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ABSTRACT

Automation and Gender: Implications for Occupational Segregation and the Gender Skill Gap*

We examine the differential effects of automation on the labor market and educational outcomes of women relative to men over the past four decades. Although women were disproportionately employed in occupations with a high risk of automation in 1980, they were more likely to shift to high-skill, high-wage occupations than men in over time. We provide a causal link by exploiting variation in local labor market exposure to automation attributable to historical differences in local industry structure. For a given change in the exposure to automation across commuting zones, women were more likely than men to shift out of routine task-intensive occupations to high-skill, high wage occupations over the subsequent decade. The net effect is that initially routine-intensive local labor markets experienced greater occupational gender integration. College attainment among younger workers, particularly women, also rose signicantly more in areas more exposed to automation. We propose a model of occupational choice with endogenous skill investments, where social skills and routine tasks are q-complements, and women have a comparative advantage in social skills, to explain the observed patterns. Supporting the model mechanisms, areas with greater exposure to automation experienced a greater movement of women into occupations with high social skill (and high cognitive) requirements than men.

JEL Classification: J16, J24

Keywords: automation, gender, occupational segregation, gender skill gap

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1 Introduction

Women have made significant gains in the U.S. labor market over the past few decades – occupational differences by gender and the gender wage gap have narrowed considerably, and women have reversed the male advantage in higher education. (Blau and Kahn, 2017).[1] Concurrent with these developments has been the widespread adoption and diffusion of information technology since the 1980s. A growing literature documents how automation has affected occupational task requirements, and the resulting impacts on the employment structure and wages (see Acemoglu and Autor (2011) for a review). Yet, we know much less about the extent to which automation differentially affects the employment opportunities of men and women.

There are several reasons why we might expect automation to have differential impacts by gender. First, high levels of occupational segregation in the early 1980s likely translated to gender differences in the exposure to automation risk.[2] Second, since computerization tends to increase the demand for analytical and interpersonal skill inputs (while substituting for routine/physical tasks), given their comparative advantage in social skills, women are likely to have benefited more from these demand shifts in terms of occupational upgrading. Moreover, if productivity in abstract/social tasks is acquired through investments in education, then automation should lead to an increase in college-going. How automation affects the relative human capital investments of women vs. men, however, likely depends on how the returns to education have changed vis-a-vis the costs of acquiring a college education for men and women.

We explore these hypotheses using U.S. Census data from 1980 to 2017, leveraging the automation wave precipitated by the introduction of personal computers in the early 1980s to: (1) quantify the effects of automation on the occupational structure of men and women, and consequently, occupational segregation, (2) examine whether automation-induced changes in occupational skill demands played a role in women's relative educational gains over the past four decades, and (3) assess the role of women's comparative advantage in social skills in generating the observed occupational shifts.

We begin by providing a descriptive account based on cross-occupation variation in the relative importance of tasks that can be replaced by automation and how it relates to changes over time in the occupational distribution by gender. This descriptive exercise reveals three facts: (1) In 1980, women were disproportionately employed in occupations with a high risk of automation relative to men, (2) the negative cross-occupation relationship between the risk of automation in 1980 and the change in employment share from 1980 to 2017 is much steeper for women than for men, and (3) over the past four decades, women were more likely to shift to high-skill occupations than men. Next,

[1]Figure 1 presents the trends in occupational segregation and the male-female college gap from 1970 to 2017.

[2]For example, papers such as Frey and Osborne (2017) and Madgavkar et al. (2019) attempt to quantify the risk of automation by gender in the medium term based on the current employment distribution of men and women across occupations and occupation-level estimates of the likelihood of automation within the next one or two decades.

we assess the extent to which differences in the types of routine-intensive occupations that men (product and craft occupations) and women (clerical occupations) were represented in might have contributed to differential occupational sorting in response to automation. The work conditions and characteristics of these occupations potentially differ in ways that might create less incentive for men to leave these occupations. We show that differences in observable job characteristics such as unionization rates, hourly wages, and education composition between routine-intensive occupations in which men vs. women concentrate cannot explain the observed patterns.

Building on these descriptive patterns, we examine whether automation plays a causal role in these differential changes by exploiting variation across commuting zones (CZ) in the exposure to automation risk at a given point in time, as proxied for by the degree of specialization of local labor markets in routine activities. We address the potential endogeneity of cross-CZ exposure to automation at baseline with an instrument developed by Autor and Dorn (2013) that isolates the component of exposure risk that is attributable to historical differences across CZs in industry structure in 1950, three decades or more prior to the changes in occupational structure that we study.

We find that commuting zones that were initially more specialized in routine occupations experienced significantly larger declines in the share of the population employed in routine-task intensive occupations over the subsequent decade. Furthermore, there is a clear gender dimension – for a given change in the risk of automation, women are much more likely than men to transition out of routine task-intensive occupations, with women largely shifting out of clerical and retail sales occupations while men shift out of production and craft occupations. Consistent with the descriptive findings, women are much more likely than men to switch into higher-skilled professional and technical occupations, whereas men are relatively more likely to shift to low-skilled and low routine-intensive occupations such as transportation and construction. Increased exposure to automation also leads to a decline in labor force participation; however these extensive margins effects are similar across gender. Importantly, we find that these effects of automation on the occupational distributions of men and women are the result of changes both within and across cohorts.

The net effect is that local labor markets that were more exposed to automation experienced greater occupational integration by gender as measured by the Duncan and Duncan (1955) segregation index. Our main results are robust to the inclusion of controls for other potentially important determinants of occupational choice and skill investments that vary across commuting zones, including offshoring potential, trade shocks, and change in gender norms. Moreover, while our baseline analysis considers non-internal migrants – that is, individuals who were born and reside in the same state – the findings are qualitatively similar when we consider the full sample including internal and international migrants. Turning to skill investments, we find that commuting zones that were initially more specialized in routine tasks saw larger increases in the college completion rates of 25- to 34-year olds over the subsequent decade. Moreover, this response was larger for women than for men, resulting in a larger change in the magnitude of the college gap in favor of women. Supporting a causal interpretation, we show that these local labor markets did not experience greater gender integration in the periods *prior* to the broad expansion of computerization.

To understand these patterns, we develop a simple model of occupational choice with endogenous educational investments where women have a comparative advantage in social skills.[3] Routine and non-routine tasks are imperfect substitutes in producing the final good, while computer capital and routine labor are perfect substitutes in performing routine tasks as in Autor et al. (2003). For tractability, we assume that uneducated workers perform only routine tasks without returns to social skills, while educated workers do non-routine cognitive tasks with returns to social skills. This modeling assumption is supported by recent work that argues that alongside analytical skills, information technology also increases the demand for interpersonal skills (Borghans et al., 2014; Caroli and Van Reenan, 2001), especially in tasks requiring high levels of cognitive skills (Weinberger, 2014; Deming, 2017). Finally, we allow females and males to differ exogenously in their distributions of education costs, and assume that they make education and occupation decisions to maximize net income.

When an automation shock arrives in the form of a decline in the price of capital, demand for non-routine labor inputs rises, pushing up the shares of educated and non-routine workers for both men and women, consistent with the data. We show that under some assumptions about the distribution of education costs and social skills, coupled with women's comparative advantage in social skills and/or lower non-cognitive costs of college, automation tends to reallocate more women to non-routine tasks, especially in routine-task-intensive regions where educated non-routine workers are initially scarce. We provide some empirical support for the model by showing that areas with greater exposure to automation tend to experience greater sorting toward occupations with high social and high cognitive task content, particularly among women. Moreover, we document that the price effects, namely the returns to college by gender and relative wages by occupation type, are consistent with an increase in relative demand as suggested by the model.

Our paper is closely related to a growing literature that studies the effects of computer adoption on gender gaps in employment and wages. Based on the premise that women have a comparative advantage in "brains" (cognitive or interpersonal skills) versus "brawn" (motor skills) (e.g. Welch, 2000), several papers argue that technological change favors women, and provide empirical evidence that the adoption of computerization in the 1980s narrowed employment and wage gaps. Most of this work, however, is based on cross-industry correlations (Weinberg, 2000) or time-series evidence linking women's relative wage increases to shifts away from routine tasks inputs to analytic and interactive inputs (Black and Spitz-Oener, 2010) and changes in the prices of cognitive and motor skills (Bacolod and Blum, 2010). An exception is Beaudry and Lewis (2014) who exploit

[3] See Hall (1978); Feingold (1994) Woolley et al. (2010) for evidence from psychology and neuroscience supporting the assumption that women have a comparative advantage in tasks requiring social skills.

cross-city variation in personal computer (PC) adoption to show that local areas that adopted PCs more quickly (for arguably exogenous reasons) experienced a larger decline in gender pay gaps. More directly related to our work, suggestive evidence that computerization may have led to more pronounced employment polarization for women and larger employment gains in high-skill occupations for women relative to men was first noted by Autor and Wasserman (2013) and investigated in follow-up work by Cerina et al. (2021). Recent work by Chuan and Zhang (2023) explores how automation differentially affects the job opportunities of non-college men and women, and the resulting implications for college enrollment. They show that the decline in routine-occupations as a result of automation led to a more pronounced decline in job opportunities for non-college women relative to non-college men, and argue that this is a key explanation for the larger increase in female college enrollment relative to men from 1980 to 2000.

Related work documents growing demand for social skills both within and across occupations that appear to strongly favor women (Borghans et al., 2014; Deming, 2017; Cortes et al., 2021). In particular, Cortes et al. (2021) document that women are increasingly sorting into "good" jobs (i.e., high-wage/cognitive occupations) relative to men and that this sorting is largely occurring within rather than between occupations. They further show that social skills have become more important within high-wage/cognitive occupations relative to other occupations, and that an increase in the importance of social skills is associated with an increase in the occupation's female employment share, consistent with an increase in the demand for female workers in these occupations. Our paper extends these strands of work by providing a comprehensive analysis of the differential effects of automation on the occupational structure and skill investment of men and women and by exploring causal mechanisms.

The rest of the paper proceeds as follows. Section 2 presents a descriptive account of the relationship between gender, occupation, and automation in the U.S. labor market from 1980 to 2017. Section 3 describes the empirical framework that uses variation in local labor market exposure to automation to assess the causal effects of automation and presents results. Section 4 outlines the model and the quantitative results. Section 5 provides empirical support for the main model mechanism and Section 6 concludes.

