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Gender, occupational segregation, and automation

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1. Introduction

It is a widely-accepted fact that automation, and other forms of technological change, has and will continue to transform the nature of work and the range of tasks that workers are engaged in. At the same time, given that occupational differences by gender remain a persistent feature of labor markets, a natural question is how automation will differentially affect the labor market prospects of men and women. A clearer understanding of the interaction between automation, occupational segregation, and gender gaps in skill acquisition and job transitions, will enable more directed policy responses to alleviate the potentially distinct set of challenges that male and female workers are likely to face.

In this framing paper, we begin by reviewing existing measures of occupation-level automation risk and trends in occupational segregation in the U.S. labor market. Next, we discuss the findings of recent papers that have sought to quantify the risk of automation separately for men and women in the medium term, based on existing patterns of occupational segregation and occupation-level estimates of the probability of automation (Section 2). These studies tend to emphasize the displacement risks associated with automation; however, the overall impacts of automation depend crucially on the extent to which workers are able to transition out of the affected occupations to growing sectors of the economy (perhaps due to automation). To provide a better sense of the impact of automation on the labor market prospects of men and women, in Section 3, we examine the recent past (from 1980 to 2017) and provide a descriptive account of how automation has differentially affected the employment of men and women across occupations. We also examine how trends in the risk of automation over time differ by gender. In Section 4, we speculate on what the future of automation entails and discuss several reasons why we expect the next automation wave to pose more of a challenge for men relative to women. Section 5 concludes and provides some suggestions for future areas of research.

2. Gender Differences in the Exposure to Automation Risk

2.1 Measuring Occupation-Level Automation Risk

Measures of automation risk essentially seek to quantify the ease with which machines are able to substitute for the work activities performed by workers. In their seminal paper, Autor, Levy, and Murnane (2003) pioneered the use of a task-based approach to determine which occupations and jobs are most likely to be disrupted by automation. Their approach has several key features. First, it explicitly distinguishes tasks from skills – in particular, a job can be characterized by a bundle of tasks, and workers with different skill endowments perform these tasks within a job. Tasks vary in terms of how easily they can be substituted for by machines while skills are embodied within workers and can be ported to other jobs with differing task compositions (Muro, Maxim, and Whiton, 2019). Within this framework, Autor et al. (2003) identify "routine" tasks as those at greatest risk of automation since these activities are sufficiently well-defined and can be executed by machines following a set of preprogrammed rules. On the other hand, non-routine tasks that require situational adaptability, problem solving, intuition, and in-person interaction or persuasion, are functions that cannot be easily codified, and hence, be replaced by machines (at least given current technological limitations). Importantly, the set of non-routine tasks can be either manual or abstract in nature, and are likely to span both ends of the occupational distribution (e.g. truck drivers and janitors vs. health practitioners and lawyers).

Based on the task-based model, Autor and Dorn (2013) propose a measure of an occupation's Routine Task Intensity (RTI) which captures the idea that occupations that require high levels of routine work but include few abstract or manual tasks face a greater risk of automation. Specifically, the RTI for each occupation is defined as follows:

$$RTI = \ln(T_R) - \ln(T_M) - \ln(T_A)$$

where T_R, T_M, and T_A, respectively, refer to the measure of routine, manual, and abstract tasks required of each occupation at a given point in time. The levels of routine, abstract and manual tasks are typically extracted from various sources, including the Dictionary of Occupational Titles (DOT) by the U.S.

Department of Labor (e.g. Autor and Dorn, 2013), the Occupational Information Network (O*NET) (e.g. Deming, 2017), and the Program for the International Assessment of Adult Competencies (PIAAC) survey (IMF, 2018).

Several studies argue that the routinization measure developed by David Autor and his co-authors is likely to underestimate how susceptible jobs are to computerization, given the potential capabilities of current and future technology. A notable example is Frey and Osbourne (2013), who propose a forward-looking approach to expanding the set of tasks that computers are suited to accomplish, drawing on recent advances in machine learning and machine robotics. In their working paper, the authors use a two-stage process to determine how susceptible an occupation is to automation. First, by relying on the descriptions of specific tasks available in the O*NET database, the authors, together with a group of ML researchers, subjectively hand-labelled 70 occupations based on whether the occupation was deemed to be fully automatable or not.[1] Next, the authors extract the O*NET ratings for the full sample of occupations based on nine specific job characteristics that they deem to be bottlenecks to computerization. These variables capture the level of perception and manipulation, creative, and social intelligence required to perform the work activities in an occupation. Finally, a probabilistic model is used to impute the probability of automation based on relating the hand labels to the nine O*NET characteristics, and extrapolating this information to obtain the predicted probabilities of automation for the full sample of 702 occupations. Based on this exercise, Frey and Osbourne (2013) estimate that close to half of all U.S. employment is at risk of automation within the next 10 to 20 years.

While Frey and Osbourne's (2013) estimates highlight the potentially far-ranging impacts of automation on the labor market, researchers have questioned the validity of their underlying assumptions. In particular, echoing the "task approach," several researchers argue that since automation usually affects tasks rather than whole occupations, the potential for automating entire occupations and workplaces are likely to be much lower than suggested by Frey and Osbourne's occupation-based

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1. [1] Occupations were labeled based on the following question: "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer-controlled equipment". Occupations were assigned as fully automatable if the researchers were confident that all tasks within that occupation could be automated (allowing for the possibility of task simplification).

approach (Arntz, Gregory, and Zierahn, 2016).[2] In a similar vein, using a procedure that also draws on task descriptions from O*NET, the McKinsey Global Institute (MGI) instead focuses on the complexity of tasks within occupations to calculate the "technical automation potential" of each occupation. In particular, the MGI researchers use a machine learning algorithm to map the work activities in a given occupation to 18 performance capabilities, based on the degree of sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities to perform each task. The ability of existing technologies to perform such activities are similarly assessed. Using this approach, McKinsey estimates that close to 50 percent of current work activities have the potential to be automated based on current technological know-how. In terms of susceptibility to automation at the occupation-level, they estimate that less than 5 percent of occupations can be fully automated. However, in 60 percent of occupations, at least 30 percent of the activities are at risk of automation.

While it is clear that automation will change the distribution of tasks within and across occupations, there remains a lack of strong consensus on the overall impact of automation on worker displacement. This reflects uncertainty both over what tasks technology can and will replace, as well as the extent to which automation would lead to growth opportunities in other occupations and sectors by complementing certain types of tasks. As much as automation has the potential to replace a wide-ranging set of tasks, it could raise the value of non-routine tasks that require a high degree of problem-solving, adaptability, and creativity (Autor, 2015). In addition, in the short run, the overall effects of automation on workers' employability and wages will also depend on how easy it is for workers to transition from the affected jobs to other types of work.

2.2 Existing Literature on Occupational Segregation and Gender Differences in Automation Risk

In this section, we consider the gender implications of occupational differences in the risk of automation. A notable feature of the labor market is that in spite of converging labor market roles, in part due to

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2. [2] 2 Using the task-based approach and individual-level data worker tasks from the Programme for the International Assessment of Adult Competencies (PIACC) Survey, Arntz et al. (2016) find that nine percent of U.S. jobs are at risk of automation.

women's progress in educational attainment and labor market attachment, occupational segregation remains a persistent feature of labor markets around the world. A commonly used summary measure of occupational segregation in a given market is the index of segregation developed by Duncan and Duncan (1955). The index, which ranges between 0 and 1, indicates the proportion of women or men that would need to change occupations for the occupational distribution of men and women to be the same. Blau et al. (2013) provide a systematic analysis of the trends in occupational segregation by gender from 1970 to 2009 in the U.S. labor market. As observed in Figure 1 (reproduced from Cortes and Pan (2018) based on Table 2 in Blau et al. (2013)), while there has been a large overall decline in the segregation index in the U.S. from 1970 to 2009, in the last two decades, the pace of gender integration appears to have slowed considerably. Moreover, as of 2009, the degree of occupational segregation remains relatively high at just above 0.5.[3]

The fact that men and women continue to work in very different occupations in the U.S. labor market can also be seen in the last two columns of Table 1, which report the share of women across 22 broad occupational categories between 1980 and 2017. In 2017, women continue to be over-represented (>60% female share) among education professionals, health technicians, health support services, food preparation and household/personal services, as well as clerical occupations. Men, on the other hand, are over-represented (>60% male share) among managers/lawyers, management-related occupations, STEM and non-education professionals, non-health technicians, building maintenance occupations, protective services, transportation, precision production occupations, construction trades, mechanics/repairers, and laborers. Nevertheless, what is also evident from Table 1 is that women have made considerable headway in entering some previously male-dominated occupations over the past four decades, in particular professional and technical occupations. Examples include managers and lawyers (17 percentage points (pp) increase in female share), management-related occupations (19 pp), STEM and social science occupations (15 pp), non-health technicians (10 pp), and protective services (12 pp).

