The Growing Importance of Social Tasks in High-Paying Occupations: Implications for Sorting*

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Abstract

We document that, since 1980, higher paying occupations in the US have experienced increases in the importance of tasks requiring social skills compared to lower paying ones. Economic theory indicates that the occupational sorting of workers depends on their comparative advantage in performing occupational tasks. Hence, changes in the relative importance of tasks across occupations change sorting. We document that the change in the relative importance of social tasks sheds light on the differential change in male/female occupational sorting.

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1 Introduction

An important literature following Autor, Levy, and Murnane (2003) characterizes occupations according to their task content. This work demonstrates how the task approach is crucial to our understanding of labor market dynamics and employment changes across the occupational wage distribution. This literature has focused on changes over the last four decades that arise through differential employment growth across occupations (see e.g. Acemoglu and Autor 2011).

In this paper, we focus on how the relative ranking of occupations along different task dimensions has changed over time due to within-occupation changes in task content. We are motivated by a basic theoretical insight: a worker's occupational choice is based on her comparative advantage in performing occupational tasks. As such, the sorting of workers is affected by changes in the relative importance of tasks across occupations. We document the changes in relative importance that have occurred in the US over the last four decades, and demonstrate how these can shed light on observed changes in worker sorting.

Following existing literature we focus on four key task dimensions: cognitive, routine, manual, and social. As in the seminal work of Goos and Manning (2007) in the UK context, which has been widely adopted in the US context following Autor, Katz, and Kearney (2006), we rank occupations by their median wage in 1980. Using data on task importance from the Dictionary of Occupational Titles (DOT) and, its successor, the Occupational Information Network (O*NET), we find that, between 1980 and 2016, higher paying occupations experienced a greater increase in the importance of tasks requiring social skills relative to lower paying ones. That is, an occupation's position in the 1980 wage distribution is systematically positively related to the change in the relative importance of social tasks over the following four decades.[1] Interestingly, there is no systematic relationship between an occupation's wage ranking and the relative change in the importance of either cognitive or routine tasks. Along with the increasing relative importance of social tasks, higher paying occupations have also experienced a decline in the importance of manual tasks relative to lower paying occupations.

These findings, and the theoretical prediction that changes in the relative importance of tasks affect sorting, lead us to consider the following question: If there are certain demo-

[1] In related work, Deming (2017) finds that employment growth has been strongest in occupations with high levels of social skill importance. His analysis does not consider the evolution of the relative importance of tasks arising from within-occupational changes, and the associated implications for sorting, which are the focus of our analysis.

graphic groups who have a comparative advantage in tasks requiring social skills, have they increasingly sorted into higher paying occupations? We note that 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 use data from the 1980 Census and the 2016 American Community Survey (ACS) in order to explore whether women have increasingly sorted into employment at the top of the occupational wage distribution *relative to men*, and whether this is related to the increasing relative importance of social tasks in these occupations. We find evidence that this is the case. Moreover, this holds within education levels, assuaging concerns that this is driven solely by rising female post-secondary educational attainment relative to that of men. There is a robust positive correlation between the change in the importance of social tasks, and the relative propensity of women to sort into an occupation. Data on occupational wages shows that this relationship is unlikely to be driven by reverse causality.

Our work is related to a small number of papers focused on *changes in task content* within occupations. To the best of our knowledge, ours is the first to study changes in the relative importance of tasks involving social skills in the US labor market during the past forty years, and its relationship to gender trends in occupational choice. The first paper to focus on task changes within occupations is Spitz-Oener (2006) for the West German economy, 1979–1999;[2] she finds occupations to have gained in complexity of tasks over time (e.g. in terms of planning and research), with the most pronounced changes in those with increased computer usage. Recently, Ross (2017) examines the evolution of the wage return to abstract relative to routine tasks in response to changes in occupational 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 following the Great Recession. Finally, Atalay et al. (2018) construct a dataset of occupation-level task demand from newspaper job advertisements from 1960–2000, and use this to quantify the importance of task changes to widening earnings inequality.

Our focus on occupational tasks requiring social skills is related to work by Borghans, Ter Weel, and Weinberg (2014) and Deming (2017). Borghans, Ter Weel, and Weinberg

[2] It is worth noting that Autor, Levy, and Murnane (2003)'s work does touch on intensive margin changes between the 1977 and the 1991 editions of the DOT, but the majority of their analysis focuses on the extensive margin, holding occupational tasks fixed.

(2014) show that the trend in social skills importance (derived from between-occupation shifts in employment, not changes within occupation) closely mimics the closing of the gender wage gap in the US, 1968-2002. Deming (2017) shows that since 1980, there has been disproportionate employment growth in occupations requiring high levels of social interaction, and especially those requiring both math and social skills.[3] While these papers document changes due to employment growth between occupations, holding the task content of occupations *fixed*, we consider changes in the relative importance of social tasks between occupations.