2 Automation and Gender: Some Descriptive Patterns

In this section, we provide a descriptive account of how widespread technological changes in the 1980s to 2010s differentially affected men and women and their corresponding responses in terms of reallocation across employment sectors and skill acquisition. In particular, we focus on (1) the displacement of men and women from certain occupations, and (2) how each gender has responded in terms of reallocation across employment sectors.

2.1 Automation Risk Measure

Measures of automation risk seek to quantify the ease with which machines are able to substitute for the work activities performed by workers. For our analysis, we follow Autor et al. (2003) who use 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 et al., 2019). Routine tasks are those at greatest risk of automation since these activities are sufficiently well-defined and can be executed by machines following a set of pre-programmed 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, replaced by machines (at least given current technological limitations). Importantly, the set of non-routine tasks tend to 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 rely on high levels of routine work but include few abstract or manual tasks face a greater risk of automation. Job task requirements are extracted from the 1977 Dictionary of Occupational Titles (DOT) by the U.S. Department of Labor and merged to the corresponding Census occupation classifications.[4] Specifically, the RTI for each occupation is defined as follows:

$$RTI_k = \ln(T_k^R) - \ln(T_k^M) - \ln(T_k^A) \tag{1}$$

where T_k^R, T_k^M and T_k^A are, respectively, the routine, manual, and abstract task inputs in each occupation k.

2.2 Gender Gaps in Automation Risk

Historically, men and women have sorted into different occupations, and such occupational differences have remained quite persistent over time (Blau et al., 2013). 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 plot the task requirements

[4] Autor and Dorn (2013) collapse the original five task measures in Autor et al. (2003) to three task aggregates for abstract, routine, and manual tasks. Specifically, for routine tasks, the variables used measure adaptability to work requiring "set limits, tolerances, and standards" and "finger dexterity." For manual task requirements, the variable used is "eye-hand-foot coordination." For abstract tasks, the variables code the importance of "direction, control and planning of activities" as well as quantitative reasoning ("ged-math") in an occupation.

of an occupation by their percentile in the distribution of the female shares in 1980. Panel A of Figure 2 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 shares in 1980 have high routine task inputs, particularly female-intensive occupations at the top-decile (greater than 89 percent female). Routine tasks are lowest in occupations with around the median share of females (25 percent female); these occupations also have the highest intensity of abstract tasks. Finally, manual task inputs are a decreasing function of female share in an occupation, with male-dominated occupations being the most manual intensive.

Panel B of Figure 2 uses the RTI index of an occupation to proxy for an occupation's risk of being automated. As indicated by the blue dashed line, the relationship between automation risk and the 1980 female share percentile in an occupation is positive, with a particularly steep relationship for occupations in the top three deciles of the share of females distribution. Overall, this figure shows that women faced a disproportional risk of their job being automated. To get a sense of the types of occupations that men and women are moving into and out of over time, the figure also includes the smoothed 1980 to 2017 change in an occupation's employment share of men (green line) and women (red line), by an occupation's female share percentile in 1980. Over the past four decades, women have moved out of female-intensive occupations (mostly clerical) toward occupations in the middle of the 1980 female share distribution. Moreover, there is a striking negative correlation between changes in female employment share and the risk of automation. A comparison of Panels A and B of Figure 2 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 in Panel B) are much more muted, with a gradual, but modest shift into female-intensive occupations. The gender differences in the patterns of employment change imply an overall decrease in occupational segregation over this period, consistent with earlier work (e.g., Blau et al., 2013).

To shed light on which occupations are driving the observed patterns in Figure 2, we turn to occupation-level (3-digit) scatterplots of the relationship between the 1980 to 2017 change in employment share for women and the RTI index (Figure 3). The size of the occupation is proportional to the area of the marker. In 1980, women were 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.[5] 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 (left panel of Figure 3). Notice, however, that there are some occupations such as registered nurses (RNs) and health aides that are

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

well above the regression line, suggesting that other factors – such as the increase in demand for healthcare in this case – are likely to also be important drivers of changes in the occupational distribution. Similarly, 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, etc.).

As observed in the right panel of Figure 3, the same graph for men shows a much flatter relationship – the slope is slightly negative and not statistically significant. A potential explanation for this is perhaps that the type of high RTI occupations that men and women concentrate in are different along dimensions that imply different incentives for switching out of the occupations. Indeed, Appendix Table 1 Panel A shows that there is a much stronger negative cross-occupational correlation between the RTI measure and unionization rates, education levels, and wages for women than for men. Nevertheless, we find that, empirically, these occupational attributes cannot explain the steeper relationship between automation risk and occupational change for women than for men (see Appendix Table 1 Panel B).[6]

The analysis so far provides us with two facts about gender and automation: (1) In 1980, women faced greater risk that their jobs would be automated than men. For example, using the routine task intensity (RTI) of an occupation as a proxy for the risk of automation, in 1980, 44 percent of female workers, compared to 26 percent of male workers were in occupations in the top tercile of the RTI distribution. (2) 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.

Where did women and men who shifted out of high RTI occupation groups go? To answer this question, in Figure 4, we divide occupations into five main groups: (1) professional and technical occupations (low RTI), (2) clerical and retail occupations (high RTI), (3) production, crafts and machine operators occupations (high RTI), and (4) transportation, construction, mechanic, farming occupations (low RTI), and (5) service occupations (low RTI) and calculate the change in the share of workers in each group between 1980 and 2017, separately for men and women.[7] As observed in the figure, the decline in employment share in high RTI occupation groups was larger for women than for men. Nevertheless, women were also more likely, both in absolute and in relative terms, to enter professional and technical occupations than their male counterparts. A larger proportion

[6]Specifically, we estimate a model of occupational change that includes RTI, the interaction between RTI and a dummy for female, and interactions between the occupational characteristics mentioned above and a dummy for female as follows:

$$\Delta OccShare_{j,g} = \alpha + \beta_1 \times I(g = female) + \beta_2 RTI_j + \beta_3 RTI_j \times I(g = female) + X'_j\beta_4 + X'_j\beta_5 \times I(g = female) + \epsilon_{j,g}$$

where $\Delta OccShare_{j,g}$ is the change in the occupation share of occupation j for gender g from 1980 to 2017 and X'_j includes the following occupation-level characteristics: share of workers unionized in 1993, share of workers with a college degree in 1980 and the average hourly wage in 1980. The estimates in Appendix Table 1 Panel B show little change in β_3 when X'_j and $X'_j * I(g = female)$ are added as controls.

[7]See Data Appendix Table for a list of occupations in each group.

of men shifted toward low-skilled services.[8] This observation that women shift differentially into high-skill/high-wage occupations constitutes our third fact.

This descriptive analysis highlights important patterns of occupational change by gender during this period. However, it is unclear whether automation is the driving force behind the differential changes observed. Indeed, there were other significant changes in the labor market during this period of time that may have given rise to similar patterns. Such changes include technological changes in household production, the timing of fertility, and childrearing (Greenwood et al., 2005; Goldin and Katz, 2002; Albanesi and Olivetti, 2016), legislation to combat discrimination, and changes in gender norms (Fernandez, 2013) that, collectively, led to the large-scale entry of women in the labor market and a decline in the educational and occupational barriers faced by women (Goldin, 2006).

Therefore, in what follows, we attempt to isolate the role of automation by exploiting variation across local labor markets in the U.S. in the exposure to automation.

3 Cross-Commuting Zone Analysis

3.1 Data

Our analysis draws on data from the 1980, 1990, and 2000 US Censuses, and the three-year aggregates of the 2010 (2008 to 2010) and 2017 (2015 to 2017) American Community Survey (ACS). The main sample consists of individuals between the ages of 25 to 64 who are not residing in group quarters. The baseline analysis focuses on the "native-born" population who reside in their state of birth. In additional specifications, we also show results for the full population, including both internal and international migrants.[9]

Our main unit of analysis is based on local labor markets. These are defined based on the concept of Commuting Zones (CZs) which are clusters of counties that are characterized by strong commuting ties (Tolbert and Sizer, 1996). We use Autor and Dorn (2013)'s geographic matching process to construct 722 CZs that cover the mainland of the United States over the period of our analysis. To create a balanced panel of occupations from 1980 to 2017 for use in our analysis, we utilize Dorn (2009)'s occupational classification which modifies the *OCC1990* Census classification to create a consistent set of occupations from 1980 to 2010. From 2010 onwards, we extend the classification using Deming (2017)'s crosswalk.[10]

[8] A similar pattern was previously noted by Autor and Wasserman (2013). These patterns are also consistent with the greater degree of employment polarization for women than for men as documented by Cerina et al. (2021).

[9] For the analysis of the occupational distribution of employed workers, we exclude unpaid family workers.

[10] See the Data Appendix for more details on the sample construction and Appendix Table 2 for descriptive statistics.

3.2 Empirical Strategy

To identify the causal effect of automation on the employment structure, we leverage variation across commuting zones in the share of workers in occupations at risk of automation. We measure routine task-intensity at the geographic level following Autor and Dorn (2013), where the RTI index is used to identify the set of occupations that are in the top employment-weighted third of routine task-intensity in 1980. These occupations can be thought of as routine intensive occupations. Then, for each commuting zone j and decade t, we compute a measure of routine task-intensity, and hence, exposure to automation, as the share of workers employed in routine intensive occupations, as given by:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \times 1 \left[RTI_k > RTI^{y,P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{2}$$

where L_{jkt} is the employment in occupation k in commuting zone j at time t, and $1[\cdot]$ is an indicator variable that takes a value of one if the occupation is routine intensive (i.e., in the top employment-weighted third of the overall RTI index) and zero otherwise. By construction, the mean of $RSH_{j,1980}$ is 0.33. Since this measure fixes the set of routine-intensive occupations, changes in RSH_{jt} over time captures reallocation in the employment share across occupations.[11]

Using the CZ-decade level measure of exposure to automation risk, we estimate the following empirical specification:

$$\Delta_{t-(t-1)} Y_j^g = \delta_t^g + \beta^g RSH_{j,t-1} + X'_{j,t-1}\alpha^g + \gamma_s^g + \epsilon_{jt}^g \tag{3}$$

where $\Delta_{t-(t-1)} Y_j^g$ is the change in outcome Y for gender g in CZ j between t and $t-1$, RSH_{jt-1} is the CZ's start of period routine employment share and, $X'_{j,t-1}$ represents a set of control variables measured at the CZ level in $t-1$. δ_t and γ_s are time period and state fixed effects, respectively. The equation stacks the four time periods covering the ten-year intervals between 1980 and 2017: 1980-1990, 1990-2000, 2000-2010 and, 2010-2017. Standard errors are clustered at the state level and observations are weighted by the CZ share of the national population in 1980.