To understand the forces driving the observed decline in occupational segregation in Figure 1, it is useful to distinguish changes in sex composition within occupation (e.g. women entering male-dominated

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3. [3] According to Massey and Denton (1993), an index of segregation of 0.3 and below is considered low, between 0.4 and 0.6 is considered moderate, and above 0.6 is considered high.

occupations and vice versa) from shifts in the occupation mix of the economy (e.g. changing occupational structure of the economy away from predominantly male or predominantly female occupations). Blau et al. (2013) document that both the sex composition and occupation mix effects accounted for the reductions in occupation segregation in each decade from 1970 to 2000. However, in the 2000s, the sex composition effect accounted for the bulk of the modest reduction in segregation.

Since occupations can be viewed as a bundle of tasks, and tasks vary in terms of their susceptibility to automation, men and women are likely to face different risks of automation by virtue of the fact that they work in different occupations and work in different jobs, even within similar occupations. Several recent papers have attempted to quantify the risk of automation separately for men and women in the medium term, based on the current employment distribution of men and women across occupations, and occupation-level estimates of the probability of automation in the next one to two decades (e.g. Frey and Osbourne (2013) or the McKinsey Global Institute (2019)). Based on this approach, these studies typically arrive at some headline number of estimated job disruptions that women and men are likely to experience.

Estimates from the Institute for Women's Policy Research and MGI indicate that in the U.S., a large proportion of workers are at risk of losing their jobs due to automation, with women facing a slightly higher risk of automation, due in large part to their greater representation in occupations most susceptible to automation (Hegewisch et al., 2019; Madgavkar et al., 2019). Across studies, however, the estimates of job displacement are wide-ranging; this is not entirely surprising since these exercises can be based on very different predictions about the automation potential of an occupation. For example, as discussed in the previous section, different studies use varying sources of task data, criteria, assumptions, and procedures to determine how likely an occupation can be automated.

While automation will certainly displace some tasks (and perhaps whole occupations), it is also well recognized that technological innovations hold the potential for creating new job opportunities by complementing tasks that are not easily substitutable by machines (e.g. those that are intensive in analytical and interpersonal task inputs). Moreover, the overall impacts of automation on the labor market will also depend on how easily workers are able to transition out of declining occupations to growing sectors of the labor market that offer stronger employment prospects.

To provide an overall sense of the potential impact of automation on men and women's employment, it is instructive to examine how widespread technological changes in the 1980s to 2010s differentially affected men and women, and their corresponding responses in terms of re-allocation across employment sectors and skill acquisition. A careful exploration of how men and women were affected and how they reacted to technological changes in the labor market in the recent past can inform predictions about how they are likely to fare in the future and help to identify policy levers to ease the transitions.

3. Assessing automation's impact on employment by gender: Descriptive evidence based on the recent past

In this section, we turn to an examination of trends in men and women's employment across occupations over the past four decades between 1980 and 2017 to provide a descriptive account of how automation has differentially affected men and women's job opportunities. In particular, we will focus on (1) the displacement of men and women from certain occupations, (2) how each gender has responded in terms of reallocation across employment sectors, and (3) the mechanisms that could account for the observed gender differences in the response to automation.

3.1 Data Sources and Measurement

We use data drawn from the 1980, 1990, and 2000 U.S. Census and the three-year aggregates of the 2007 (2005 to 2008) and 2017 (2016 to 2018) American Community Survey (ACS).[4] For most of our analysis, we restrict the sample to individuals aged 18 to 64 who are currently employed in the civilian labor force at the time of the survey and reported an occupation.[5] Labor supply is measured as weeks worked multiplied by the usual number of hours worked per week.[6] In analyses where we aggregate the individual-level data to the occupation-level outcomes, we weight each occupation using the product of Census person weights and annual labor supply. To calculate hourly wages, we divide annual labor income

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4. [4] The U.S. Censuses are 5 percent samples, while the three-year aggregate ACS samples cover about 3 percent of the population (the yearly ACS covers 1 percent of the U.S. population).

5. [5] We drop workers in Agricultural Occupations.

6. [6] Starting in 2008, the Census stopped providing the continuous measure of weeks, and instead reports ranges of weeks worked. We use the most common number in the range reported in previous Censuses.

by the product of weeks per year and hours per week.[7] Throughout, full-time, full-year (FTFY) workers are defined as those working at least 35 hours per week and 52 weeks per year. Finally, to ensure that we have a consistent set of occupations over the sample period, we use Dorn's (2009) occupational classification to create a balanced panel of occupations from 1980 to 2017.[8] In the analyses that follow, we adopt Autor and Dorn's (2013) measures of an occupation's routine, abstract, and manual task inputs, as well as a slight modification of the routine-task intensity (RTI) summary index as proxies for the degree to which an occupation is susceptible to computerization or automation. Our preferred RTI measure is defined as:

$$RTI = \ln(T_R) - \ln(\max\{T_A, T_M\})$$

We choose to specify the RTI measure in this way to capture the idea that for occupations with similar routine-task content, an occupation that is high in *either* manual or abstract tasks uses routine tasks less intensely (in a relative sense). Like the Autor and Dorn (2013) measure, our preferred measure is also rising in the importance of routine tasks in an occupation and declining in importance of manual and abstract tasks. The main advantage of specifying the RTI measure in this way is that it circumvents potential issues that might arise when occupations have particularly low levels of manual or abstract task content. For example, using the Autor and Dorn formulation, lawyers and judges are in the top decile of occupations with the highest RTI. This is because despite having a relatively low routine task index (1.41, average of 4.47) and high abstract task index (3.31, average of 2.98), the manual task index is very close to zero (0.002, average of 1.19).

3.2 Occupational Segregation and Gender Gaps in Automation Risk

As discussed in the previous section, there is large heterogeneity across occupations in the share of its workers who are female and occupational differences between men and women remain persistent over time. To examine how occupational segregation translates into gender differences in the exposure to automation risk at the beginning of our sample period, we use a locally weighted smoothing regression to

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7. [7] Following Autor (2015), we multiply the 1980 top code by 1.4 and drop observations with hourly wages lower than 25% of the federal minimum wage.

8. [8] We extend Dorn's (2009) crosswalk using Deming's (2017) crosswalk from 2010 onwards.

plot the task requirements of an occupation by their percentile in the distribution of the female shares in 1980. Figure 2A shows a clear U-shaped relationship between an occupation's routine task inputs and the degree of female representation in an occupation. Occupations at both ends of the distribution of female share in 1980 have high routine task inputs, particularly female-intensive occupations at the top-decile (those with female share higher than 89 percent). Routine tasks are lowest in occupations with around the median share of females (25 percent). Conversely, occupations around the median of female concentration have the highest requirements of abstract tasks. Finally, manual task inputs are a decreasing function of female concentration in an occupation, with highly male-dominated occupations also the most manual intensive.

Figure 2B uses our preferred summary measure of the RTI of an occupation to proxy for an occupation's risk of being automated (solid line). The relationship between automation risk and the 1980 female share percentile in an occupation is U-shaped, mirroring the patterns for routine task intensity in Figure 2A. To get a sense of the types of occupations that men and women are moving into and out of over time, Figure 2B also plots the smoothed 1980 to 2017 change in an occupation's employment share of men and women, separately, by the female share percentile in 1980. We observe that over the past four decades, women moved out of female-intensive occupations to occupations in the middle of the 1980 female share distribution. As will be explored in greater detail later, most of the affected female-intensive occupations are clerical occupations. Moreover, there is a striking negative correlation between changes in female employment share and the risk of automation. A comparison of Figures 2A and 2B reveals that women have moved out of occupations with high routine task inputs to occupations with high abstract task inputs. The employment changes for men (green line) are more muted. While they have disproportionately moved into female-intensive occupations, these changes have been quite small. Consistent with previous work (e.g. Blau, Brummund, and Liu, 2013), the gender differences in the patterns of employment change imply an overall decrease in occupational segregation over this period.

That automation may result in a more gender integrated labor market is further bolstered by the fact that gender-integrated occupations have the lowest RTI levels, and appear to be least at risk for automation. Nevertheless, whether or not these patterns of employment change ultimately lead to an overall decline in occupational segregation depends crucially on whether the entry of women into gender integrated and/or majority male occupations results in occupational tipping and re-segregation (Pan, 2015).

Another interesting feature of Figure 2 that is worth highlighting is that automation risk appears to increase for women in jobs female-intensive occupations (> 60% female share in 1980). This is suggestive of the possibility that an occupation's risk of automation may be endogenous to the gender composition of an occupation. Goldin (2013) outlines a "pollution" model of discrimination whereby female entrants into an occupation may convey information that the job has undergone a negative productivity shock, even if it has not. If the employers perceive that female jobs require less skill and are more easily substitutable, this may accelerate the process of technological adoption. While purely speculative at this point, the possibility of endogenous automation is an area that warrants further research.