We also contribute to an extensive body of work that studies gender differences in labor market outcomes (see Blau and Kahn (2017) and Goldin (2014) for broad overviews of this literature). A number of papers consider how changes in demand, coupled with differences in male/female comparative advantage, have impacted gender gaps in the labor market. Galor and Weil (1996), Welch (2000), Beaudry and Lewis (2014), Bhalotra, Fernández, and Venkataramani (2015), Yamaguchi (2018), and Rendall (2017), for example, 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]

The rest of the paper is organized as follows. Section 2 documents the changing relative importance of tasks across occupations and its relation to the occupational wage distribution. Section 3 presents a simple theoretical framework to illustrate how occupational sorting can change in response to changes such as those observed in Section 2. Section 4 demonstrates that women are increasingly sorting into high-wage occupations relative to men, and its relationship to the increasing relative importance of social tasks in these occupation. Finally, Section 5 concludes. The various online appendices contain details on data construction and robustness checks of our results.

[3] Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) also demonstrate that the return 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.

[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; Olivetti and Petrongolo (2014) on the role of industrial structure in accounting for international differences in gender outcomes; and Ngai and Petrongolo (2017) on the role of structural transformation.

2 Changes in Relative Task Importance

Autor, Levy, and Murnane (2003) pioneered the use of information from the Dictionary of Occupational Titles (DOT) and, its successor, the Occupational Information Network (O*NET) to characterize occupations along various dimensions. These datasets provide detailed measures of skills and aptitudes that are required to perform tasks associated with specific occupations, as well as information on the main work activities performed by job incumbents.

A major challenge in analyzing task changes within occupations over long time periods is in the nature of this data: the way in which information is elicited and recorded changed between the DOT (conducted in 1977 and 1991) and the O*NET (available in a consistent format since 2002, with major updates being released roughly at an annual frequency). As such, most of the literature has implicitly assumed that the task content of occupations has remained constant over time. Aggregate changes in task importance in the labor market have been documented through changes in employment shares across occupations characterized by different levels of task content. The key finding in this literature is that occupations that are intensive in routine tasks have shrunk, while occupations that are intensive in non-routine tasks, including social tasks have grown (Autor, Levy, and Murnane 2003; Deming 2017).

In practice, the task content of occupations may change over time as documented, for example, by Spitz-Oener (2006) for Germany. In the US setting, the changes between the DOT and O*NET make it impossible to compare the *levels* of task intensity. It is straightforward, however, to consider how the *relative ranking* of occupations along particular task dimensions has changed over time. As we discuss in Section 3, this *relative* importance of tasks across occupations is relevant in determining occupational sorting when workers differ in their comparative advantage.

Here we analyze the evolution of the relative importance of tasks across the occupational wage distribution over time. We work with occupational information at the 3-digit level, crosswalked across successive coding systems using the harmonized codes from Autor and Dorn (2013). Throughout the paper, occupations are ranked into percentiles according to their median hourly wage and hours-weighted employment in 1980 using data from the US Census, as provided by IPUMS (Ruggles et al. 2018).[5] We then attach task information

[5]As is standard, we compute individual-level wages from the Census as total annual wage and salary income, divided by (weeks worked last year $\times$ usual hours worked per week). Annual income in 1980 is multiplied by 1.4 for top-coded individuals (see Firpo, Fortin, and Lemieux (2011)). We restrict attention to

from the DOT and the O*NET to each 3-digit occupation. We focus on four key task dimensions: cognitive, social, routine, and manual tasks. Our task measures follow Autor, Levy, and Murnane (2003), Borghans, Ter Weel, and Weinberg (2014) and Deming (2017). Details regarding the occupational classification and the assignment of task measures is contained in Appendix A. To capture the relative ranking of occupations, we normalize task indices at each point in time 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 an occupation is interpreted as a one standard deviation increase in the relative position of that occupation within the employment-weighted distribution of that task. Our analysis focuses on long changes in these relative task content rankings between the 1977 DOT (ICPSR 1981) and the August 2016 O*NET release (version 21.0), available at https://www.onetcenter.org/db_releases.html.

Figure 1 illustrates our primary result regarding changes in relative task importance. We find that an occupation's position in the wage distribution is systematically related to the change in the importance of tasks involving social skills: higher paying occupations became relatively more intensive in social tasks compared to lower paying ones. This relationship is significant at the 1% level (coefficient 0.012; p-value<0.001).

Meanwhile, there is no systematic relationship between an occupation's wage ranking and the relative change in the importance of either cognitive or routine tasks, 1977–2016. The estimated coefficient values for cognitive and routine (-0.001 and 0.001, respectively) are an order of magnitude smaller than for social tasks, and not statistically significant (p-values of 0.39 and 0.79, respectively). Note that this is in no way inconsistent with the facts that: (i) occupations in the middle of the wage distribution tend to be more routine-task intensive, and (ii) the employment share of these occupations has been declining over time. Figure 1 simply points out that middle-wage occupations have not experienced *disproportionate* declines in routine task content compared to other occupations. Similarly, occupations at the top of the distribution, which are known to be cognitive task-intensive, have not become disproportionately more cognitive task-intensive over time. Finally, there is also a systematic relationship between an occupation's wage ranking in 1980 and the change in its relative importance of manual tasks between 1977 and 2016, with higher-paying occupations becoming relatively less manual-intensive (coefficient -0.008; p-value<0.001).