The control variables that we include in our main specifications are factors that the literature has identified as potentially important determinants of occupational choice and skill investments and that vary across local labor markets. On the supply side, we include proxies for factors that affect women's willingness to engage in market work and to pursue higher-paying jobs such as gender norms and the cost of outsourcing household production. We proxy for gender norms using the labor force participation of college-educated married women, and for the cost of outsourcing

[11] To the extent that automation leads to within-occupation changes in routine-intensiveness, this measure potentially overestimates the share of workers engaged in routine-intensive work. We are not able to capture within-occupation changes as we lack a consistent time-varying measure of occupational tasks over our period of study. Nevertheless, previous work by Deming (2017) shows that similar measures constructed using the 1977 DOT and 1998 O*NET track each other closely in terms of average task intensity from 1980 to 2013.

household production using the share of the non-college population in the CZ that is foreign born.[12] We also include proxies for the marriage market returns to investing in a college degree, namely, the difference in the marriage rates between women with and without a college degree, as well as the gap in household income between college and non-college women. On the demand side, we include variables that proxy for lower barriers to entry for women in top occupations (female share in the top 10% highest paying occupations), longer-term structural transformation that have facilitated the entry of women into the labor market (service sector share of employment in a CZ),[13] and the growth in the healthcare sector (share of the population aged 65 and older). We note that some of these controls could be "bad controls" in the sense that they might, in fact, be the outcome of exposure to automation; nevertheless, we include these variables in some specifications to assess the extent to which these factors may be driving the results, and exercise caution in interpreting the main coefficient estimates accordingly.

3.3 Correlational Evidence Across Commuting Zones

3.3.1 Graphical Evidence

Before we discuss the main regression estimates, Figures 5 and 6 provide graphical evidence that commuting zones that specialized in routine task-intensive jobs experienced differential employment shifts over the subsequent decades, particularly for women. Figure 5 plots the change between 1980 and 2017 in the employment share at each female share percentile in commuting zones with routine employment share above and below the weighted median in 1980. Routine-intensive commuting zones exhibit a more pronounced drop in the share of women working in occupations with the highest female share, which, as Figure 2 shows, are also the occupations that are at the greatest risk of automation. These commuting zones also see a larger increase in the share of women working in the more integrated occupations, which are also occupations most intensive in abstract skills. These differential changes imply that routine-intensive commuting zones experienced more occupational gender integration. Men's occupational change is much more muted, but changes are slightly larger in more routine-intensive commuting zones.

Autor and Dorn (2013) show that CZs with initially higher routine employment share were more likely to adopt information technology and, at the same time, saw larger declines in employment in routine-intensive occupations. To illustrate our empirical strategy, we explore the latter relationship graphically, focusing on the gender dimension. Panel A of Figure 6 plots the relationship between the share of routine employment in a CZ in 1980 on the x-axis and the 1980 to 2017 change in the

[12] Cortes and Pan (2019) show that by facilitating outsourcing household production, low-skilled immigrants have enabled women to enter occupations with higher returns to working long hours and shifted them toward higher-paying jobs within occupations.

[13] See Ngai and Petrongolo (2017) for quantitative evidence on the role of the rise of the service economy in raising women's relative labor supply and wages in the U.S.

share of workers aged 25 to 64 in a CZ working in high routine task-intensity (RTI) occupations on the y-axis, separately by gender (blue dots for men, orange dots for women). A few observations stand out. First, there is significant variation in our explanatory variable – the share workers employed in routine-intensive occupations in a CZ varies from around 20% to 40%. Second, for both men and women, the 1980 to 2017 change in the employment share in high RTI occupations is negatively correlated with the initial (1980) share of workers in routine occupations – that is, local labor markets that were more exposed to automation risk at the beginning of the period experienced larger declines in the share of workers in high RTI occupations, implying that the risk of automation did indeed translate to employment declines in routine-intensive occupations within a local labor market over time. Third, although the observed negative relationship is statistically significant for both genders, it is much steeper for women ($p < 0.01$). Women appear to have reacted more strongly to the risk of automation in terms of employment shifts out of high RTI occupations. Panel B is similar to Panel A, but with the change in the share of workers in professional and technical occupations on the y-axis instead. As observed, the decline in employment share in routine-intensive occupations in commuting zones initially more specialized in routine tasks is accompanied by an increase in the employment share in professional and technical occupations over the same time period. The positive relationship is statistically significant for both genders, but substantially steeper for women, implying that in response to exposure to automation risk, women were much more likely to shift into these high-skill, high-wage occupations than men. Overall, these results echo the differential patterns of occupational change by gender documented in the earlier descriptive analysis.

3.3.2 OLS Estimates

The OLS estimates of equation (3) that looks at the relationship between initial routine employment share (RSH) and the subsequent 10-year change in the employment share of various occupation groups by gender are reported in Columns (1) and (2) of Table 1. Our main sample is restricted to individuals who reside in the state that they were born in to distinguish between natives switching occupations or choosing new occupations when entering the labor market from migration flows.[14] Panel I focuses on changes in the employment share in top routine task-intensive occupations while Panel II examines changes in the employment share across broad occupation groups to study the effects of automation on the entire occupational distribution in a given local labor market. For the latter, we include individuals who are not in the labor force as a separate category to capture

[14] Although our focus is not on migration, Autor and Dorn (2013) show in their model that places that specialize in routine task-intensive industries should experience a net inflow of high-skill labor. In the 2SLS results that follow, we assess the migration margin by additionally reporting estimates from the full sample that includes both internal and international migrants.

potential effects of automation on the extensive margin of participation.[15]

The OLS estimates with just period and state fixed effects broadly confirm the visual evidence presented above. Not surprisingly, given the initial occupational distribution, we find that in local labor markets with high exposure to automation risk, women shift out of clerical and retail sales occupations, whereas men mostly shift out of production and craft operations.[16] Consistent with our previous analysis, initial exposure to automation risk is correlated with women being much more likely to enter professional and technical occupations, while men disproportionately switch to less routine, but lower-skilled occupations, such as transport, construction, mining, and farming occupations. In these routine-intensive CZs, women, however, also appear to be more likely than men to drop out of the labor force.

3.4 Instrumental Variables Approach

A natural challenge with interpreting the OLS estimates as causal is that variation across CZs in routine employment share (RSH) is not random, and could very well capture unobserved attributes or contemporaneous shocks that are unrelated to the risk of automation, but are correlated with subsequent changes in the occupational distribution of men and women. Ideally, we would like to isolate stable differences in production structures across CZs that give rise to pre-existing differences in initial specialization in routine tasks. We use the instrument proposed by Autor and Dorn (2013) that exploits historical cross-CZ differences in industry specialization. The instrument is constructed by predicting the component of RSH that is attributable to a CZ's local industry mix and the occupational structure of industries at the national-level in 1950 as shown in the equation below:

$$\widehat{RSH_j} = \sum_{i=1}^{I} E_{i,j,1950} \times R_{i,-s,1950}, \tag{4}$$

where $E_{i,j,1950}$ is the employment share of industry i in commuting zone j in 1950 and $R_{i,-s,1950}$ is the routine occupation share among workers in industry i in 1950 in all U.S. states except the state s that includes commuting zone j. The $RSH_{j,t-1}$ in each base year in equation (3) is instrumented with $\widehat{RSH_j}$ interacted with time dummies. Appendix Table 3 presents the first stage. In all our specifications, the coefficients are of the expected sign, highly statistically significant, and have large F-statistics. The instrument is less predictive of initial RSH for later decades; this is to be

[15] To limit the number of groups, and given that unemployment rates are low, we include the unemployed in the group labeled "not in the labor force." Results for occupational groups, and the category "not in the labor force" are robust to adding a separate category for the unemployed. We find no effects of the risk of automation on a CZ's change in unemployment.

[16] There is not a perfect correspondence between top RTI occupations and the other occupational groups. 75% of workers in Clerical and Retail Sale Occupations and 50% of those in Production/Craft/Machine Operators are in top RTI occupations. Much smaller shares are observed in Professional and Technical Occupations (19%), Service Occupations (28%), and Transport/Construction/and farming Occupations (7%). See Appendix Table 4.

expected, since 1950 industry composition is less predictive of current industry composition over time.

Columns (3) to (6) of Table 1 show that the qualitative findings are generally similar when we estimate the model using 2SLS. In our preferred specifications that include controls, relative to the OLS estimates, we find larger gender differences in the share working in professional and technical occupations, with the female coefficient almost double that of male's. The 2SLS estimates for the extensive margin also suggest that CZs more specialized in routine tasks saw larger declines in labor force participation for both men and women, with slightly larger negative effects for women ($p = 0.13$).[17] The results are robust to including controls as well as to the inclusion of domestic and international migrants in the sample (see Columns (7) and (8)). In other words, the occupational patterns of migrants in response to the automation shock appear to be similar to the "native-born" population (i.e., those who reside in their state of birth). Additionally, we show in Appendix Table 5 that our results remain largely unchanged when we use alternative measures of a CZ's exposure to automation (i.e., how RSH is defined) such as varying how we measure the routine-task intensity of an occupation as well as the threshold used to define occupations at high risk of automation.

To summarize how the risk of automation has changed the occupational distribution of men relative to women, we use the change in the Duncan Segregation Index (1955) as an outcome in a similar specification as equation (3).[18] 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. Table 2 presents the results. We find strong evidence that the automation wave has led to gender integration across occupations. The magnitude of the coefficient of our preferred specification suggests that moving from the 20th to the 80th percentile in RSH in 1980 will imply 1 percentage point per decade larger decline in occupational segregation. This is a large effect, as the mean decadal change in the occupation segregation index was 1.9 percentage points over the period from 1980–2017.

To provide suggestive evidence that our estimates are capturing the effect of automation and not pre-existing trends in changes in the occupational distribution that are correlated with the instrument, we conduct placebo tests where we estimate equation (3) using the period *prior* to the start of the computer revolution. If we observe similar effects during this earlier period, we would be concerned that our main estimates could be due to the instrument picking up other differences across CZs rather than the effects of automation. The first three columns of Appendix Table 6, Panel A, reproduce the previous results from Tables 2 and 3 while the last three columns

[17] Our results of a negative effect of automation on labor force participation are consistent with Acemoglu and Restrepo (2020) who find that robots reduce the employment to population ratio and with Grigoli et al. (2020) who leverage cross-country variation in the routinizability of occupations and occupational composition and estimate negative effects of automation on the participation rates of prime-age men and women.