Figure 2 provides a clear visualization of the correlation between automation risk, female intensity in an occupation, and changes in the occupational distribution over time. However, from these figures, it is not apparent which occupations are driving the observed patterns. Therefore, we turn to occupation-level (3-digit) scatterplots of the relationship between our preferred measure of RTI and female share in 1980 (Figure 3) and the relationship between the 1980 to 2017 change in employment share for women and the RTI index (Figure 4). In these figures, the size of the occupation is proportional to the area of the marker. In 1980, women are heavily concentrated in a few occupations: clerical occupations (the largest circle represents secretaries), teachers (primary and secondary), nurses and health aides, and in management occupations.[9]

Figure 3 shows a strong positive correlation between RTI and the female share in the occupation, suggesting that in 1980, females were at greater risk of being affected by routine-replacing technological change.[10] In particular, clerical occupations, which accounted for 30% of total female employment in 1980 faced among the largest automation risks in 1980. When we use working in an occupation in the top tercile of the RTI distribution as a measure of being at risk of losing a job to automation, we find that in 1980, 44 percent of female workers, but just 26 percent of male workers were in this group.

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9. [9] The largest circle within the group of management occupations represents managers that are not elsewhere classified.

10. [10] The regression coefficient is 1.46 with a standard error of 0.4.

Supporting the view that occupations with high levels of routine task input relative to manual or abstract tasks are more likely to be affected by technological change, we find a strong negative relationship between an occupation's RTI index in 1980 and the change in female employment share from 1980 to 2017 (Figure 4A). Notice, however, that there are some occupations such as registered nurses (RNs) and health aides that are well above the regression line, suggesting that other factors – such as the increase in demand for healthcare in this case – are also important drivers of changes in the occupational distribution. In a similar vein, the observed decline in female employment in clerical occupations is significantly larger than would be predicted based on the occupations' task requirements, implying that women may have been moving out of these occupations for reasons other than automation (e.g. declining barriers to entering professional occupations, increases in women's educational attainment). As observed in Figure 4B, the same graph for men shows a similarly negative, but much flatter relationship.

To further distinguish employment changes due to automation from reductions in gender-based occupational segregation, we estimate a series of regression models that relate the 1980 to 2017 change in the occupational employment share to the female share in the occupation in 1980 and measures of occupational task inputs. Column (1) of Table 2 reports the results from regressing the change in the occupational employment share of women on the female share in an occupation in 1980 and separate indexes for routine, abstract, and manual task inputs. We find that the strongest predictor of women leaving an occupation is a high routine task index. The coefficients for the abstract and manual task indexes are positive, albeit imprecisely estimated. Column (2) replaces the three separate task indexes with the summary RTI measure. Controlling for an occupation's female share, there is a significant negative association between the change in employment share of females in an occupation and the RTI index. Although the estimates of female share in Columns (1) and (2) are marginally insignificant, the large and negative point estimates provide suggestive evidence that the female flight from female-intensive occupations is not entirely driven by occupational differences in task requirements.

Column (3) shows that the relationship between the RTI index and female changes in employment at the occupational-level is robust to excluding clerical occupations. Notwithstanding, the negative coefficient on female share is largely due to the female flight from clerical occupations. Once those occupations are excluded from the regression, the magnitude (and statistical significance) of the coefficient on female share in an occupation is reduced considerably.[11] While we can only speculate on possible explanations for women's flight from clerical occupations (for reasons unrelated to automation and occupational task requirements), some possibilities include changes in the barriers women face in choosing other careers such as changes in gender norms (Goldin, 2006; Fernandez, 2013), the pill (Goldin and Katz, 2002; Bailey, 2006), technological changes in household production and childrearing (Greenwood, Seshadri, and Yorukoglu, 2005; Albanesi and Olivetti, 2016), and secular demand shifts that favored women in clerical work (Goldin, 1990).

The corresponding analysis of changes in the male occupation distribution shown in Columns (4) to (6) of Table 2 points to two interesting patterns. First, men are moving towards more female-intensive occupations, and this trend cannot be explained by variation in occupational task requirements. If anything, we would have expected men to move away from female-intensive occupations given their higher risk of automation. Again, this suggests that there are other important factors driving the observed changes in the employment distribution, and that these factors generally work in the direction of reducing occupational segregation. Second, although the coefficient on the RTI index is negative, the magnitude of the point estimate suggests a much lower sensitivity of male employment to automation risk.

3.3 Gender differences in changes in the occupational distribution from 1980 to 2017

We documented that workers, especially women, disproportionately shifted out of routine-intensive occupations. In this section, we explore whether men and women (both existing workers and new cohorts) differed in terms of which occupations they entered. To facilitate this analysis, we aggregate the 3-digit occupations into 22 groups and examine occupational characteristics and changes in employment share at this level. Table 1 reports, for each occupation group, the observed change in employment share from 1980 to 2017 by gender, and selected characteristics in 1980 and 2017 (i.e. task requirements, wages, female share, and overall employment share).

Focusing first on women, we observe a very large decline (close to 20 pp) in the share working in nonprofessional and non-technical occupations with high RTI (those in the top-half of RTI in 1980 among

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11. [11] This is consistent with the large negative residual of clerical occupations as observed in Figure 4A.

non-professional and non-technical occupations). Most of this decline is accounted for by clerical occupations and machine operators and assemblers – within the latter group, the largest drop is for textile workers. The large decline is mostly offset by an increase in professional and technical occupations, in particular, management-related occupations and medical professionals. We also observe a small increase in the employment share in low-skilled service occupations, mainly health support services (i.e. home aides).

We observe smaller changes in the male employment distribution from 1980 to 2017. Occupations in the manufacturing sector (specifically machine operators, assemblers, inspectors and precision production occupations) experienced the largest decline in employment share (-11 pp). Male workers also moved out of construction trades (-1.7 pp), a low-skilled, but not particularly routine intensive occupation. The observed decrease in male employment in these occupations is accompanied by a shift toward employment in high-skill occupations, particularly in STEM and low-paid service occupations such as cooks, janitors, and guards. Autor and Dorn (2013) argue that the decline in routine middle-skill jobs and the growth in low-skill service jobs is the result of two forces, technological substitution of routine tasks and the increase in demand for low-skilled services generated by complementarity between consumption of services and goods.

Overall, as previously noted by Autor and Wasserman (2013), the patterns of employment change suggest that, given the occupational distribution of men and women, if anything, women were more negatively affected by the decline in middle-skill routine intensive occupations.[12] However, men and women appear to have responded somewhat differently, with women relatively more likely to enter high-skill occupations and men shifting toward low-skill service occupations.[13]

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12. [12] Black and Spitz-Oener (2010) also document that patterns of employment polarization were more pronounced for women relative to men in West Germany.

13. [13] It is worth noting that the relatively larger employment gain of women in professional occupations is unlikely to be explained by women selectively dropping out of the labor force. In fact, over this time period, labor force participation increased by close to 9 pp for women and stayed constant for men.

3.4 Trends in the risk of automation by gender

The changing occupational structure in the labor market implies that over time, we would expect exposure to routine-intensive tasks to change, and most likely, differentially for men and women. To summarize these trends, Figure 5 presents the evolution of the mean routine task input and RTI index by gender and education group from 1980 to 2017. Consistent with the larger shifts in female employment away from routine-intensive occupations as shown in Table 2, female workers experience a much larger decline in the average level of absolute (routine task level) and relative routine task input (RTI index) relative to their male counterparts. The decline is particularly pronounced among workers without a college degree. In 1980, the gender gap (female-male) in routine task inputs was largest among workers with some college education. By 2017, the gender gap narrowed significantly, with the exception of college-educated workers, where has increased (Panel A) or remained mostly constant (Panel B). Strikingly, among workers with at most a high-school degree, the gender gap in routine task inputs actually reversed in favor of women (Panel A); the female-male gap using the RTI index is still positive, but small.

Table 3 presents the aggregate trends at the national level. The mean gender gap (female-male) in the RTI index has narrowed by close to 85 percent, while the gap in a routine task inputs has changed signs, indicating that, on average, women today are in occupations that use less routine task inputs (in absolute terms) relative to men (see Panels A and B). These trends suggest that changes in the occupational structure of men and women in the past four decades have substantially closed the gender gap in exposure to automation risk, as proxied for by the intensity of routine tasks in an occupation. It is worth pointing out that there are important caveats to this analysis. First, the data do not allow us to capture gender differences in task inputs within the 3-digit occupations. Second, our analysis uses a measure of the task content within an occupation at a single point in time (based on the 1977 DOT), abstracting from the possibility that the task content within an occupation is likely to have changed over time. To address the second concern, we show in Panel C of Table 3 that the patterns are similar using a more recent source of data on occupational task content from the 1998 O*NET based on the work by Deming (2017).