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those who report positive income and working ≥ 250 annual hours. 3-digit occupations are ranked by their median wage, and assigned to percentiles according to their position in the hours-weighted distribution of employment.

3 Comparative Advantage and Occupational Sorting

Here we present a simple modeling framework to illustrate how changes in occupational sorting can result from changes in the relative importance of tasks across occupations. Let there be a high-wage and a low-wage occupation, H and L, respectively. Employment in each involves the performance of tasks requiring *social* skills and (a composite of) *other* skills (denoted by S and O, respectively). For simplicity, the importance of tasks is reflected in occupational wages:

$$W_H = \alpha_{S,H} S + \alpha_{O,H} O,$$
$$W_L = \alpha_{S,L} S + \alpha_{O,L} O,$$

by the coefficients, $\boldsymbol{\alpha} \equiv \{\alpha_{S,H}, \alpha_{O,H}, \alpha_{S,L}, \alpha_{O,L}\}$.

Workers are endowed with both social and other skills, drawn from a joint distribution $\Gamma(S, O)$. Workers make a wage-maximizing occupation choice, given their skill endowment and $\boldsymbol{\alpha}$. This results in a "diagonal cutoff" rule as depicted in Figure 2; for each value of O there is a value of S, denoted by S^*, that makes a worker indifferent between choosing occupation H or L:

$$S^* = O \times \frac{\alpha_{O,H} - \alpha_{O,L}}{\alpha_{S,L} - \alpha_{S,H}}. \tag{1}$$

For a given value of O, all workers with $S > S^*$ choose one occupation, and workers with $S \leq S^*$ choose the other. Sorting is dictated by the *relative* importance of tasks (across the two occupations) as represented by $\boldsymbol{\alpha}$. Any change in the relative importance of tasks across occupations affects occupational sorting.

To illustrate this in a parsimonious way, assume that social tasks were initially more valued in the L occupation than in H, $\alpha_{S,L} - \alpha_{S,H} > 0$, while the opposite was true for the other task, $\alpha_{O,H} - \alpha_{O,L} > 0$. This implies that for any value of O, workers were initially negatively selected on social skills to the higher paying occupation, H: those with skills in the hatched region of Figure 2 would sort into occupation L, while those with skills in the striped region would sort into H.

Consider now a change in the relative importance of social tasks, $\alpha_{S,H} - \alpha_{S,L} > 0$, such that workers are now positively selected on social skills to occupation H.[6] For graphical simplicity, assume that the location of the diagonal cutoff in Figure 2 remains the same.

[6] Without a corresponding change in the relative importance of the O tasks, all workers would sort into the H occupation. We thus proceed by assuming that a $\alpha_{O,L} - \alpha_{O,H} > 0$ change occurs, so that a sorting reversal takes place. We note that the relative importance of manual tasks indeed shows such a reversal in Figure 1.

Now workers with skills in the hatched region sort into the H occupation, and those in the striped region sort into L.

To anticipate the analysis of Section 4, we extend the model to include two types of workers, female and male (F and M). Evidence from the psychology and neuroscience literatures indicates that women have a comparative advantage in tasks requiring social and interpersonal skills.[7] To represent comparative advantage in a parsimonious way, we assume that the marginal distribution of S for women, $\tilde{\Gamma}_F(S|O)$, first order stochastically dominates that for men, $\tilde{\Gamma}_M(S|O)$, for any value of O.

A change in the relative importance of tasks as considered above would generate a change in male/female occupational sorting. Given our assumption regarding first order stochastic dominance, it follows unambiguously that the propensity of women to sort into the H occupation would rise, while the corresponding propensity for men would fall.[8] We verify these predictions below.

4 The Rise of Women in High-Paying Occupations

Did the change in the relative importance of social skill-intensive tasks induce a change in male/female occupational sorting? We first provide evidence of an increase in the propensity of women to work in high-wage occupations relative to men over the last forty years. We then show that the change in the relative propensity of women and men to sort into occupations is associated with the change in the relative importance of social tasks.

In what follows, we associate task data from the 1977 DOT (4th edition) to employment outcomes from the 5% sample of the 1980 US Census, and task data from the August 2016 release of O*NET to the 2016 American Community Survey (ACS); both the Census and ACS data are taken from IPUMS (Ruggles et al. 2018). We restrict attention to the 20-64 year old, civilian, non-institutionalized population. We exclude individuals employed in

[7] Appendix Table A.1 shows that occupational employment outcomes are consistent with female comparative advantage in jobs requiring skills in social tasks. We compute the probability of working in each 3-digit occupation for women relative to men and regress this on the occupation's task content. Both in 1980 and in 2016, women are more likely to work in occupations that are more intensive in social tasks.

[8] We note that in order for the H occupation to remain the high paying one, a sufficient condition is that the *levels* of $\alpha_{S,L}$ and $\alpha_{S,H}$ increase sufficiently relative to that of $\alpha_{O,L}$ and $\alpha_{O,H}$. See Deming (2017) for evidence of the former. Note also that a change in male/female occupational sorting can occur without requiring a reversal in selection on S skills across occupations, i.e. it can occur with only a change in $\alpha_{S,L}$ and $\alpha_{S,H}$ that alters the slope of the diagonal cutoff in Figure 2. However, such an example would require stronger assumptions on the shapes of the skill distributions, $\Gamma_F(S,O)$ and $\Gamma_M(S,O)$, and a less transparent representation of comparative advantage.

farming, forestry or fishing occupations.