[18] The only difference is that the estimating equation does not have a gender dimension.

re-estimate equation (3) using data from 1950 to 1980.[19,20] We find that, if anything, CZs with higher RSH in the initial period experienced a larger increase in occupational segregation during this period. These findings are reassuring and provide some evidence supporting the idea that the instrument is not simply capturing cross-CZ differences, unrelated to the diffusion of computers, that are correlated with greater occupational integration over time.

3.5 Effects on Skill Investments

Next, we examine the impact of automation on skill investments. Since computer capital substitutes for routine tasks and complement abstract/social tasks (Autor et al., 2003; Autor and Dorn, 2013; Deming, 2017), to the extent that productivity in abstract/social tasks is acquired through investments in education, we would expect automation to increase the skill investment of workers. We therefore test whether CZs that were initially more specialized in routine tasks saw larger increases in the share of individuals with a college degree, and how this relationship varies by gender.

Panel A of Table 3 presents the 2SLS estimates from equation (3) using the ten-year change in the share of college graduates among individuals 25 to 34 years old as the dependent variable. We focus on a younger age range for this analysis (rather than those between the ages of 25 to 64) since this group is young enough to alter their skill investments in response to automation risk at the local level in the preceding ten year period. Consistent with our hypothesis, college attainment of both men and women increased significantly more over the subsequent decade in CZs that were initially more exposed to automation.[21] The education response, however, is significantly larger for women than for men. Confirming these gender-specific results, Panel B shows that when we use the college gap (male − female) as the dependent variable instead, areas with higher routine share experienced a larger change in the college gender gap favoring women. The magnitude of the estimate from our preferred specification in Panel B, Column (4), implies that moving from the 20th to 80th percentile in RSH in 1980 reduces the gender pap in college by about 0.7 percentage points per decade, or 25% of the mean decadal change over 1980-2017.

The last two columns of Table 3 indicate that the observed relationship between automation and skill investments is much larger for the sample that includes both domestic and international immigrants. This implies that areas with a higher risk of automation also experienced a larger inflow of educated workers, particularly college-educated women.[22] Supporting the interpretation

[19]For the 1950 to 1980 panel, we use the 1950 to 1970 and 1970 to 1980 changes since the 1960 Census does not provide the geographic information required to construct comparable CZs.

[20]For the 2SLS estimates, we construct a similar instrument for the 1950 – 1980 panel based on predicted RSH in a given time period as outlined in equation 4.

[21]Our results are consistent with Autor and Dorn (2013), who find that CZs with higher share of workers in high RTI occupations experienced greater polarization of education attainment. However, they do not distinguish between immigrants and natives (and thus cannot identify what share of the effect comes from a change in skill investments and what share from increases in mobility) and present results for both genders combined.

[22]The model in Autor and Dorn (2013) predicts that the increase in the returns to abstract tasks as a result of

that the education results are driven by automation, Panel B of Appendix Table 6 shows that the negative relationship between initial RSH and the change in the college gender gap in the earlier period from 1950 to 1980 are small and not statistically significant. Overall, these results suggest that automation played some role in the observed reversal of the gender gap in college attainment since the 1980s.

3.6 Between vs. Within Cohorts Effects

The observed changes in the occupational distribution in response to automation could be the result of new cohorts entering different occupations, or occupational changes within cohort (i.e., people switching occupations later in life). We conduct two empirical exercises to distinguish between these two possibilities. First, since the data that we use is based on repeated cross-sections of the population, assuming that the cohort size is relatively stable over ten-year periods, we can infer within-cohort changes by examining changes in the occupational distribution of a given cohort across adjacent Census decades. Specifically, we construct our dependent variables within groups of cohorts; for example, we calculate the change in the share of a particular cohort working in a given occupational group between 1980 to 1990, 1990 to 2000, etc. We have six groups of cohorts, from the 1926 to 1935 cohorts observed in 1980 and 1990 to the 1976 to 1985 cohorts observed in 2010 and 2017. We pool all cohorts together, and estimate equation (3), adding cohort-by-year fixed effects, and instrumenting for $RSH_{j,t-1}$ in each base year with $\widehat{RSH_j}$ interacted with time dummies. Second, to identify changes due to new entrants to the labor market, we restrict the sample to individuals between the ages of 25 to 34 and estimate the 2SLS version of equation (3) to examine the effects of automation on changes across decades in the occupational decisions of these cohorts of young workers.

Table 4 presents the results from the two sets of regressions. We find evidence for occupational changes that vary by gender both across and within cohorts, with somewhat larger effects of the risk of automation on changes across cohorts of new entrants to the labor market. Women are more likely to switch out of top RTI occupations and into professional and technical occupations in both exercises. For skill investment decisions, exposure to automation increased college-going for both genders within and across cohorts. While the within cohort changes in education are similar by gender, newer cohorts of women were much more likely to obtain a college degree relative to their male counterparts in areas that were more exposed to automation.

automation would attract high-skill workers from CZs with lower initial specialization in routine tasks. Their paper, however, does not focus on the gender dimension.

3.7 Alternative Hypotheses: Trade Shocks, Offshoring Potential, and Gender Norms

There are at least three other phenomena taking place during our period of study that could potentially lead to shifts in occupational choices and skill investments, with impacts that are likely to vary by geography: the increasing offshoring of jobs, the growing import competition, and changes in gender norms. To examine if our results are capturing the effects of these phenomena rather than the exposure to automation, in our main specification, we include variables that have been used in the literature to measure exposure to these factors as controls. The Data Appendix provides a comprehensive description of the data sources and outlines the methods used to construct these variables.

A plausible alternative channel is that similar to the automation shock, growing offshoring of jobs and import competition might displace workers from routine-intensive occupations into sectors that are non-offshorable or less affected by import competition. Appendix Table 7 shows that the findings on occupational distribution and skill investments are similar when we control for offshoring potential and trade shocks. Moreover, in accordance with previous research (Autor et al., 2015), we observe the most pronounced negative effects of exposure to automation and to import competition in routine-intensive occupations (production, clerical, and retail sales occupations). The fact that the point estimates of automation are not affected much by the inclusion of import competition, are consistent with a weak overlap in the geographic exposure of CZs to automation and import competition (Autor et al., 2015).

Another alternative explanation for our results is that places with high exposure to automation may also be those that have more progressive gender norms or have experienced larger shifts in gender norms that might result in greater occupational upgrading for women relative to men. To test for this possibility, we add more direct measures of gender norms as controls in our regressions. More specifically, we use measures of state-level gender norms derived from questions about the appropriate role of women in society from the General Social Survey (GSS) from Charles et al. (2022) and Kleven (2023).[23] The index from Charles et al. (2022) ("sexism index") is time-invariant and uses data from the 1977 to 1998 waves of the GSS while the index from Kleven (2023) ("Kleven index") varies at the decade-level and uses data from the 1972 to 2018 GSS.[24] For the time-invariant index, we interact it with year fixed effects; for the time-varying index, we include it both in levels as well as in changes. As shown in Appendix Table 8, all of our main results are robust to controlling for these measures of gender-role attitudes – including them does not change the effect of exposure to automation on the occupational distribution by gender, or on college attainment.

[23]The small sample sizes in the GSS do not permit the construction of measures at a more disaggregated level.

[24]The set of questions used in both indices have some overlap but differ slightly in that the index from Charles et al. (2022) includes five additional gender-related questions.

4 Model

In this section, we develop a model of occupational choice with endogenous educational investments to understand how and why automation might differentially affect the occupational distribution and skill investments by gender.

Agents. Our model has two types of agents indexed by $i \in \{f, m\}$: females (f) and males (m). There is a measure one of each gender. As we discuss below, males and females might differ in their skill endowment and in their education costs.[25]

Technology. Our technology requires only two tasks: routine and non-routine as in Autor et al. (2003). Uneducated workers engage in routine intensive jobs, earning an equilibrium wage of w_R. Educated workers supply labor in skilled non-routine tasks, which also rewards social skills.[26] The two genders differ exogenously in their endowed distribution of social skills, $s \sim F_i(s), i = f, m$, where $F_f(s)$ first-order stochastic dominates $F_m(s)$.

Goods are produced based on a constant-elasticity-of-substitution (CES) production function, where routine and non-routine outputs are imperfect substitutes:

$$Y = \left[\gamma(C + L_R)^\sigma + (1-\gamma)(A_H X_H)^\sigma\right]^{\frac{1}{\sigma}}, \; 0 < \gamma, \sigma < 1, \tag{5}$$

where C and L_R are computer capital input and labor input in the routine task, A_H and X_H are productivity and the total labor input in efficiency units in the non-routine task, γ is the weight of the routine task in production, and $\frac{1}{1-\sigma}$ is the elasticity of substitution between the outputs of the routine and non-routine tasks.

Total routine labor is the sum of female and male routine labor: $L_R = L_R^f + L_R^m$. The total efficiency units of labor inputs in non-routine tasks is given by $X_H = \int_{\Omega_H^f}(1-\tau)s ds + \int_{\Omega_H^m} s ds$, where Ω_H^f and Ω_H^m are the set of female and male non-routine workers. We assume τ to be between zero and one so that it represents the constraints women face in entering/working in the skilled non-routine sector. The wedge τ includes gender norms, discrimination, and other barriers that prevent women to flourish in the non-routine sector. We expect τ to have been quite high at the beginning of our study period. Given the perfect substitutability of routine tasks and computer capital, the wage of routine task input is pinned down by the price of computer capital (ψ):

$$w_R = \psi. \tag{6}$$

[25] Appendix B contains all proofs and derivations for the model.

[26] The returns to social skills might arise because teams often operate more efficiently than people working on isolation. In an experiment, Weidmann and Deming (2021) find that social skills predict team performance about as much as IQ.

Skilled non-routine workers earn their marginal products in the competitive market,

$$w_H^i = (1 - \tau \mathcal{D}^f)(1-\gamma)Y^{1-\sigma} A_H^\sigma X_H^{\sigma-1}, i = f, m, \tag{7}$$

where $\mathcal{D}^f$ is a gender dummy such that $\mathcal{D}^f = 1$ if the agent is female and zero otherwise.