The last three columns of Table 3 assess the extent to which the aggregate changes in routine task inputs and RTI are driven by gender differences in trends in educational attainment (which likely affects sorting across occupations) versus changes in occupation structure (and hence, RTI) within education groups. To gauge the relative importance of these two mechanisms, we perform two exercises. First, we compute the predicted routine task inputs and RTI by gender in 2017, holding the education distributions of each gender constant at the 1980 level (Column (4)). Second, we keep constant the routine task inputs or RTI levels by education group at their 1980 values, but allow the educational distribution to change (Column (5)). We find that both forces contribute to the aggregate decline in routine task inputs and intensity for both genders as well as the narrowing of the gender gap over time. Moreover, we find that changes in exposure to routine task *within* education groups account for a larger portion of the observed decline in automation risk faced by women as well as the narrowing of the gender gap in routine task exposure.

To broadly summarize, our examination of employment trends by gender in the recent past points to a few important facts. First, in 1980, women faced a larger risk of being displaced by routine-replacement technological change. Second, over the past four decades, there has been a much larger shift out of occupations characterized by high levels of routine-task intensity by women relative to men. This has occurred because women were not only at a greater risk of automation, but they also appeared to have responded more strongly. Moreover, we provide evidence suggesting that these patterns are not entirely driven by concurrent shifts toward greater gender integration of occupations over the sample period. Third, we show that men and women adapted differently to declining job opportunities in middle-skill and routine-intensive occupations, with women disproportionately entering high-skill occupations, and men to low-skill occupations. Women achieved this by raising their educational profile and improving their occupational stature within education groups.

4. The future

The preceding analysis suggests that while women faced greater displacement risks due to routine-replacement technological change in the 1980s to 2010s, women appear to have adapted more successfully than men overall. These observations suggest that simply thinking about the substitution potential of automation without considering how technology might complement other jobs and worker responses is likely to lead to an incomplete and perhaps unduly pessimistic view of how technology interacts with employment.

While one can only speculate on what the future might entail, there are several reasons to expect that moving forward, automation may pose more of a challenge for men relative to women. First, declines in gender-based occupational segregation have resulted in substantial convergence in the gender gap in exposure to routine tasks (see Table 3). Using alternative measures of the automation potential of an occupation that utilize an expanded set of tasks and occupations that are computers are deemed to be suited to accomplish in the medium term, such as those proposed by Frey and Osbourne (2013), we find similarly modest gender gaps in the overall exposure to automation risk based on present day gender differences in occupational structure.[14] Moreover, as shown in Figure 6, when we examine the relationship between the Frey and Osbourne (2013) measure of the probability of automation and the female share percentile of an occupation in 2017, we find a U-shaped pattern, but with male-intensive occupations facing a much higher risk of automation. The relationship between the RTI index and current female share percentile is also U-shaped, with both female-intensive and male-intensive having similarly high levels of routine-task intensity. These patterns suggest that, if anything, male-intensive occupations may be somewhat more exposed to higher automation risks moving forward.

Second, women's educational attainment has increasingly outpaced that of men, suggesting that women are more likely to possess the skills that are complemented by technological change. Several studies suggest that men's lower rates of college-going could be due, in part, to higher costs that men face as a result of their lower levels of non-cognitive skills (e.g. behavioral problems) (Jacob, 2002; Goldin, Katz, and Kuziemko, 2006; Becker, Hubbard, and Murphy, 2010).

A third related factor is that women's comparative advantage in another dimension of non-cognitive skills – namely, interpersonal and social skills, is likely to put them at a further advantage in riding the next wave of technological advancement. As argued by Autor (2015), computers remain poor substitutes for tasks that require a high level of human interaction and tacit knowledge since

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14. [14] On average, across all occupations, the estimated probability of automation is 0.50 for men and 0.48 for women in 2017, using the Frey and Osbourne (2013) estimates. The corresponding numbers when the Frey-Osbourne measures are applied to the 1980 occupational distribution of men and women are 0.54 and 0.65, respectively. Ideally, we would have liked to conduct a similar exercise using the McKinsey Global Institute (MGI) estimates of the technical automation potential of each occupation. However, the data is not publicly available.

programmers “do not know the rules.” Borghans, ter Weel, and Weinberg (2014) document that the relative employment of women is higher in occupations that place a greater emphasis on people tasks, consistent with the idea that they are more well-endowed in interpersonal skills. They present some evidence that the spread of computers appears to have increased the relative demand for interpersonal interactions which can potentially explain the rise in women’s relative wages from the late 1970s to the early 1990s. Deming (2017) shows that social skills are increasingly rewarded in the U.S. labor market, and social-skill intensive occupations have experienced particularly rapid growth in terms of both employment share and wages. Among all other managerial or professional occupations, many of the fastest growing occupations are those that require significant interpersonal interactions, and are female-dominated (e.g. teachers, nurses, therapists, social workers, pharmacists, and physician assistants), or becoming increasingly gender integrated (e.g. physicians, lawyers, and dentists).[15] Moreover, in an earlier working paper, Deming (2015) shows that much of the increase in the social skill content of work between 1980 and 2012 is driven by females. The decline in routine task intensity for women was almost entirely offset by an increase in social skill inputs for women. By contrast, there appears to be much more modest changes in the task content of men’s work.[16], [17] While Deming (2017)’s main focus is on the role of social skills in high-paying and cognitive-intensive occupations, Autor (2015) conjectures that the middle-skill jobs of the future will comprise workers who are able to combine routine technical tasks with non-routine tasks that require a high level of human interaction, judgement, and flexibility.

5. Conclusion

Non-neutral technological change in the form of automation, has, and will continue to be a major disruptive force in the labor market. The widespread use of computers during the IT-era has resulted in the hollowing out of traditionally middle-skill, routine-task intensive jobs, and a shift in employment toward occupations at both ends of the skill distribution. We show that women’s greater representation in

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15. [15] For the 2010 cohort, women accounted for close to 50% of medical and law school graduates and close to 45% of MBA graduates and dental school graduates (Goldin and Katz, 2011).

16. [16] See Figures 8 and 9 from Deming (2015) which can be found at the following link: http://economics.mit.edu/files/11112

17. [17] Black and Spitz-Oener (2010) find similar patterns using data from West Germany – women appear to have experienced a large decline in routine task inputs and increases in non-routine analytic and non-routine interactive tasks. By contrast, men experienced little change.

occupations facing particularly high risks of automation in 1980, in particular the clerical sector, led to women experiencing larger employment displacement in the middle of the skill distribution relative to men from 1980 to 2017. Alongside technological change, the shift toward more gender-integrated occupations also played some role in patterns of employment polarization, especially for women.

While the effects of automation may have appeared to be bleaker for women, we find that women adapted to the new labor market realities by shifting disproportionately toward more high-skill occupations; by contrast, men had a greater tendency to shift toward low-skill occupations. We speculate that women's smoother transition to high-skill occupations may be due, in part, to their higher educational qualifications and willingness to undertake additional human capital investments (e.g. retrain as health professionals). Another possibility is that the set of skills required in the clerical sector are more general and transferable to high-skill professional or managerial occupations relative to the skills used by machine operators and production workers. Finally, automation is likely to have strong complementarities with tasks that require a high level of human interaction. Given women's comparative advantage in interpersonal and social skills, these demand shifts are likely to have benefited women more so than men. It would be worthwhile for future research to explore specific factors that can help explain why women appear to have an easier time adapting to the new labor market realities brought about by automation.

Another area for future work is to more carefully assess the extent to which changes in the occupational structure of men and women are indeed the outcome of automation. While the patterns documented in this paper suggest a potentially important role for automation, the associations and trends explored are by no means causal and may capture the effects of other concurrent changes in the labor market, such as the large-scale entry of women into the labor market, declines in occupational barriers faced by women, and women and men's converging roles in society. In addition, future work should also explore the extent to which automation, in itself, may have created new opportunities in the labor market. For example, the risk of automation may have spurred an increase in human capital investments, especially for groups of workers that were most at risk of displacement. We also know little about the causal role that automation has played in increasing the demand for certain types of occupations (e.g. high-skill occupations, social-skill intensive occupations, etc.). A better understanding of these issues will provide a more nuanced and complete understanding of the factors that can help workers to adapt more readily to future waves of automation, as well as the potential opportunities that arise from technological change.

Looking forward, over the past four decades, women have rapidly closed the gender gap in exposure to automation risk. The fact that women are increasingly outpacing men in terms of educational attainment and are more well-endowed in the skills required to succeed in the labor market of the future gives us reason to believe that unless men are better able to rise to the challenges (and promises) of technological change, they may emerge as the weaker sex.