Table 1 reports the propensities for men and women to be employed in occupations in the top decile of the 1980 occupational wage distribution, and its change over time. As indicated in the first column of Panel A, nearly 12% of men worked in a top decile occupation in 1980. The probability of working in these top jobs was much lower for women, at 2%. The literatures on skill-biased technical change and job polarization have documented the strong overall employment growth in these high-paying occupations (see e.g. Acemoglu and Autor 2011). However, between 1980 and 2016, the probability of working in one of these occupations *fell* by 0.8 percentage points (pp) for men, to 11%.[9] By contrast, the female propensity to work in top decile jobs more than doubled, *increasing* by 3.5 pp between 1980 and 2016.

As is well known, the female labor force participation rate and employment rate (relative to population) rose substantially over this period, while the reverse pattern for labor force participation was observed for men; the last rows of Panel A show that the employment rate of men decreased by 3.8 pp, while that of women increased by 12.2 pp. However, the rightmost columns of Table 1 show that changes in employment rates cannot account for the gender divergence in the probability of working in top decile jobs. Conditional on working, the probability of working in a top decile occupation decreased by 0.2 pp for men and increased by 4.5 pp for women, 1980–2016.

The propensity to work in a high paying occupation is obviously increasing in education. As such, the results of Panel A may be driven by the increase in educational attainment of women relative to men. As shown in Panel B, the number of college-educated workers more than doubled for men between 1980 and 2016, but it increased more than 3.5-fold for women.[10] Strikingly, between 1980 and 2016, the fraction of college-educated men working in a top decile occupation fell by 5.2 pp, much more than in Panel A. By contrast, the propensity for college-educated women to work in top decile jobs increased by 5.2 pp. The rightmost columns of Panel B indicate that, again, the gender divergence is not due to the (relative) increase in female participation.

Panel C displays the same results for non-college individuals. Again, either in the population or conditional on working, there has been a quantitatively important change in occupational choice, with women increasingly sorting into high paying occupations relative

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

[10]Given changes in the survey questionnaire over time, we define college graduates as those with at least four years of post-secondary attainment in 1980, and those with at least a bachelor's degree in 2016.

to men.[11]

In Appendix Table A.2, we perform a Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973) to determine whether the differential changes in top decile employment probability across genders can be attributed to changes in demographic characteristics, namely changes in the composition of age, race, and nativity. Our results indicate that they cannot; all of the increase in the probability of working in top decile occupation for women, and the vast majority of the decrease for men, is due to propensity change.

The divergence in gender trends is widespread throughout the US. When we disaggregate the data by state, we find that the likelihood of working in a top decile occupation increased for college-educated women in all 50 states and the District of Columbia, and fell for college-educated men in all states except South Dakota. Among those without a college degree, the probability of working in a top decile occupation increased for women in all states except Alaska, and it fell for men in all states except Alaska and South Dakota.

Table 2 illustrates the fact that the choice of the top decile cutoff for the definition of a high paying job is not crucial. The table reports the coefficient estimate on a simple bivariate linear regression. The dependent variable is the *differential* change in the probability of working in a specific occupation for women relative to men: $\Delta Prob_{jF} - \Delta Prob_{jM}$, where $Prob_{ji}$ is the probability of working in occupation j for gender i, and Δ represents the percentage point change, from 1980 to 2016. The regressor is the occupation's percentile wage rank. Columns (1) and (4) report results for all individuals, without conditioning and conditioning on working, respectively. The higher paying the occupation is, the greater is the increase in the female propensity relative to men; this is statistically significant at the 1% level. The same relationship holds for college and non-college educated individuals, as displayed in Columns (2) and (5), and (3) and (6), respectively.

The key question of interest in this section is whether women have increasingly sorted, *relative to men*, into occupations that have seen larger increases in the relative importance of social tasks; that is, whether there is a systematic relationship between the dependent variable of Table 2 and the vertical axis variable of Figure 1, Panel B. This is analyzed in Table 3. Column (1) considers the simple bivariate relationship. At the 3-digit occupation level, an increase in the relative importance of social skills is associated with an increase in the female propensity of working in that occupation relative to that of men. Occupations

[11] These gender differences are similar to those noted by Blau and Kahn (2017, Table 3), who consider managerial occupations and "male-dominated" 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."

that experienced a one standard deviation increase in social task importance compared to the average saw a female propensity change 0.475 pp greater than that for men. This relationship is clearly significant at the 1% level. We emphasize that this is conceptually distinct from Deming (2017), who shows that *overall* employment growth (without reference to gender) has been strongest in occupations with high *levels* of social task importance. By contrast, our result indicates the increased relative *sorting of women* into occupations with a greater *change* (i.e. increase) in relative social task importance.

