET task data at the Dorn code level. There are a small number of Dorn codes for which the corresponding SOC codes do not appear in O*NET. As with the DOT data, we impute the task information

[37]For the 2002 O*NET, we use national-level data from the 2002 OES, while for the 2016 O*NET we use analogous OES data for 2016. In some cases, SOC codes need to be slightly aggregated to the "broad" level (i.e. ignoring the last digit) in order to match to OES.

Table A.4: Imputation of O*NET task data for occ1990dd codes without a corresponding SOC code that appears in O*NET

| occ1990dd codes with no SOC code in O*NET | occ1990dd codes used for imputation | O*NET year for which imputation is required |
|---|---|---|
| 37 | 22 | 2002 |
| 76 | 73 | 2002 |
| 346 | 354 | 2002 |
| 349 | 348 | 2002 and 2016 |
| 415 | 423 | 2002 and 2016 |

Table A.5: Dorn code reassignment

| original occ1990dd code | re-assigned occ1990dd code |
|---|---|
| 583 | 579 |
| 644, 645 | 634 |
| 703, 708, 709 | 707 |
| 723, 724 | 719 |
| 745 | 744 |
| 764 | 763 |
| 825 | 824 |

for these occupations using a closely related occupation for which we do have O*NET data. The details are in Table A.4.

Finally, there are a few Dorn codes for which we do not have ACS data in 2016. The reason is that the occupation codes used by the ACS are a slightly aggregated version of the 2010 Census Occupation Codes. Certain 2010 Census Occupation Codes that would map to particular Dorn codes do not exist in the 2016 ACS Occupation Coding system. In order to work with a consistent set of occupation codes, we re-assign workers in the Dorn code categories that do not appear in the 2016 ACS. The details are in Table A.5. Workers who in 1980 or 2000 would have been categorized into the Dorn codes in the left-hand column are re-assigned to the Dorn codes in the right-hand column instead. The Dorn code system has a total of 330 codes, of which 7 correspond to occupations in farming, which we exclude from our analysis. Given the reassignment of the 11 codes detailed in Table A.5, we end up with a consistent set of 312 codes for all of our analyses at the 3-digit Dorn code level.

For the 2000–2016 analysis where we consider patterns at the 2000 Census Code level, the procedure is the same as above for the 2002 O*NET (stopping at step 4). For the 2016 O*NET, we first crosswalk from 2010-SOC codes to 2000-SOC codes; we compute simple averages of the task indices at the 2000-SOC code level; we merge in the employment data for 2002 from the OES, and then proceed as in steps 3 and 4 above.

Once again, there are some 2000 Census Occupation codes that do not have a corresponding SOC code that appears in O*NET, so we impute the task information using a

Table A.6: Imputation of O*NET task data for 2000 Census Occupation Codes (COC) without a corresponding SOC code that appears in O*NET

| 2000-COC with no SOC code in O*NET | 2000-COC used for imputation | O*NET year for which imputation is required |
|---|---|---|
| 2, 6 | 1 | 2002 |
| 3, 43 | 1 | 2002 and 2016 |
| 21 | 20 | 2002 |
| 70 | 71 | 2002 and 2016 |
| 73 | 72 | 2002 |
| 95 | 80 | 2002 and 2016 |
| 142 | 153 | 2002 |
| 176 | 172 | 2002 and 2016 |
| 206 | 205 | 2002 and 2016 |
| 276 | 275 | 2002 and 2016 |
| 363 | 362 | 2002 |
| 370 | 371 | 2002 |
| 373 | 371 | 2002 and 2016 |
| 465 | 461 | 2002 and 2016 |
| 484 | 485 | 2002 and 2016 |
| 503 | 501 | 2002 and 2016 |
| 542 | 540 | 2002 and 2016 |
| 556 | 554 | 2002 |
| 593 | 586 | 2002 and 2016 |
| 713 | 172 | 2002 |
| 824 | 823 | 2016 |

closely related occupation for which we do have O*NET data. The details are in Table A.6.[38]

As with the DOT, and following Deming (2017), we rescale all of the O*NET task variables so that they range from 0 to 10. We then construct our composite task measures, and rescale these to range from 0 to 10. Finally, we normalize the task indices to have mean zero and standard deviation one across the employment-weighted occupational distribution in the 1980 Census. For the 2000–2016 analysis, we normalize the task indices to have mean zero and standard deviation one across the employment-weighted occupational distribution in the 2000 Census.

[38] We exclude 2000 Census Occupation codes 513 and 676 in both years.

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