REFERENCES

Albanesi, Stephania and Claudia Olivetti. 2016. "Gender Roles and Medical Progress." Journal of Political Economy. Vol. 124(3): 650-695.

Arntz, M., T. Gregory, and U. Zierahn. 2016. "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis." OECD Social, Employment, and Migration Working Papers, No. 189, OECD Publishing, Paris.

Autor, David H. 2010. "The Polarization of Job Opportunities in the U.S. Labor Market: Implications for Employment and Earnings." Washington, DC: Center for American Progress and The Hamilton Project.

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." Journal of Economic Perspectives. Vol. 29(3): 3-30.

Autor, David H. and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." American Economic Review. Vol. 103(5):1553-1397.

Autor, David H. and Melanie Wasserman. 2013. "Wayward Sons: The Emerging Gender Gap in Labor Markets and Education." Washington, DC: Third Way.

Autor, David H., Frank Levy and Richard J. Murnane. 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. The Quarterly Journal of Economics. Vol. 118(4): 1279-1333.

Bailey, Martha J. 2006. "More Power to the Pill: The Impact of Contraceptive Freedom on Women's Lifecycle Labor Supply." Quarterly Journal of Economics. Vol. 121 (1): 289–320.

Becker, Gary S., William H. J. Hubbard, and Kevin M. Murphy. 2010. "Explaining the Worldwide Boon in Higher Education of Women." Journal of Human Capital. Vol. 4(3): 203-241.

Black, Sandra and Alexandra Spitz-Oener. 2010. "Explaining Women's Success: Technological Change and the Skill Content of Women's Work." The Review of Economics and Statistics. Vol. 92(1): 187-194.

Blau, Francine D., Peter Brummund, and Albert Yung-Hsu Liu. 2013. Segregation by Gender 19702009: Adjusting for the Impact of Changes in the Occupational Coding System." Demography. Vol. 50(2): 471-92.

Borghans, Lex, Bas ter Weel, and Bruce Weinberg. 2014. "People Skills and the Labor-Market Outcomes of Underrepresented Groups." ILRReview. Vol. 67 (2): 287-334.

Brussevich, Mariya, Era Dabla-Norris, Christine Kamunge, Pooja Karnane, Salma Khalid, and Kalpana Kochhar. 2018. "Gender, Technology, and the Future of Work." International Monetary Fund Staff Discussion Note.

Cortes, Patricia and Jessica Pan. 2018. "Occupation and Gender." The Oxford Handbook of Women and the Economy. Eds. Susan L. Averett, Laura M. Argys, and Saul D. Hoffman.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." Quarterly Journal of Economics. Vol. 132(4): 1593-1640.

Dorn, David. 2009. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." Dissertation University of St. Gallen no. 3613.

Fernandez, Raquel. 2013. "Cultural Change as Learning: The Evolution of Female Labour Force Participation over a Century." American Economic Review. Vol. 103(1): 472-500.

Frey, Carl B., Michael A. Osborne. 2013. "The Future of Employment: How Susceptible are Jobs to Computerization?" Working Paper, Oxford University.

Goldin, Claudia. 1990. Understanding the Gender Gap: An Economic History of American Women. New York: Oxford University Press.

Goldin, Claudia. 2006. "The Quiet Revolution That Transformed Women's Employment, Education, and Family." American Economic Review. Vol. 96 (2): 1-21.

Goldin, Claudia and Lawrence F. Katz. 2002. "The Power of the Pill: Oral Contraceptives and Women's Career and Marriage Decisions." Journal of Political Economy. Vol. 110 (4): 730–70.

Goldin, Claudia, Lawrence F. Katz and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." Journal of Economic Perspectives. Vol. 20(4): 133-156.

Goldin, Claudia and Lawrence F. Katz. 2011. "The Cost of Workplace Flexibility for High-Powered Professionals." The Annals of the American Academy of Political and Social Science. Vol. 638(1): 4567.

Goldin, Claudia. 2013. A Pollution Theory of Discrimination: Male and Female Differences in Occupations and Earnings. In Human Capital and Hisotry: The American Record. University of Chicago Press.

Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu. 2005. "Engines of Liberation." 2005. Review of Economic Studies. Vol. 72 (1): 109–133.

Hegewisch, Ariane, Chandra Childers, and Heidi Hartmann. 2019. "Women, Automation, and the Future of Work." Institute for Women's Policy Research Report #C476. (Accessed August 2019: http://iwpr.org/wp-content/uploads/2019/03/C476_Automation-and-Future-of-Work.pdf).

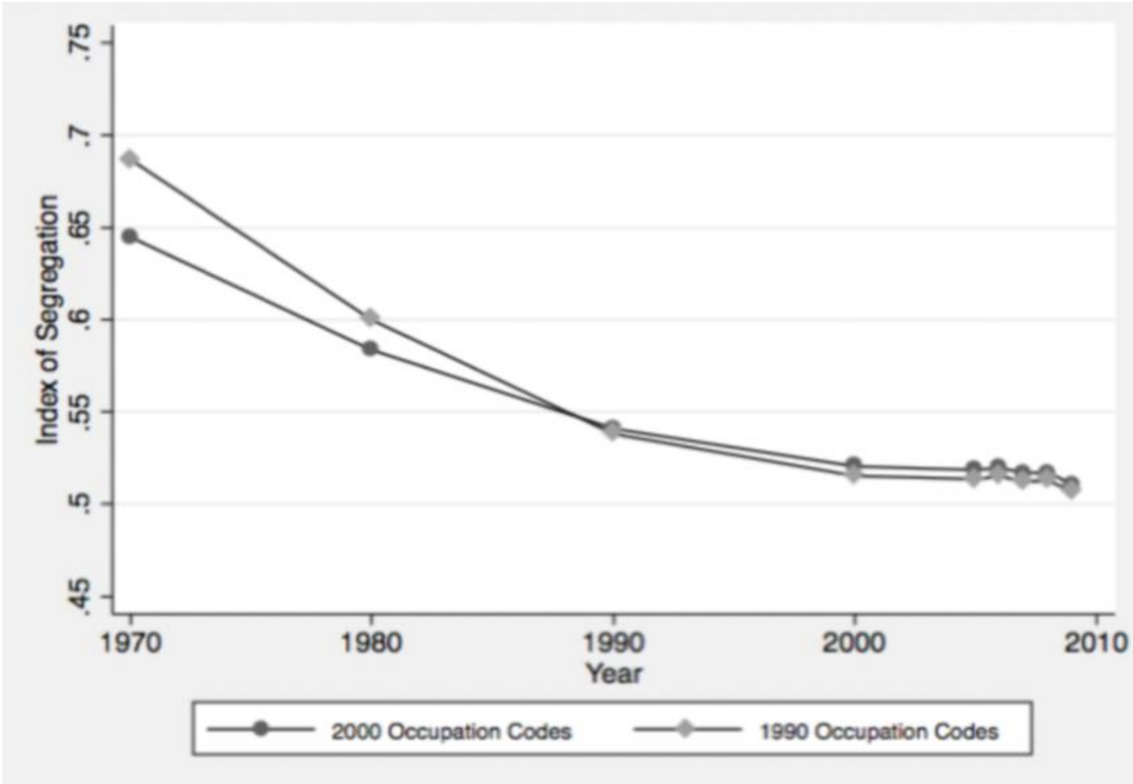
Jacob, Brian A. 2002. "Where the Boys Aren't: Non-cognitive Skills, Returns to School and the Gender Gap in Higher Education." Economics of Education Review. Vol. 21(6):589–98.

Madgavkar, Anu, James Manyika, Mekala Krishnan, Kweilin Ellingrud, Lareina Yee, Jonathan Woetzel, Michael Chui, Vivian Hunt, and Sruti Balakrishnan. 2019. "The Future of Women at Work: Transitions in the Age of Automation." McKinsey Global Institute.

Massey, Douglas S. and Nancy A. Denton. 1993. American Apartheid: Segregation and the Making of the Underclass. Cambridge: Harvard University Press.