Recall from Figure 1 that high-paying occupations also experienced a fall (relative to other occupations) in the importance of manual tasks. Column (2) of Table 3 shows, however, that women tended to disproportionately sort into occupations where the importance of manual tasks increased. This positive correlation implies that changes in manual task importance do not help us understand the rise of women in good jobs. Given the potential correlation at the occupational level between changes in the importance of social and manual tasks, Column (3) controls for changes along both dimensions jointly. The sign of the coefficient estimates are unchanged relative to the bivariate specifications of Columns (1) and (2). Again, changes in manual importance have not contributed to the rise of women in high-paying jobs, whereas changes in social task importance have.

Finally, Column (4) of Table 3 shows that our key result is robust to controlling for changes in all other task importance measures. The estimated coefficient on the change in social task importance remains positive and statistically significant, with point estimate essentially unchanged. The coefficient estimates on the changes in cognitive and routine task importance are statistically significant at conventional levels. But recall from Figure 1 that these change are not systematically related to occupational wage rankings, so do not help us understand the rise of women in good jobs. Columns (5) and (6) indicate that these patterns also hold separately for the college and non-college education groups.

To summarize, the finding that women have disproportionately sorted into occupations where the relative importance of social tasks has increased is robust. Note that the R-squared in Column (1) implies that changes in the importance of social tasks can explain nearly 20% of the variation in relative sorting patterns. The R-squared in Column (2), meanwhile, implies that changes in the importance of manual tasks explain less than 2% of this variation. Analogous bivariate regressions with changes in the importance of cognitive and changes in the importance of routine tasks as controls exhibit R-squared values of 0.01, and 0.03, respectively. This confirms the predominant explanatory power of changes in the importance of social tasks in driving relative sorting. Given that the importance of social tasks has increased disproportionately in high-paying occupations, our results indicate that these changes help account for the rise of women in these jobs.

An alternative hypothesis for why women have disproportionately sorted into good jobs would be related to changes in discrimination. While there has been much work documenting changes in the gender wage gap, directly measuring discrimination is challenging, as discussed by Blau and Kahn (2017). Moreover, testing the hypothesis that women have disproportionately sorted into good jobs due to changes in discrimination is similarly, if not more challenging. In a regression framework, as we consider in Table 3, one would need to measure changes in discrimination that are occupation-specific.[12] We are not aware of any measure of discrimination change that varies across occupations. While we cannot rule out that changes in discrimination may have contributed to the rise of women in good jobs, our results suggest that changes in the task content of occupations, and in particular changes in the importance of social tasks, have also played an important role.

Reverse Causality? A 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 information 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). But it is possible that when DOT experts analyze an occupation, they may spuriously infer that social skill-intensive tasks 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 measure of the occupational tasks employers demand and its change over time. 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 by translating job ad titles to Standard Occupational Classification (SOC) codes, and grouping keywords in the job ad according to their meaning. By doing so, Atalay et al. (2018) generate measures of

[12] An across-the-board fall in discrimination could account for rising female participation, but it would not account for the change in occupational choice that we have documented. Blau and Kahn (2017) have found that the gender pay gap has declined much more slowly at the top of the wage distribution than at the middle or the bottom, which may be interpreted as suggestive evidence that discrimination has, if anything, declined less in high-paying occupations. In their case study on University of Michigan Law School graduates, Noonan, Corcoran, and Courant (2005) find that the discrimination effect on the gender wage gap for this group has remained largely constant over time. For analysis that assumes varying discrimination change at the occupational level, see Hsieh et al. (2019).

advertised task demands and requirements at the occupational level.[13] 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.[14]

In the final two columns of Table 3 we consider the same regression specification as in Column (4), solely replacing our benchmark measure of changes in the importance of social tasks based on the DOT and O*NET data with measures based on the job ad data, 1980–2000.[15] The measure used in Column (7) is analogous to the social skill measure used by Deming and Kahn (2018), 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. The results show that changes in the demand for social tasks within an occupation are again positively associated with changes in women's differential propensity to sort into the occupation.[16] Finally, Column (8) uses 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 these words are deemed to be related to the original Deming and Kahn (2018) set of words through a machine learning algorithm. Using this alternative measure, our key result remains: an increase in the importance of social skill-intensive tasks is associated with a differential increase in an occupation's female employment propensity (relative to men).

As a final piece of evidence against reverse causality, we consider occupational wages. Suppose the change in the social task index of an occupation does not reflect a true change in the importance of social tasks. Instead, assume it merely reflects a change in the female employment share in that occupation relative to others. All else equal, if the supply of women to an occupation increases, with no increase in the demand for the tasks that they provide, we would expect female occupational wages in that occupation to fall. Hence, if

[13] 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`. 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 task index for 1980 and 2000 using five year averages (1976-1980 and 1996-2000, respectively), and generate the change in the importance of social tasks across the two periods.

[14] 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.

[15] Since the time period differs, we compute the measures of changes in manual, cognitive and routine task importance using data from the 1977 DOT and the 2002 O*NET (instead of the 2016 O*NET), and use differential propensity changes across the 1980 and 2000 Census as the dependent variable.

[16] The magnitude of the coefficient estimates cannot be compared with those in Columns (1) to (6) given that the way in which the explanatory variable is measured differs.

the changes in the social task index merely reflected changes in female labor supply, we would expect female occupational wage premia to be *negatively correlated* with changes in the social task index.