Education Decisions. Agents are heterogeneous in the cost of obtaining education $a \sim \Gamma_i(a), i = f, m$, as in Feng et al. (2023). We assume this reduced form for tractability, although, practically, the education cost can be a function of one's general learning ability, family wealth, and many other factors. The distribution of education costs might also differ by gender.

Individuals make education decisions to maximize their expected income. A worker indexed with social skill and education cost (s, a) chooses the non-routine task if and only if the education cost is below the following thresholds:

$$w_R = w_H s - a \Rightarrow \begin{cases} a^{*f} = (1-\tau)(1-\gamma)Y^{1-\sigma}A_H^\sigma X_H^{\sigma-1}s - w_R, \\ a^{*m} = (1-\gamma)Y^{1-\sigma}A_H^\sigma X_H^{\sigma-1}s - w_R. \end{cases} \tag{8}$$

If $\tau > 0$ and large, our model predicts that a lower share of women will invest in college, even if they have the same or more advantageous distribution of education costs as men and have a comparative advantage in social skills. This scenario is consistent with what we observe in our baseline period (1980), where, as Figure 1 shows, men were 5 percentage points more likely to attend college than women.

Equilibrium. A competitive equilibrium is defined by education choices (a^{*m}, a^{*f}), market wages (w_R, w_H^i) and labor allocation $\{L_R^i\}_{i=f,m}$, such that:
(i) individuals make optimal education choices where men with $a < a^{*m}$ and women with $a < a^{*f}$ obtain an education, while others do not;
(ii) given the prices, the representative firms maximize profits by choosing production inputs and individuals maximize income;
(iii) given the optimal choices of firms and households, market wages clear the labor market for females and males:

$$L_R^i + \int_{\Omega_H^i} \Gamma(a^{*i}(s))ds = 1, i = f, m; \tag{9}$$

4.1 Analytical Predictions

Following Autor and Dorn (2013), we model the automation process as a decline in the price of capital, ψ. This is a natural choice as in our model: i) routine workers are more substitutable with capital input than non-routine workers, and ii) an increase in routine inputs raises the marginal productivity of non-routine inputs. We start with the most direct predictions of our model.[27]

[27]Proofs are presented in Appendix B

Proposition 1. *Automation increases the share of educated workers for both females and males in equilibrium.*

Proposition 2. *A lower price of capital ψ leads to a replacement of routine workers by machines, reallocating labor from routine jobs to skilled jobs.*

The model prediction on labor reallocation is consistent with standard automation models where education decisions are exogenous. And as in those models, automation has a direct positive effect on the wage premium ($\frac{w_H^i}{w_R}$). However, unlike models with fixed-sized skill groups, this positive impact is attenuated by the general equilibrium effect of an increase X_H. As long as the general equilibrium effect is dominated by the direct effect, we should observe an increase in the returns to college.

Regional Variation in Technology and Labor Reallocation and Educational Attainment by Gender. To map the model predictions to our empirical exercise, we need to introduce regional variation in production technologies and separately look at the effects by gender. For tractability, we simplify equation (5) by considering the case of $\sigma \to 0$, where the production function is reduced to the Cobb-Douglas form:

$$Y = (C + L_R)^{\gamma}(A_H X_H)^{1-\gamma}, \gamma \in (0,1), \tag{10}$$

where γ is the region-specific factor share of routine tasks. All regions have access to the capital input at price ψ and the Cobb-Douglas technology, while they differ in the routine task intensity; regions with larger γ are more intensive in routine tasks. To obtain analytical predictions, we further assume that college education cost a is independent of social skill and is drawn from a uniform distribution on $[0, \mu_i N]$, where N is a constant, $\mu_m = 1$, and $0 < \mu_f \leq 1$.[28]

Proposition 3. *Normalize $0 < \psi \leq 1$. Automation leads to a larger decline in routine workers in the initially routine-intensive (larger γ) regions for males and females; hence, also a larger increase in educational attainment for both genders.*

Proposition 4. *If average female social skills, adjusted for constraints and education costs, are higher than for males, i.e., $\left[\frac{1-\tau}{\mu}\mathbb{E}_f s - \mathbb{E}_m s\right] > 0$, for a given capital price decline, automation leads to a larger decline in routine workers in the initially routine-intensive (larger γ) regions for females compared to males; hence, also a larger increase in educational attainment for females.*

See Appendix B for proofs. We also show in the appendix that the initial $L_R^f - L_R^m > 0$ holds under reasonable parameter values even if females have a comparative advantage in social skills and/or more favorable distribution of education costs.[29] Furthermore, we show that within a given

[28]We can relax these assumptions and show that Proposition 4 holds under a set of reasonable parameter values.

[29]See equation (24) in Appendix B; for example, set $\psi = 1$, normalize $N = 1$, $A_H = 1$, $\mathbb{E}_m s = 1$, let $\mu = 0.7$, $\tau = 0.2$, $\gamma = 0.5$, and $\mathbb{E}_f s$=1.1, we have $L_R^f - L_R^m = 0.4$ initially.

region and under the same condition as in Proposition 4, a decline in the price of capital, ψ leads to a decrease in $(L_R^f - L_R^m)$.

In summary, our model predicts that as the price of capital falls, we should observe a reallocation of workers from routine task to non-routine tasks within a given region, and that local labor markets with greater initial specialization in routine tasks will experience a larger change. Additionally, if women have a comparative advantage in social skills and/or a more favorable distribution of education costs, this reallocation will be larger for women than for men. The next section examines the evidence supporting these gender differences in skills and costs, and tests additional implications derived from our model.

4.2 Evidence for Model Assumptions and Empirical Implications

4.2.1 Evidence for Model Assumptions

For the model to match the empirical results we need at least one of two conditions to hold: (1) women have comparative advantage in social skills, and (2) women face a more favorable distribution of non-pecuniary education costs. In this section, we discuss existing evidence on both these conditions.

Evidence of gender differences on several dimensions of social skills go back several decades. Hall (1978) summarizes results of 75 studies on decoding nonverbal communication, finding a moderate and statistically significant female advantage. A more recent paper, Greenberg et al. (2023) documents a female advantage in "reading the mind in the eyes" test across multiple countries. Furthermore, in personality tests women score higher in agreeableness, tendency towards cooperation, and extraversion (Weisberg et al., 2011). Women also place higher importance on the job attributes "working with people" and being "helpful to society" than men (Fortin, 2008).

Girls also tend to perform better in school, even conditional on test scores (Cornwell et al., 2013), suggesting an advantage in non-cognitive skills. In a study including 346 effect sizes extracted from 227 studies representing 820,158 females and 826,629 males at all school levels, O'Dea et al. (2018) find that girls have significantly higher grades than boys by 6.3%, with 10.9% less variation among girls than among boys. Similarly, Becker et al. (2010) argue that women's distribution of the non-pecuniary costs of going to college has a lower mean and lower variance than men's, implying a more elastic supply of college educated women (at current returns).[30] Other papers document persistent behavioral and developmental differences between boys and girls and argue that these are likely to have contributed to the growing female advantage in college attendance and completion (e.g., Goldin et al., 2006; Jacob, 2002; Bertrand and Pan, 2013).

[30] Becker et al. (2010) show that the gender difference in the distribution of non-pecuniary costs to college provides an explanation for the reversal of the gender gap in college attainment favoring women even if women's overall returns to college (both labor market and non-labor market) are not higher than that of men's.

4.2.2 Evidence on Empirical Implications

Shift Towards Social Skills-Intensive Occupations. The model suggests that the complementarity between computerization and abstract/social skills would lead to the expansion of both abstract and social skill-intensive occupations; moreover, women's comparative advantage in social skills implies that this shift would be disproportionately larger for women relative to men, particularly in regions with a large routine sector. This would provide a natural explanation for women's disproportionate shift into professional and technical occupations since these occupations are characterized by high levels of both analytical and social skills.[31]

We test these empirical implications by exploring whether (1) CZs with higher initial specialization in routine-intensive tasks experience a larger expansion in high social skills occupations, (2) if the sorting towards social skill-intensive occupations is stronger among occupations that also require high levels of cognitive skills, and (3) if these aspects of sorting are more pronounced for women relative to men. Following Deming (2017), we use the 1998 O*NET to classify occupations into those with high and low social skill requirements. Top social skill occupations are defined as those in the top tercile of the weighted social skill distribution in 1980. We further divide occupations into four types: 1) top social, top math, (2) top social, non top math, (3) non top social, top math, and (4) non top social, non top math. The grouping is based on whether or not the occupation is in the top tercile of the social skill and non-routine analytical task-intensity distributions.[32,33]

Table 5 presents the 2SLS estimates from equation (3) using as dependent variables the ten-year change in the employment share in top social skill occupations (Panel I) and the ten-year change in employment share in each of the four occupation groups plus those outside the labor force (Panel II). For both genders, we find that local labor markets with higher RSH in the initial period experienced a larger increase in the share of workers in occupations requiring high social skills, especially in occupations that have high analytical task requirements. We also observe a decrease in the employment share in occupations requiring low-social skills, independent of math requirements. We find little effect on the share working in high social, low math occupations. Furthermore, the effect sizes are much larger for women (and statistically different from that of men's), consistent with the model prediction of differential shifts for women toward high social/high abstract occupations as well as the empirical observation of a larger shift toward professional and technical occupations among women. Taken together, these findings provide empirical support for

[31] 85% of workers in professional and technical occupations work in top social skills occupations and 62% in top social top math occupations. See Appendix Table 4.

[32] E.g., top math, top social occupations are those that are in the top tercile of both the social skill and/or non-routine analytical task distributions; non top math, top social occupations are those in the top tercile of the social skills distribution, but not in the top tercile of non-routine analytical task distribution, and so on.

[33] The social skill task intensity index includes ratings in coordination, negotiation, persuasion, and social perceptiveness. The math task intensity index includes (i) the extent to which an occupation requires mathematical reasoning; (ii) whether the occupation requires using mathematics to solve problems; and (iii) whether the occupation requires knowledge of mathematics. The Data Appendix presents the occupations in each category.

the main model mechanisms.