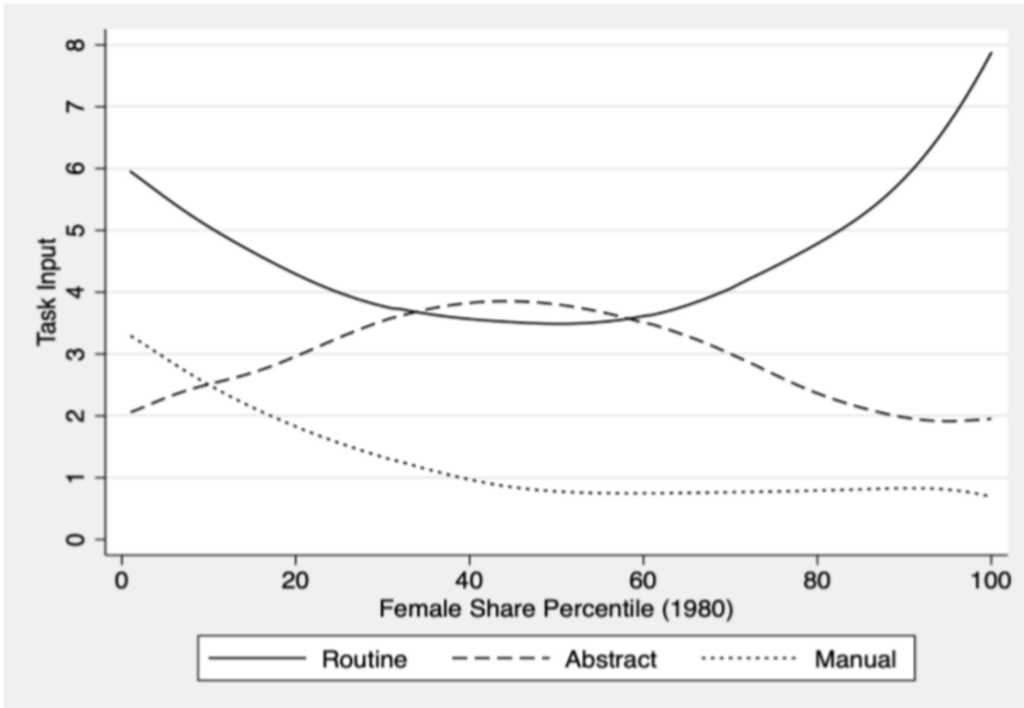
Muro, Mark, Robert Maxim, and Jacob Whiton. 2019. "Automation and Artificial Intelligence: How Machines are Affecting People and Places". Brookings Institution, Metropolitan Policy Program.

Figure 1. Trends in Occupational Segregation by Gender in the United States, 1970 to 2009



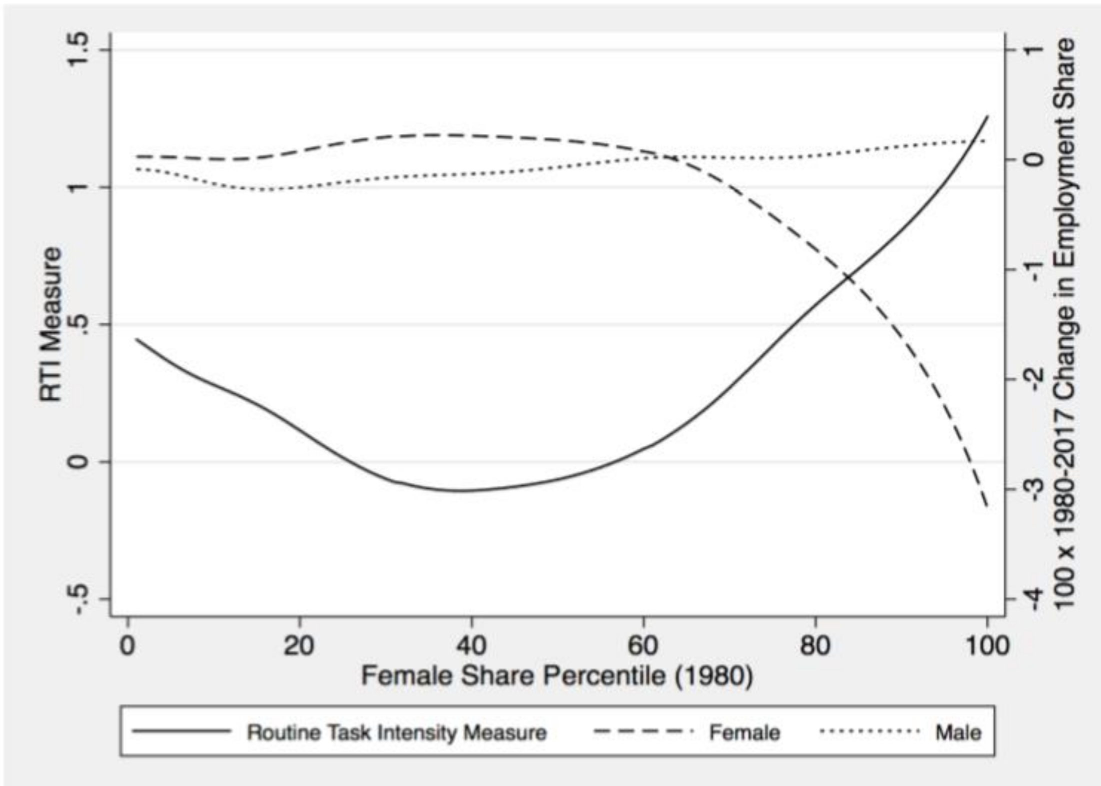
Notes: The figure is reproduced from Cortes and Pan (2018). The data is obtained from Table 2 of Blau, Brummund, and Liu (2013). The index of segregation is computed using Census data and the gender-specific, CPS-based crosswalk using year 2000 and 1990 occupational codes.

Figure 2A. Occupational Task Inputs by 1980 Female Share Percentile



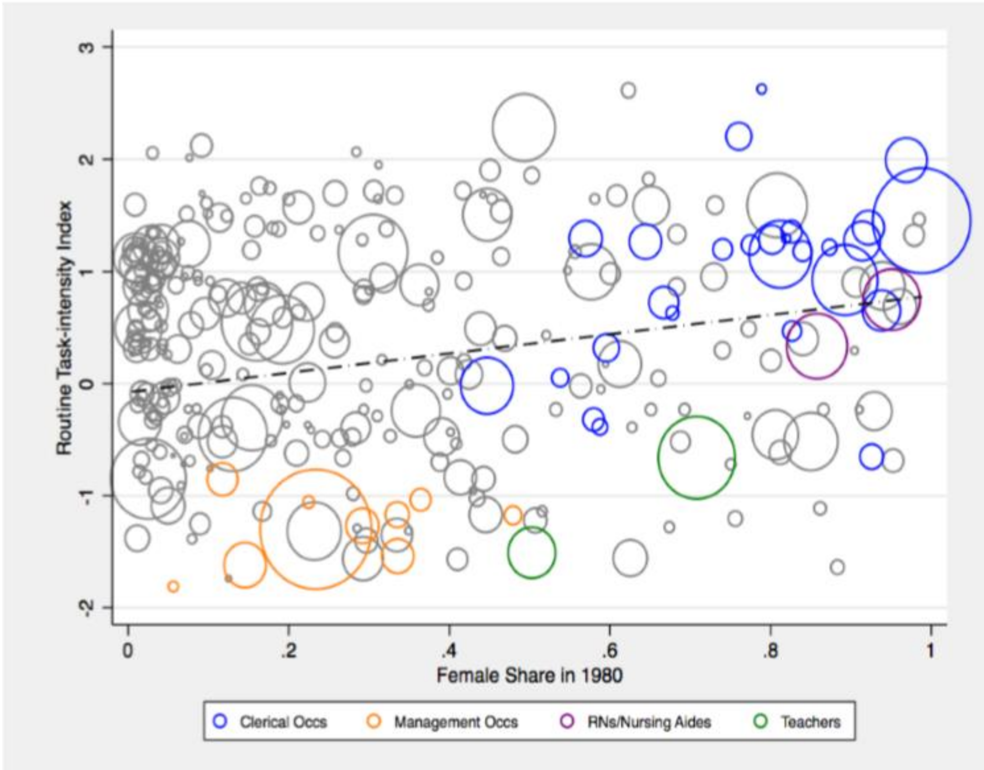
Notes: Data on occupational task content (routine, abstract, manual) are from Autor and Dorn (2013). Task inputs are measured on a 0 to 10 scale. Occupations are ranked based on their female share in 1980 as calculated from the 1980 Census. Task inputs by female share percentile are plotted using a locally weighted smoothing regression.