To test this, using data for female workers only, we estimate wage premia for each 3-digit occupation 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. We then regress the change in the estimated wage premiun in each occupation on the within-occupation change in the social task index between 1977 and 2016. Rather than being negative, the coefficient estimate is positive at 0.069 and statistically significant at the 1% level (p-value<0.001). Adding controls for changes in the cognitive, routine, and manual task measures increases the coefficient on social tasks slightly to 0.071 (p-value<0.001). Hence, increases in the relative importance of social tasks are associated with *increases* in relative female wages across occupations between 1980 and 2016. As such, we do not find evidence that the increase in the social task index, as measured in the DOT and O*NET, merely reflects an increase in the relative employment of women.

5 Conclusions

Our analysis shows that an occupation's position in the wage distribution is systematically and positively related to the relative change in importance of tasks requiring social skills. Based on a simple model of occupational choice, we show that such a change can lead to changes in the sorting of individuals based on their comparative advantage. We provide empirical evidence indicating that the relative increase in the importance of social tasks over the past four decades is associated with increases in the propensity of females to work in higher paying occupations relative to males.

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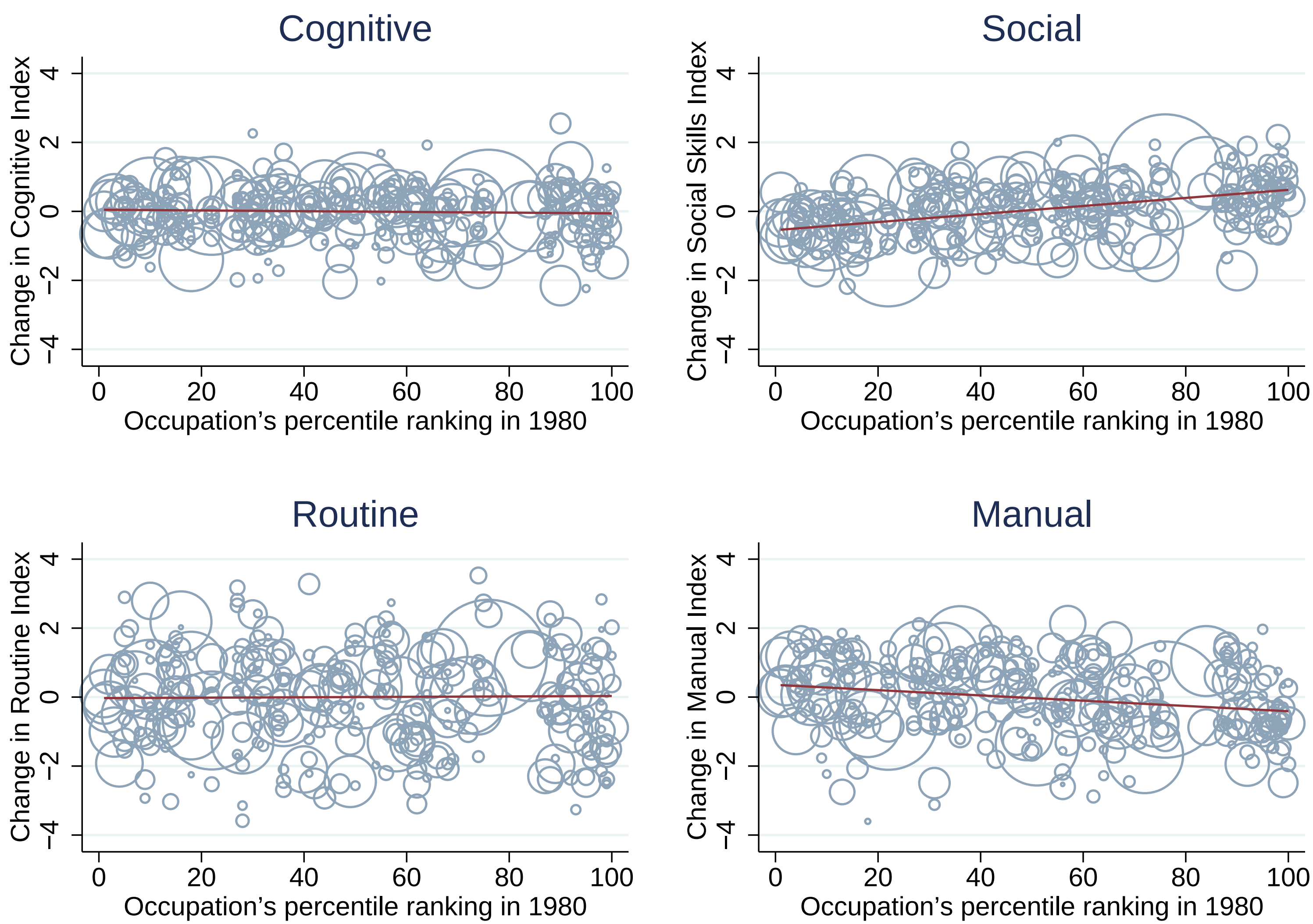
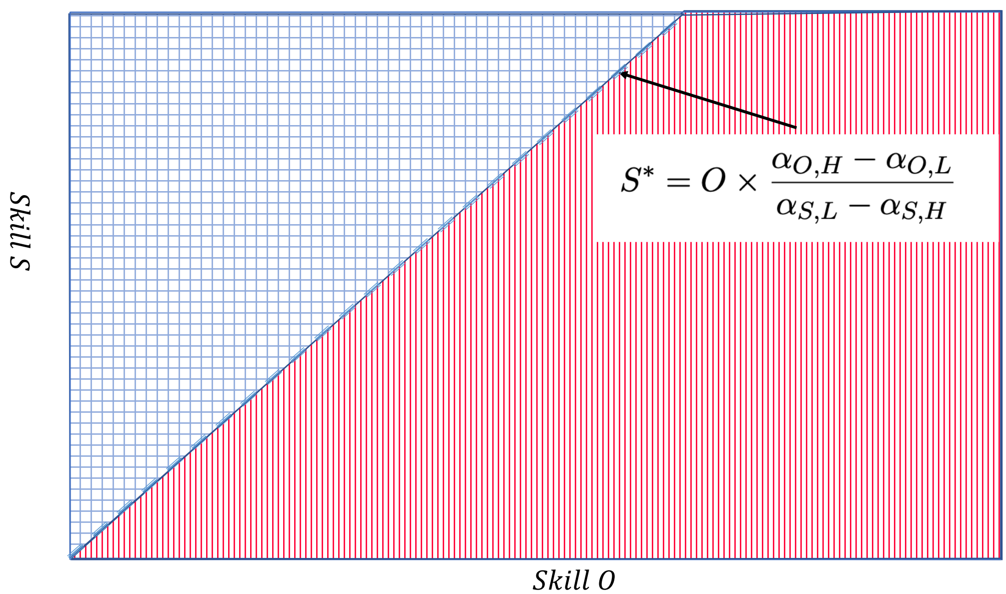
Figure 1: Occupational Changes in Task Ranking (1977-2016) along the Occupational Wage Distribution (1980)