Price effects. The model suggests that a decrease in the price of capital (or automation) increases the returns to working in the non-routine sector, and also implies an increase in the returns to going to college. To explore these implications, we examine whether routine-intensive labor markets experienced an increase in the returns to college by gender, as well as an increase in the relative wages of occupations with high social and high analytical task requirements.[34] Specifically, we follow Autor and Dorn (2013) and estimate the following wage equation at the individual level using log hourly wages from the 1980 Census and the 2017 three-year aggregate ACS (2017–2019):

$$\begin{aligned}\ln w_{ijet} = \gamma_{je} &+ \lambda_c[College \times \widehat{RSH_j} \times 2017] + \lambda_{sc}[SomeCollege \times \widehat{RSH_j} \times 2017] \\ &+ \lambda_{hsd}[HSdrop \times \widehat{RSH_j} \times 2017] + X_i'\beta_t \\ &+ \phi_{jt} + \delta_{et} + \epsilon_{ijet}\end{aligned} \tag{11}$$

where i denotes workers, and as in the previous specifications, j, e, and t refer to commuting zone, education, and year (1980 or 2017), respectively. We control for education × year, CZ × year, and CZ × education fixed effects. X_i' is a vector of individual characteristics (age, race, potential experience and marital status). The effects of individual characteristics are allowed to vary over time. We are interested in the λs, which tell us the long run differential changes in the returns to education in CZs with high vs. low risk of automation. We estimate the reduced form OLS regression for the full sample, and separately by gender. We conduct a similar exercise to examine the wage returns to working in various occupation groups by estimating the same equation as (11) but replacing education groups with occupation groups defined by their social and math task requirements.[35]

Panel A of Table 6 presents the estimates for the returns to college. We find that CZs with higher exposure to automation experienced larger increases in the relative wages of college educated workers relative to those with only a high school degree, with somewhat larger effects for women ($p = 0.14$). The magnitudes of the coefficients suggest that CZs in the 80th vs. 20th percentile of the 1980 $\widehat{RSH}$ distribution saw a 10 (8) percentage point larger increase in the returns to college for women (men). This is a sizable effect relative to the mean change in the relative wages of college vs. high school graduates of 32 (41) percentage points for women (men) from 1980 to 2017.

Panel B focuses on relative wages by occupation type. For both genders, relative hourly wages in occupations with top math and top social skills requirements rise by significantly more in CZs with

[34] We acknowledge that our estimates are capturing both changes in the actual returns to a college education and changes in the composition of who goes to college. As is clear from our model, the marginal agent that goes to college (non-routine sector) as a result of an automation shock might have lower skills than the average worker with a college degree.

[35] The reference group is occupations that are not at the top of the social skills distribution and the analytical (math skill) distribution.

higher initial routine employment shares, and the increase is slightly larger for women ($p = 0.07$). The magnitudes suggest that a 9 percentage point higher predicted routine share (i.e., the difference between the 80th and 20th percentile CZ) leads to about 7 log points greater wage growth in high math and high social occupations relative to occupations with low math and low social skill requirements. The results also show uniformly positive, but smaller, wage effects for occupations with either low social/high math or high social/low math requirements.

Finally, in Panel C, we explore the net effect of these employment and wage changes on the gender pay gap. We re-estimate equation (11) this time focusing on the interaction between gender and our measure of automation exposure at the local level. We find that CZs with higher predicted RSH in 1980 experienced a larger narrowing of the gender gap in log hourly wages between 1980 and 2017. This suggests that, overall, the automation wave of the 1980s can account for at least part of the increase in women's relative wages in the U.S. over this period.[36]

5 Conclusion

A large literature demonstrates how the widespread adoption of computers has affected the occupational structure and the wages and employment prospects of workers with different skills. Yet, the gender dimension of these shifts remains relatively understudied.

In this paper, we show that although women were disproportionately represented in occupations facing a high risk of automation in 1980 and were subsequently more likely than men to be displaced from routine-intensive occupations, they were more likely than men to shift toward more high-skill, high wage occupations over the last four decades. Leveraging cross-commuting zone variation in the initial exposure to automation as proxied for by the share of workers in routine-intensive occupations, we show that women were significantly more likely than men to transition out of routine-intensive occupations to professional and technical occupations. The net effect is that local labor markets that were initially more specialized in routine tasks experienced greater occupational integration by gender. Young people in these labor markets were also significantly more likely to attain a college degree, with larger effects on the skill investments of women relative to men.

We show that a model of occupational choice with endogenous educational investments and where women have a comparative advantage in social skills can qualitatively match the observed empirical patterns. As empirical support for the main model mechanisms, we further show that areas with greater exposure to automation experience larger shifts toward occupations with high social and high analytical task requirements, especially among women. Moreover, the estimated employment and wage changes are consistent with demand-induced shifts resulting from automation. Overall, we find that automation is likely to have played an important role in women's relative

[36] This result is consistent with Beaudry and Lewis (2014) who also study the effects of computerization on relative skill prices. However, they do not examine the various channels that we emphasize in this paper such as differential occupational shifts, skill investments, and social skills.

progress in the labor market between 1980 and 2017.

Looking forward, our findings suggest that automation – to the extent that it shares features of the computerization shock of the 1980s – is likely to pose more of a challenge for the labor market prospects of men relative to women. Over the past few decades, women have closed the gender gap in exposure to automation risk in the form of representation in routine-intensive jobs, and their educational attainment has increasingly outpaced that of men's. These developments raise important concerns as to how the present generation of men can rise to the challenges (and promises) of technological change.

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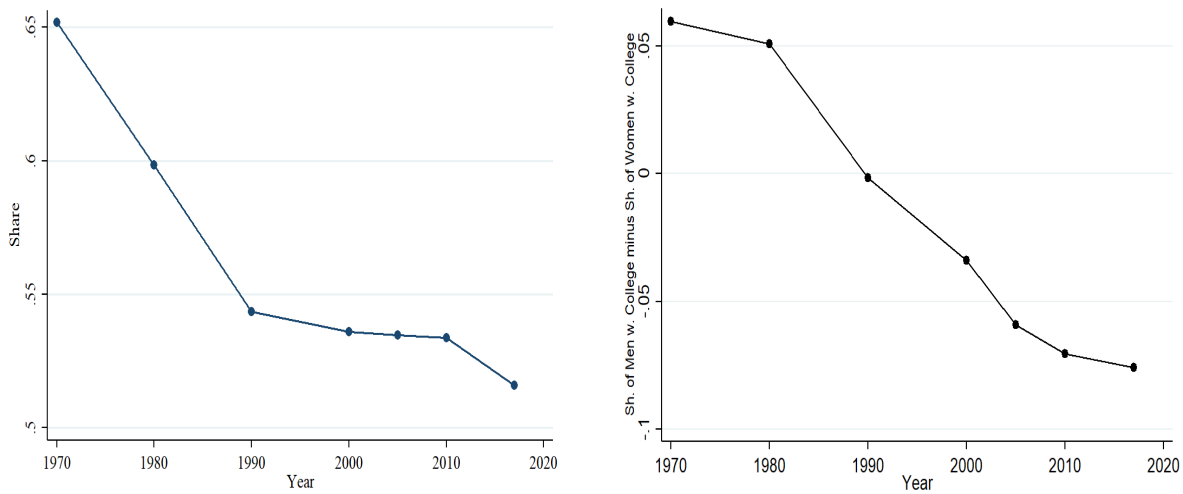
Figure 1: Trends in Occupational Segregation and the Gender College Gap

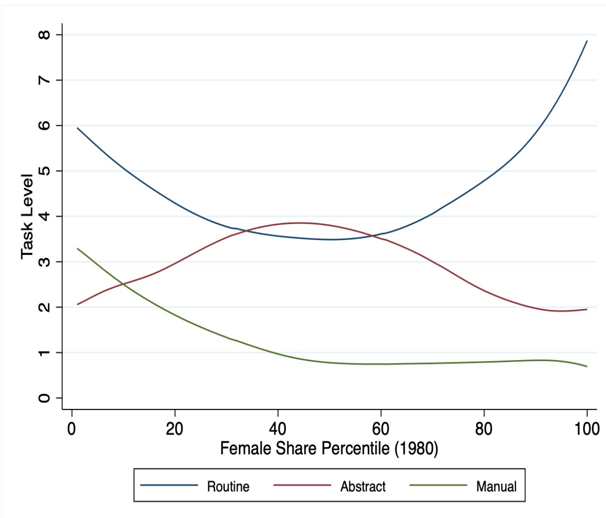
A. Occupational Segregation, Age 25 to 64　　　B. Male-Female College Gap, Age 25 to 34



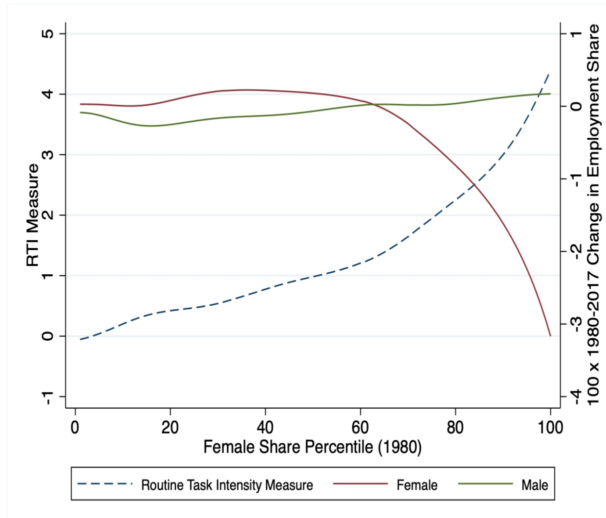
Notes: Data comes from the 1970, 1980, 1990, and 2000 Census, and the 2005, 2010 and 2017 ACS. Our measure of occupational segregation is the Duncan Index. The index measures the share of one gender that would have to move to another occupations for men and women to have the same occupational distribution. In Panel B the college gap is defined as the share of men minus the share of women with at least a college degree.