Figure 2B. Routine Task-Intensity and Changes in Occupation Shares by 1980 Female Share Percentile



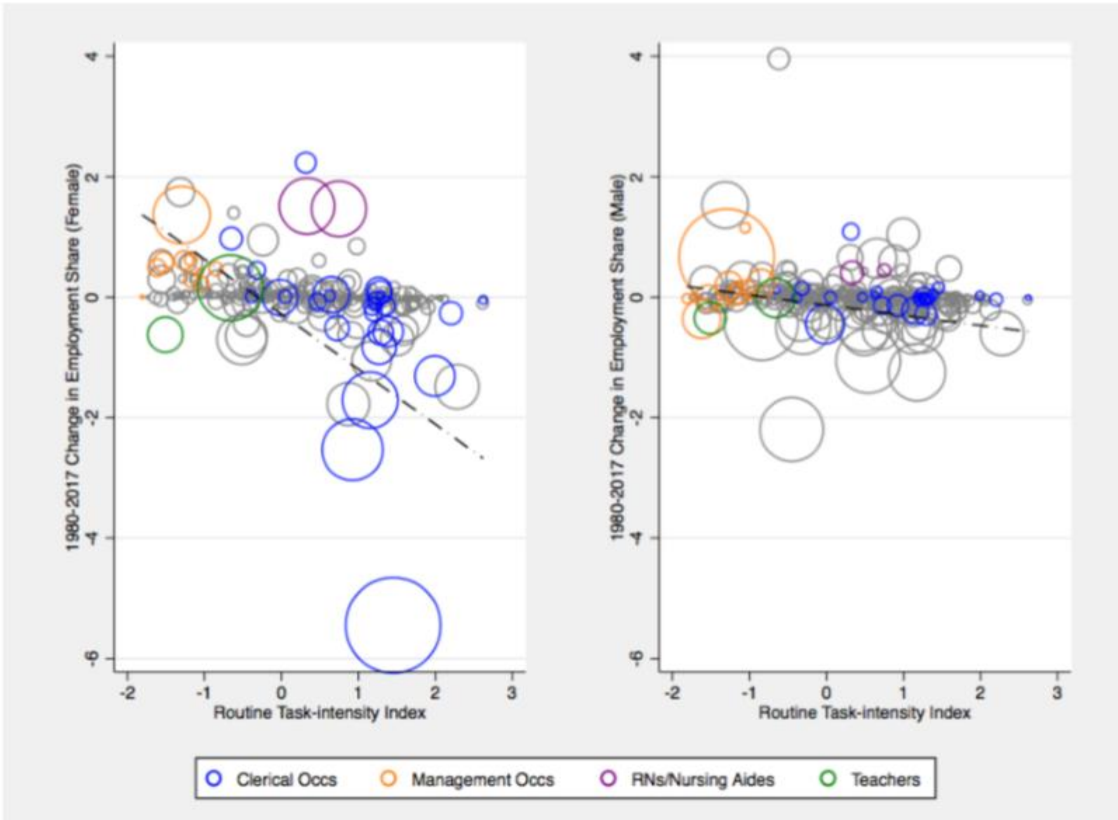
Notes: The data are from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. A balanced panel of occupations from 1980 to 2017 is constructed using Dorn's (2009) occupational classification scheme. The figure plots the smoothed change in the occupational employment share of males and females from 1980 to 2017 as a function of the occupation's rank in terms of female share in 1980.

Figure 3. Routine Task Intensity (RTI) Index and Female Share in 1980



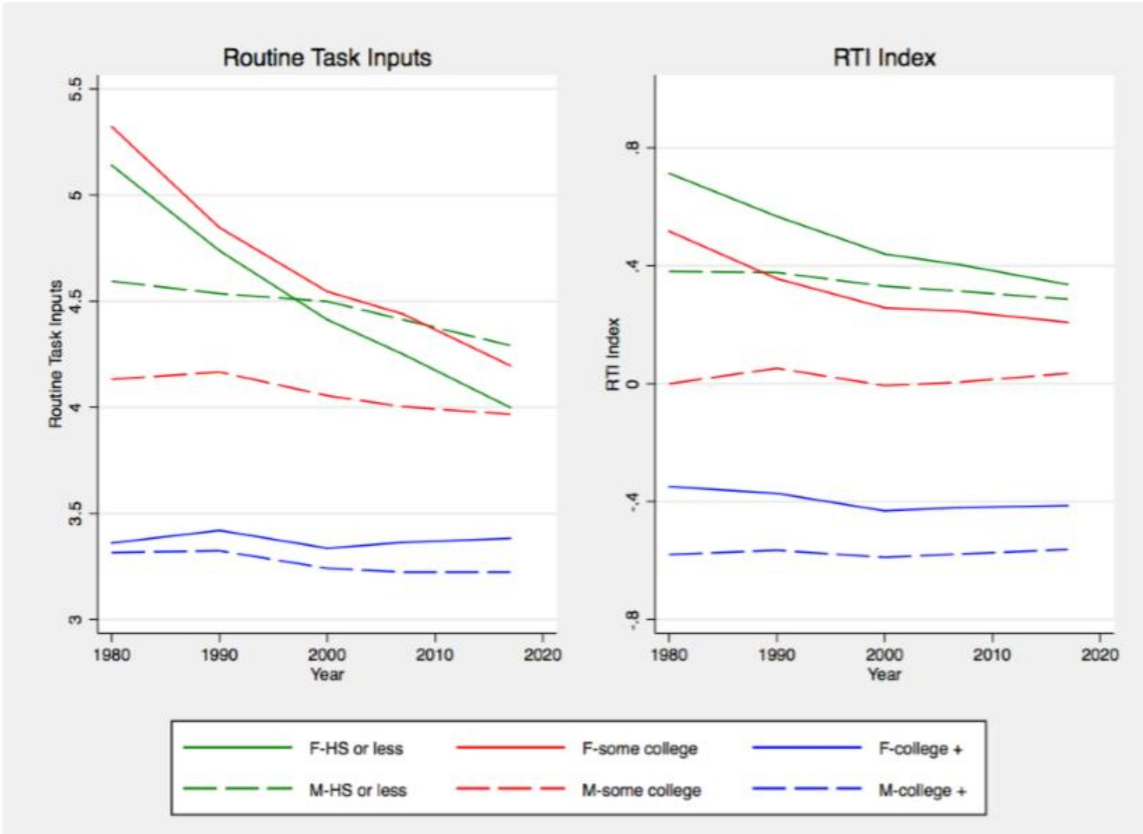
Notes: The unit of observation is an occupation. The size of the marker indicates the employment share of the occupation. The female share in 1980 is computed using data from the 1980 Census. The task data used to construct the routine-task intensity index is obtained from Autor and Dorn (2013). We use our preferred measure of RTI which is given by RTI = ln(Routine Task Input)-max{ln(Abstract Task Input), ln(Manual Task Input)}. The dashed line is a fitted line based on a weighted regression of the RTI index on the female share in 1980, using employment share as weights.

Figure 4. Change in Employment Share from 1980 to 2017 and Routine Task Intensity, by Gender



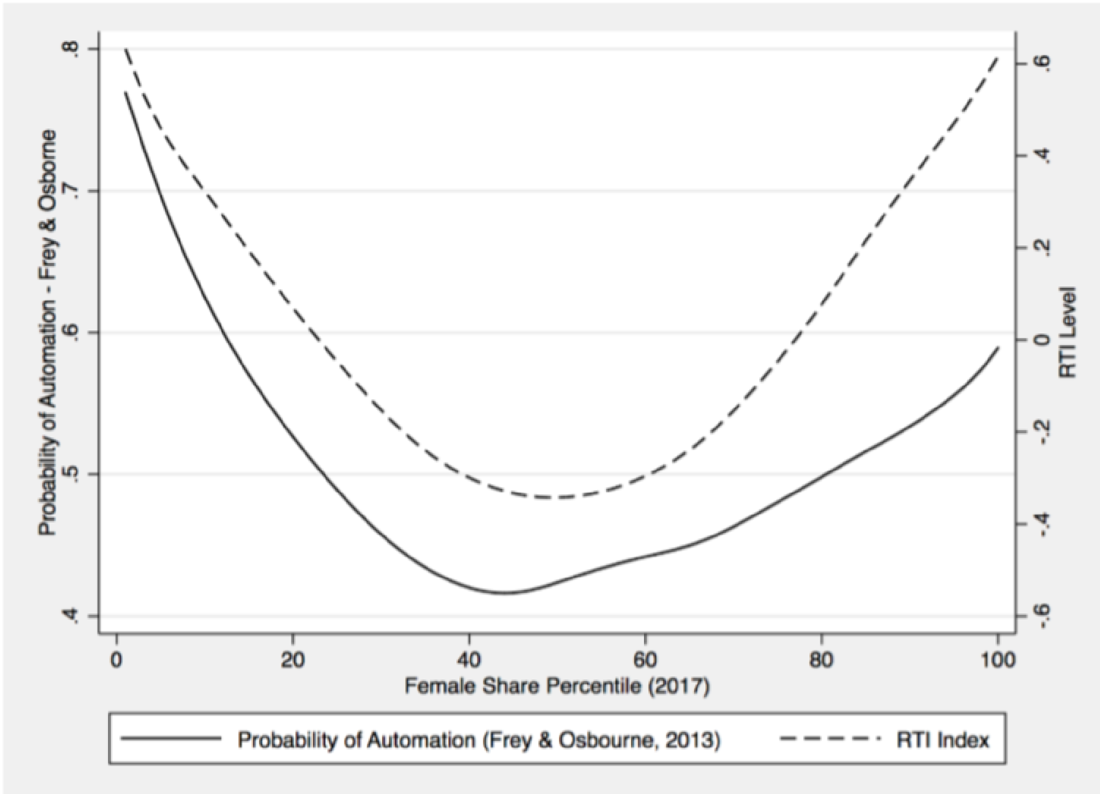
Notes: The unit of observation is an occupation. The size of the marker indicates the employment share of the occupation for each gender. The employment changes are computed from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. The task data used to construct the routine-task intensity index is obtained from Autor and Dorn (2013). We use our preferred measure of RTI which is given by RTI = ln(Routine Task Input)-max{ln(Abstract Task Input), ln(Manual Task Input)}. The dashed line in each figure is a fitted line based on a weighted regression of the employment change for females (left panel) and men (right panel) on the female share in 1980, using the employment share of females and males, respectively, as weights.