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

Figure 2: Occupational Sorting by Social and "Other" Skills



Notes: Workers sort across occupations following a "diagonal cutoff" rule. In the initial equilibrium, workers in the hatched (striped) region choose occupation L (occupation H). In the subsequent equilibrium, after the change in the relative importance of tasks involving social skills, workers in the hatched (striped) region choose occupation H (occupation L).

Table 1: Occupational and Employment Status: 1980–2016

	1980	2016	Change	Conditional on Working 1980	Conditional on Working 2016	Conditional on Working Change
A. All						
Male (000's)	*58814*	*91142*		*48549*	*71744*	
Top 10%	11.8	11.0	−0.7	14.2	14.0	−0.2
Bottom 90%	70.8	67.7	−3.1	85.8	86.0	+0.2
Not Working (%)	17.5	21.3	+3.8			
Female (000's)	*65221*	*95698*		*36847*	*65780*	
Top 10%	2.0	5.5	+3.5	3.5	8.0	+4.5
Bottom 90%	54.5	63.2	+8.7	96.5	92.0	−4.5
Not Working (%)	43.5	31.3	−12.2			
B. College						
Male (000's)	*11982*	*26580*		*11035*	*23513*	
Top 10%	29.6	24.4	−5.2	32.1	27.6	−4.5
Bottom 90%	62.5	64.1	+1.6	67.9	72.4	+4.5
Not Working (%)	7.9	11.5	+3.6			
Female (000's)	*8874*	*31561*		*6457*	*25077*	
Top 10%	7.5	12.7	+5.2	10.3	15.9	+5.6
Bottom 90%	65.3	66.8	+1.5	89.7	84.1	−5.6
Not Working (%)	27.2	20.5	−6.7			
C. Non-College						
Male (000's)	*46832*	*64562*		*37514*	*48232*	
Top 10%	7.2	5.5	−1.7	9.0	7.4	−1.6
Bottom 90%	72.9	69.2	−3.7	91.0	92.6	+1.6
Not Working (%)	19.9	25.3	+5.4			
Female (000's)	*56347*	*64137*		*30390*	*40702*	
Top 10%	1.1	2.0	+0.9	2.1	3.2	+1.1
Bottom 90%	52.8	61.5	+8.7	97.9	96.8	−1.1
Not Working (%)	46.1	36.5	−9.6			

Notes: Labor Force statistics, 20-64 year old, civilian, non-institutionalized population, excluding individuals employed in farming, forestry or fishing occupations. Data from 1980 Census and 2016 ACS. Employment categorized by ranking in occupational wage distribution of 1980. See text for details.

Table 2: Correlation Between Female-vs-Male Employment Probability Changes by Occupation (1980-2016) and Occupational Wage Ranking (1980)

	Propensities			*Cond on Working*		
	All	*College*	*Non-College*	*All*	*College*	*Non-College*
	(1)	(2)	(3)	(4)	(5)	(6)
Occup Rank	0.013***	0.009***	0.009***	0.020***	0.007*	0.016***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Observations	312	312	300	312	312	300
R^2	0.182	0.032	0.086	0.168	0.009	0.090

Notes: Observations are at the occupation level, weighted by their aggregate employment share in 1980. The dependent variable is the differential change in the probability of working in a particular occupation for women relative to men between 1980 and 2016. Occupations are ranked by their median wage in 1980 and assigned to percentiles according to their position in the hours-weighted distribution of employment in that year.