Figure 2: Task Inputs, Changes in Occupational Shares, and Occupational Segregation

A. Occupational Tasks

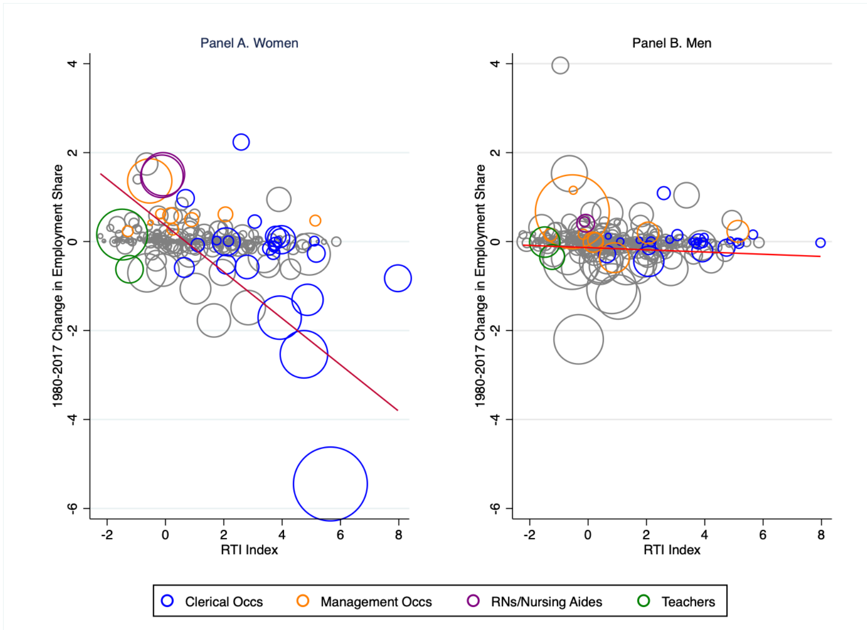


B. RTI and Change in Occupational Shares



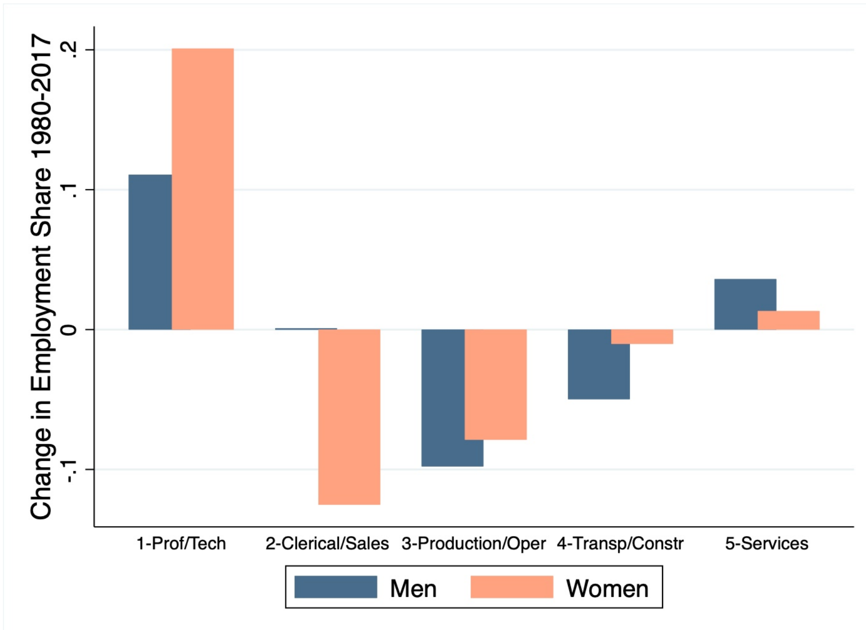
Notes: Data on female share and occupational distributions are from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. A balanced panel of occupations from 1980 to 2017 is constructed using Dorn's (2009) occupational classification scheme. Data on occupational task content (routine, abstract, manual) are from Autor and Dorn (2013). Task inputs are measured on a 0 to 10 scale. $RTI = \ln(\text{Routine Task Input}) - \ln(\text{Abstract Task Input}) - \ln(\text{Manual Task Input})$. Occupations are ranked based on their female share in 1980. Outcomes by female percentile are plotted using a locally weighted smoothing regression.

Figure 3: Change in Employment and RTI by Gender



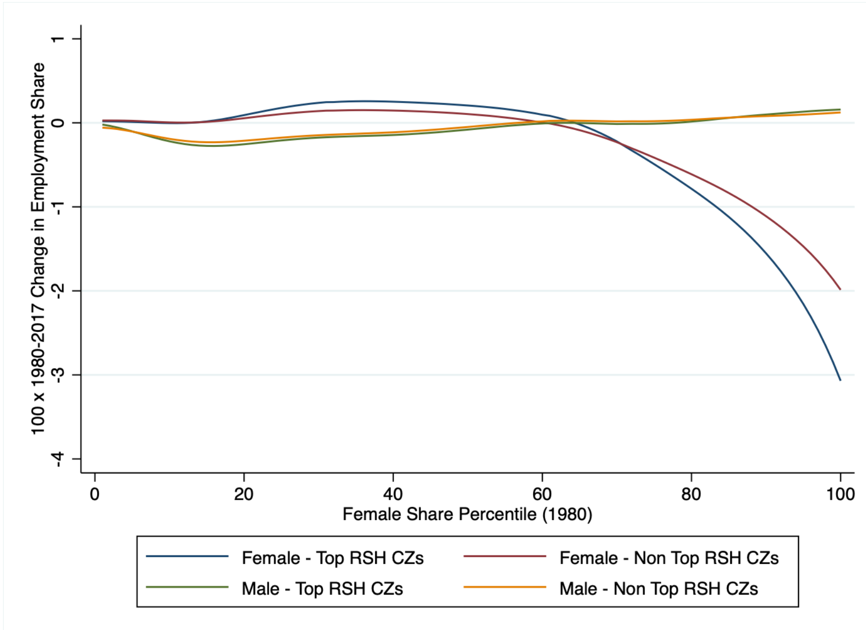
Notes: The unit of observation is an occupation. The size of the marker indicates the employment share of the occupation for each gender. The employment changes are computed from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. $RTI = \ln(\text{Routine Task Input}) - \ln(\text{Abstract Task Input}) - \ln(\text{Manual Task Input})$. The 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 RTI, using the employment share of females and males in 1980, respectively, as weights.

Figure 4: Change in Aggregate Employment Share from 1980 to 2017 Across Broad Occupation Groups by Gender



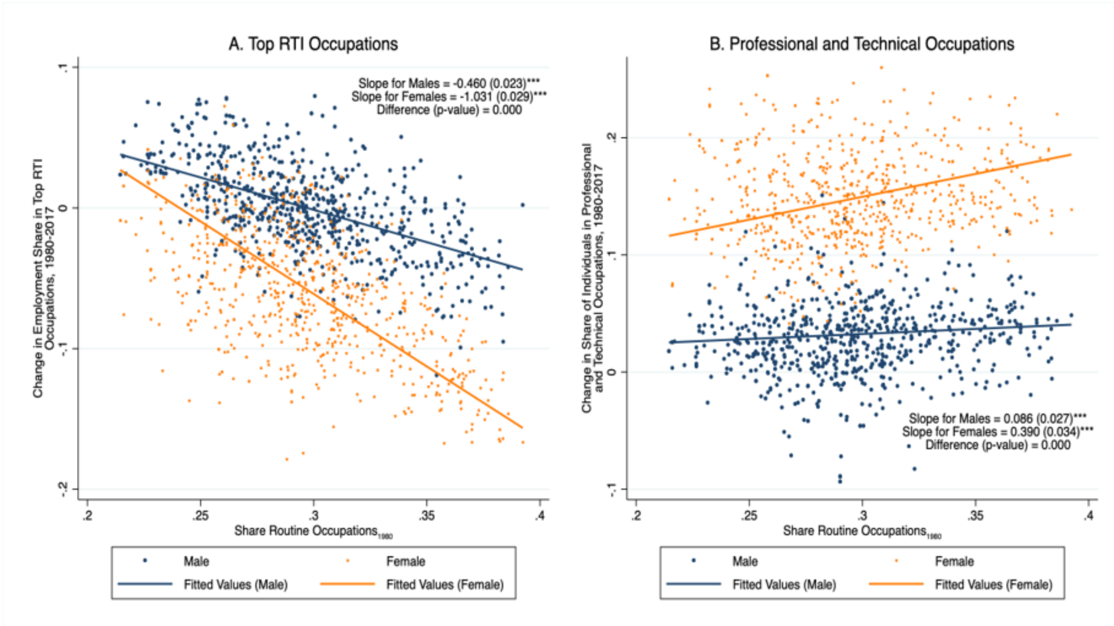
Notes: The employment changes are computed from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. See Data Appendix for a list of the occupations included in each category.

Figure 5: Change in Employment by Female Share Percentile and CZ group



Notes: Data on female share and occupational distributions are from the 1980 Census and the 2017 (2016-2018) three-year aggregate ACS. Occupations are ranked based on their female share in 1980. Top RSH CZs are defined as those with an RSH higher than the (weighted) median. Changes in the occupational distribution are constructed separately by gender and by CZ group.

Figure 6: Change in Employment Share by CZ and Gender



Notes: The unit of observation is at the CZ × gender level. The lines in each figure are fitted lines based on a weighted regression of the employment change on the CZ's RSH, using the employment share by gender in 1980 as weights. Top RTI occupations are those with an RTI in the top tercile of the (weighted) RTI distribution. See Data Appendix for the occupations included in Professional and Technical Occupations.