Figure 5. Trends in the Task Composition of Jobs by Gender and Education, 1980 to 2017



Notes: The task data is obtained from Autor and Dorn (2013). The left panel reports the trends over time in routine task inputs, while the right panel reports the trends in the routine task intensity (RTI) index. We use our preferred measure of RTI which is given by RTI = ln(Routine Task Input)-max{ln(Abstract Task Input), ln(Manual Task Input)}. Plotted values indicate the employment-weighted mean of each outcome across occupations in the indicated year.

Figure 6. Measures of Automation Risk and Female Share Percentile in 2017



Notes: The probability of automation is based on the estimates by Frey and Osbourne (2013). The RTI Index is defined as RTI = ln(Routine Task Input)-max{ln(Abstract Task Input), ln(Manual Task Input)} and constructed using task data from Autor and Dorn (2013). The female share percentile is computed using the 2017 (2016-2018) three-year aggregate ACS. The lines are plotted using a locally-weighted smoothing regression.

Table 1. Changes in the Occupation Distribution by Gender between 1980-2017

	100 x Change in Share in Occupation 1980-2017		Occupation Task Inputs			Log(Hourly wage)		Female Share		Share in Total Employment	
	Females	Males	Abstract	Manual	Routine	1980	2017	1980	2017	1980	2017
Professional/Technical Occupations											
Manager/Lawyer	5.2	2.4	6.66	0.38	1.80	3.10	3.49	0.24	0.40	8.5%	12.0%
Education Prof	1.7	0.3	4.49	1.52	1.57	2.82	3.05	0.59	0.71	5.4%	6.6%
Mngment Related	2.9	0.8	6.66	0.25	3.94	2.98	3.41	0.37	0.55	2.8%	4.6%
STEM & Social Science	2.4	4.0	6.95	1.21	5.38	3.26	3.56	0.11	0.26	2.7%	5.7%
Non Health Technicians	-0.2	-1.0	4.36	1.08	6.27	2.94	3.26	0.24	0.34	2.5%	1.8%
Medical Prof	3.1	0.9	4.91	1.82	5.89	3.00	3.58	0.64	0.72	2.5%	4.6%
Other Prof	1.4	0.6	4.31	0.57	2.80	2.72	3.07	0.39	0.54	2.1%	3.1%
Health Technicians	1.3	0.7	2.32	1.67	6.36	2.60	2.94	0.81	0.74	1.1%	2.2%
Total Change	17.9	8.7									
Non Professional/ Non Technical Occupations											
High RTI											
Mechanics/Repairers	-0.1	-1.3	2.18	2.05	7.11	2.85	2.97	0.03	0.04	4.1%	3.0%
Precision Production Occ	-0.6	-3.6	4.12	0.83	5.65	2.91	2.94	0.13	0.21	4.5%	2.2%
Laborers	-1.0	-1.5	0.74	1.79	3.32	2.64	2.67	0.16	0.14	5.6%	4.0%
Sales	-0.3	0.9	3.66	0.26	2.81	2.77	3.03	0.38	0.45	9.2%	9.6%
Machine Op, Assemblers, Inspectors	-6.9	-5.5	1.08	1.26	6.26	2.65	2.76	0.37	0.29	10.1%	3.8%
Operators/Mail	-0.6	-0.3	1.92	0.20	4.01	2.74	2.77	0.37	0.39	3.1%	2.7%
Clerical	-10.5	0.4	2.27	0.13	6.68	2.58	2.85	0.83	0.78	15.5%	11.9%
Total Change	-19.9	-11.0									
Non-service Low RTI											
Transportation	0.2	-0.4	1.11	4.51	1.97	2.77	2.81	0.05	0.11	3.6%	3.2%
Construction Trades	0.0	-1.7	2.76	2.90	6.40	2.90	2.95	0.02	0.03	4.4%	3.2%
Total Change	0.2	-2.0									
Service Occupations Low RTI											
Protective Ss	0.5	0.8	1.33	2.91	1.39	2.80	3.07	0.08	0.20	1.7%	2.2%
Health Support Ss	1.5	0.4	1.56	1.96	3.40	2.28	2.53	0.87	0.85	1.8%	3.0%
Hld & Personal Ss	-0.4	0.0	1.47	1.11	2.37	2.19	2.40	0.78	0.81	2.4%	2.5%
Food Prep Ss	-0.4	2.3	1.35	1.10	2.88	2.16	2.39	0.65	0.50	3.9%	5.2%
Building Maintenance Occ	0.5	0.8	1.24	2.33	3.68	2.51	2.61	0.19	0.25	2.5%	3.1%
Total Change	1.9	4.3									

Notes: The data are from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. A balanced panel of occupations from 1980 to 2017 (constructed using Dorn's (2009) classification scheme are aggregated to 21 broad groups as listed in the table. Task measures at the 3-digit level are obtained from Autor and Dorn (2013) and aggregated (using employment share as weights). The broad occupations are further subdivided into two groups, professional and technical occupations and non-professional/non-technical occupations. Within the group of non-professional/non-technical occupations, High (Low) RTI occupations are those in the top-half (bottom-half) of the RTI distribution.

Table 2. Cross-occupation Correlations of Task Requirements, Female Share and Changes in Occupational Share

	Dep. Var: 100 x Change in Occupational Share 1980-2017					
	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
Female Share in Occupation in 1980	-1.482	-2.050	0.083	0.482*	0.531**	0.576**
	[0.971]	[1.285]	[0.592]	[0.252]	[0.214]	[0.259]
Routine Task Index	-0.298**			-0.040		
	[0.128]			[0.026]		
Abstract Task Index	0.121			0.056		
	[0.096]			[0.049]		
Manual Task Index	0.377			0.017		
	[0.246]			[0.029]		
Routine Task-Intensive Index		-0.684***	-0.308***		-0.174*	-0.173*
		[0.228]	[0.110]		[0.095]	[0.097]
Occupations Excluded	None	None	Clerical	None	None	Clerical
Observations	308	308	281	309	309	282
R-squared	0.465	0.328	0.151	0.091	0.092	0.094

Notes: The data are from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. The unit of observation is an occupation. A balanced panel of occupations from 1980 to 2017 is constructed using Dorn's (2009) occupational classification scheme. The Routinte Task Intensity (RTI) Index is defined as RTI = ln(Routine Task Input)-max{ln(Abstract Task Input), ln(Manual Task Input)}. Regressions are weighted by the 1980 employment share of each occupation. *** significant at 1%, **5%, *10%.

Table 3. Aggregate Trends in Routine Task Inputs and Routine-Task Intensity by Gender, 1980 to 2017

	Level		1980-2017 Change		
	1980	2017	Observed	Educ composition constant at 1980 level	Routine index for each educ group constant at 1980 level
	(1)	(2)	(3)	(4)	(5)
			A. Routine Task Inputs (DOT)		
Females	4.87	3.80	-1.075	-0.939	-0.418
Males	4.21	3.84	-0.369	-0.228	-0.172
			B. Routine-Task Intensity (RTI Index, DOT)		
Females	0.490	-0.007	-0.497	-0.309	-0.267
Males	0.088	-0.068	-0.156	-0.044	-0.131
			C. Routine Task Inputs (O*NET, 1998)		
Females	4.986	4.017	-0.969	-0.811	-0.372
Males	4.432	4.262	-0.170	-0.062	-0.170

Notes: The task measures for routine task inputs (DOT) and routine-task intensity (RTI Index, DOT) are from Autor and Dorn (2013). The routine task input measure (O*NET, 1998) is from Deming (2017). Columns (1) and (2) report the overall mean for females and males (age 18 to 64) who were in the civilian labor force and reported an occupation for each of the routine task or RTI measures as indicated in a given panel in 1980 and 2017, respectively. Column (3) is the observed difference in routine task or RTI levels between 1980 and 2017. Column (4) reports the predicted routine task (or RTI) change holding the education distribution constant at the 1980 level. Column (5) reports the predicted routine task (or RTI) change holding constant the routine task inputs or RTI levels by education group at the 1980 value, and allowing the educaution distribution to change.