Table 3: Differential Change in Occupational Employment Propensities for Women Relative to Men

	1980–2016						1980–2000	
	Full Sample				*Non-College*	*College*	*Newspaper*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Social	0.475***		0.468***	0.533***	0.454***	0.756***		
	(0.056)		(0.056)	(0.055)	(0.057)	(0.099)		
Δ Social (DK)							2.065***	
							(0.733)	
Δ Social (Extended)								1.389***
								(0.466)
Δ Manual		0.125**	0.104**	0.108**	0.195***	0.308***	-0.040	-0.034
		(0.051)	(0.046)	(0.043)	(0.045)	(0.079)	(0.040)	(0.040)
Δ Cognitive				-0.346***	-0.339***	-0.351***	-0.038	-0.047
				(0.069)	(0.072)	(0.125)	(0.066)	(0.066)
Δ Routine				0.126***	0.128***	0.210***	0.130***	0.132***
				(0.036)	(0.037)	(0.065)	(0.034)	(0.034)
Observations	312	312	312	312	300	312	307	307
R^2	0.189	0.019	0.202	0.289	0.264	0.225	0.068	0.071

Notes: The dependent variable is the differential change in the probability of working in a particular occupation for women relative to men between 1980 and 2016 in Columns (1) to (6) and between 1980 and 2000 in Columns (7) and (8) based on Census and ACS data. The regressors in Columns (1) through (6) are based on occupational task characteristics from the 1977 Dictionary of Occupational Titles and the 2016 O*NET. The social task indices in Columns (7) and (8) are based on newspaper ad data from Atalay et al. (2018). Controls for other task changes in Columns (7) and (8) are based on the 1977 Dictionary of Occupational Titles and the 2002 O*NET. Occupations are weighted according to their share of aggregate employment in 1980.

Online Appendix for:

The Growing Importance of Social Tasks in High-Paying Occupations: Implications for Sorting

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Nir Jaimovich (University of Zurich and CEPR)
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A Data Appendix and Additional Results

Following Autor, Levy, and Murnane (2003), 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 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).

To construct a measure of the importance of social tasks 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 tasks:

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.[1]

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 tasks 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.

We use information from the 4th Edition of the DOT, published in 1977, and made available through the Interuniversity Consortium for Political and Social Research (ICPSR 1981; ICPSR 1991). Regarding O*NET, we rely on information from the August 2016 release (O*NET version 21.0), whish is available at `https://www.onetcenter.org/db_releases.html`.

DOT-77 has its own occupational coding scheme, which is much more disaggregated than the Census Occupation Code (COC) classification. In order to aggregate the information to the COC level, we follow an approach similar to Autor, Levy, and Murnane (2003).

[1] 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).

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 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 task measure is generated by adding the (rescaled) scores for the four temperaments listed above. 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 Employment Statistics (OES) dataset, which provides data on employment by occupation at the SOC code level.[2]

3. We use crosswalks from the Census Bureau and from O*NET to map SOC-2010 codes to 2010 Census Occupation codes.

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

[2]We use national-level data from the 2016 OES. 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.

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 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.

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. 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.

Table A.1: Relative Female-to-Male Employment Probability (Conditional on Working) and Occupational Tasks

	1980	1980	2016
	(1)	(2)	(3)
Social	0.613	1.505	0.75
	(0.153)***	(0.129)***	(0.158)***
Cognitive		-1.149	-1.199
		(0.121)***	(0.14)***
Routine		1.534	0.241
		(0.119)***	(0.109)**
Manual		-.667	-.573
		(0.115)***	(0.121)***
Obs.	312	312	312
R^2	0.05	0.518	0.246

Notes: Data on employment probabilities from the 1980 decennial census and the 2016 American Community Survey. Data on 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.

Table A.2: Probability of Working in Top Decile Occupations: Oaxaca-Blinder Decomposition

	Prob Top Decile		Percentage Point Difference		
	1980	2016	Total	Explained	Unexplained
Males	11.8	11.0	−0.7	−0.5	−0.2
Females	2.0	5.5	+3.5	−0.3	+3.8
College Males	29.6	24.4	−5.2	+0.1	−5.4
College Females	7.5	12.7	+5.2	−0.1	+5.3
Non-College Males	7.2	5.5	−1.7	−0.5	−1.2
Non-College Females	1.1	2.0	+0.9	−0.2	+1.0

Notes: Labor Force statistics, 20-64 year old, civilian, non-institutionalized population, excluding individuals employed in farming, forestry or fishing occupations. Data from 1980 Census and 2016 ACS. Employment categorized by ranking in occupational wage distribution of 1980. The explanatory variables for the Oaxaca-Blinder decomposition are age (nine 5-year bins), race (dummies for black, Hispanic, and other non-white) and nativity (dummy for whether native-born). See text for details.

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

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
349	348
415	423

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