Table 1: Routine Employment Share and Change in the Occupational Employment Shares within Commuting Zones, 1980-2017

Dep. Variable: 10 × Annual Change in Employment Share in Specific Occupation Groups

	OLS		2SLS					
	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				I. Top RTI Occupations				
Routine	-0.202‡	-0.414‡	-0.152‡	-0.422‡	-0.221‡	-0.370‡	-0.214‡	-0.318‡
Occ Share$_{-1}$	(0.022)	(0.027)	(0.022)	(0.039)	(0.026)	(0.04)	(0.028)	(0.027)
				II. Occupational Distribution				
				A. Professional and Technical Occupations				
Routine	0.102‡	0.219‡	0.146‡	0.283‡	0.177‡	0.320‡	0.175‡	0.268‡
Occ Share$_{-1}$	(0.017)	(0.025)	(0.021)	(0.024)	(0.042)	(0.05)	(0.025)	(0.030)
				B. Clerical and Retail Occupations				
Routine	-0.070‡	-0.271‡	-0.078‡	-0.317‡	-0.042†	-0.232‡	-0.039†	-0.265‡
Occ Share$_{-1}$	(0.019)	(0.031)	(0.019)	(0.035)	(0.018)	(0.048)	(0.016)	(0.044)
				C. Production/Craft/Machine Operators				
Routine	-0.192‡	-0.089‡	-0.251‡	-0.021	-0.399‡	-0.159‡	-0.414‡	-0.151‡
Occ Share$_{-1}$	(0.028)	(0.027)	(0.035)	(0.033)	(0.032)	(0.025)	(0.035)	(0.023)
				D. Service Occupations				
Routine	-0.015†	-0.026*	0.011	-0.039†	-0.001	-0.098‡	0.013	-0.095‡
Occ Share$_{-1}$	(0.007)	(0.015)	(0.015)	(0.019)	(0.02)	(0.026)	(0.016)	(0.023)
				E. Transport/Construction/Mech/Mining/Farm				
Routine	0.188‡	0.007	0.139‡	0.008	0.157‡	-0.020†	0.082‡	-0.031‡
Occ Share$_{-1}$	(0.02)	(0.004)	(0.022)	(0.005)	(0.035)	(0.009)	(0.032)	(0.010)
				F. Not in Labor Force/Unemployed				
Routine	-0.013	0.160‡	0.033	0.086*	0.108‡	0.190‡	0.183‡	0.274‡
Occ Share$_{-1}$	(0.025)	(0.037)	(0.029)	(0.05)	(0.036)	(0.053)	(0.04)	(0.069)
Controls	None		None		Levels		Levels	
Observations					2,888			

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 64. The sample in Columns (1) to (6) is restricted to individuals who are residing in their state of birth. Columns (7) and (8) consider all individuals, including internal and international migrants to a particular state. The unit of analysis is at the CZ × decade level (4 time periods × 722 commuting zones). Each coefficient is from a separate regression. For the 2SLS specifications, the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p<0.10, †p<0.05, ‡p<0.01.

Table 2: Routine Employment Share and Changes in Occupational Segregation by Gender within Commuting Zones, 1980-2017

Dep. Variable: Decadal Change in Segregation Index

	OLS	2SLS		
	Born and residing in the same state			All
	(1)	(2)	(3)	(4)
Routine Occupation Share_{-1}	-0.161‡	-0.266‡	-0.127‡	-0.181‡
	(0.027)	(0.029)	(0.042)	(0.037)
Controls	None	None	Levels	Levels
Observations			2,888	

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 64. The sample in Columns (1) to (3) is restricted to individuals who are residing in their state of birth. Columns (4) considers all individuals, including internal and international migrants to a particular state. The unit of analysis is at the CZ $\times$ decade level (4 time periods $\times$ 722 commuting zones). Each coefficient is from a separate regression. For the 2SLS specifications, the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. The dependent variable is the 10-year change in the Duncan segregation index. The segregation index ranges between 0 and 1, and 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. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p<0.10, †p<0.05, ‡p<0.01.

Table 3: Routine Employment Share and Changes in College Share by Gender and the College Gap, 1980-2017

	OLS		2SLS					
	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dep. Var: 10 × Annual Change in Share of Population age 25 to 35 With College							
Routine	$0.185^{\ddagger}$	$0.312^{\ddagger}$	$0.257^{\ddagger}$	$0.400^{\ddagger}$	$0.165^{\ddagger}$	$0.355^{\ddagger}$	$0.316^{\ddagger}$	$0.475^{\ddagger}$
Occ Share_{-1}	(0.031)	(0.035)	(0.042)	(0.040)	(0.054)	(0.062)	(0.049)	(0.049)
	B. Dep. Var: 10 × Annual Change in the College Gap (Men-Women)							
Routine	$-0.132^{\ddagger}$		$-0.137^{\ddagger}$		-0.105^{*}		$-0.112^{\ddagger}$	
Occ Share_{-1}	(0.023)		(0.033)		(0.057)		(0.034)	
Controls	None		None		Levels		Levels	
Observations	2,888							

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 34. The sample in Columns (1) to (6) is restricted to individuals who are residing in their state of birth. Columns (7) and (8) consider all individuals, including internal and international migrants to a particular state. The unit of analysis is at the CZ × decade level (4 time periods × 722 commuting zones). In Panel B, the dependent variable is the 10-year change in the college gap, defined as the share of men minus the share of women with at least a college degree. Each coefficient is from a separate regression. For the 2SLS specifications, the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in brackets. *p<0.10, †p<0.05, ‡p<0.01.

Table 4: Between and Within Cohorts Effects. Routine Employment Share, Changes in Occupational Distribution and Skill Investments, 1980-2017

	I. Restricted to Individuals Aged 25-34		II. Within Cohort Changes	
	(1)	(2)	(3)	(4)
	Men	Women	Men	Women
Dep. Variable: 10 × Annual Change in Employment Share in Specific Occupation Groups				
	I. Top RTI Occupations			
Routine Occ Share$_{-1}$	-0.142‡	-0.275‡	-0.089‡	-0.203‡
	(0.048)	(0.045)	(0.025)	(0.040)
	II. Occupational Distribution			
	A. Professional and Technical Occupations			
Routine Occ Share$_{-1}$	0.237‡	0.272‡	0.105‡	0.172‡
	(0.073)	(0.066)	(0.031)	(0.038)
	B. Clerical and Retail Occupations			
Routine Occ Share$_{-1}$	-0.011	-0.288‡	-0.046†	-0.149‡
	(0.030)	(0.050)	(0.018)	(0.031)
	C. Production/Craft/Machine Operators			
Routine Occ Share$_{-1}$	-0.348‡	-0.093‡	-0.230‡	-0.023
	(0.055)	(0.028)	(0.033)	(0.022)
	D. Service Occupations			
Routine Occ Share$_{-1}$	-0.012	-0.162‡	-0.018	-0.114‡
	(0.033)	(0.049)	(0.015)	(0.022)
	E. Transport/Construction/Mech/Mining/Farm			
Routine Occ Share$_{-1}$	0.081	-0.027†	0.136‡	-0.002
	(0.053)	(0.013)	(0.047)	(0.009)
	F. Not in Labor Force/Unemployed			
Routine Occ Share$_{-1}$	0.054	0.298‡	0.053	0.117†
	(0.058)	(0.069)	(0.053)	(0.052)
Dep. Variable: 10 × Annual Change in Share of Population Aged 25 to 34 With College Education				
Routine Occ Share$_{-1}$	0.165‡	0.355‡	0.198‡	0.160‡
	(0.054)	(0.062)	(0.029)	(0.027)
Observations	2888	2888	8664	8664

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample in Columns (1) and (2) is restricted to individuals between the ages of 25 to 34 (excluding internal and international migrants), and the unit of analysis is at the CZ × decade level (4 times period × 722 commuting zones). In Columns (3) and (4) the sample is restricted to individuals aged 25 to 64 (excluding internal and international migrants), and the unit of analysis is at the CZ × decade × cohort level (4 times period × 722 commuting zones × 6 cohorts; each cohort enters on average 2 time periods). Each coefficient is from a separate 2SLS regression where the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions in Columns (3) and (4) include cohort by year fixed effects. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p<0.10, †p<0.05, ‡p<0.01.

Table 5: Changes in Employment Share of Specific Occupation Groups Defined Based on Social/Math Skill Intensity, 1980-2017

Dep. Variable: 10 × Annual Change in Employment Share in Specific Occupation Groups

	OLS		2SLS					
	Born and residing same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I. Top Social Skills Occupations (Top Tercile)							
Routine	0.065‡	0.183‡	0.083‡	0.236‡	0.053	0.252‡	0.069†	0.203‡
Occ Share_{-1}	(0.017)	(0.021)	(0.023)	(0.022)	(0.045)	(0.040)	(0.028)	(0.027)
	II. By Occupation Groups							
	A. Top Math and Top Social							
Routine	0.106‡	0.143‡	0.131‡	0.186‡	0.080†	0.204‡	0.109‡	0.178‡
Occ Share_{-1}	(0.020)	(0.013)	(0.022)	(0.017)	(0.038)	(0.031)	(0.030)	(0.022)
	B. Non Top Math and Top Social							
Routine	-0.041‡	0.041‡	-0.049‡	0.050‡	-0.027	0.048‡	-0.041‡	0.025*
Occ Share_{-1}	(0.010)	(0.012)	(0.010)	(0.014)	(0.019)	(0.017)	(0.008)	(0.014)
	C. Top Math and Non Top Social							
Routine	-0.060‡	-0.019*	-0.083‡	0.004	-0.062‡	0.020	-0.075‡	0.011
Occ Share_{-1}	(0.009)	(0.010)	(0.010)	(0.013)	(0.012)	(0.014)	(0.010)	(0.012)
	D. Non Top Math and Non Top Social							
Routine	0.008	-0.325‡	-0.033	-0.325‡	-0.098†	-0.461‡	-0.176‡	-0.488‡
Occ Share_{-1}	(0.018)	(0.030)	(0.021)	(0.045)	(0.040)	(0.061)	(0.034)	(0.057)
	E. Not in the Labor Force/Unemployed							
Routine	-0.013	0.160‡	0.033	0.086*	0.108‡	0.190‡	0.183‡	0.274‡
Occ Share_{-1}	(0.025)	(0.037)	(0.029)	(0.050)	(0.036)	(0.053)	(0.040)	(0.069)
Controls	None		None		Levels		Levels	
Observations	2,888							

Notes: The data is from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 64. The sample in Columns (1) to (6) is restricted to individuals who are residing in their state of birth. Columns (7) and (8) consider all individuals, including internal and international migrants to a particular state. The unit of analysis is at the CZ × decade level (4 time periods × 722 commuting zones). For the 2SLS specifications, the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. Each coefficient is from a separate regression. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p<0.10, †p<0.05, ‡p<0.01.

Table 6: Routine Employment Share and Change in Wage Levels within Commuting Zones, 1980-2017, Reduced Form OLS Estimates

	Dep. Var.: Log Hourly Wages		
A. Changes in Returns to Education			
	Coefficient on Pred share of Routine Occ in 1980 × 2017 ×		
	College	Some College	HS Drop
	(reference category: HS Grad)		
All	$0.965^{\ddagger}$	$0.125^{\dagger}$	$-0.485^{\ddagger}$
	(0.097)	(0.050)	(0.087)
Women	$1.128^{\ddagger}$	-0.029	-0.132
	(0.117)	(0.066)	(0.114)
Men	$0.892^{\ddagger}$	$0.185^{\ddagger}$	$-0.621^{\ddagger}$
	(0.129)	(0.068)	(0.109)
B. Changes in Returns to Tasks			
	Coefficient on Pred share of Routine Occ in 1980 × 2017 ×		
	Top Social and Top Math	Non Top Social and Top Math	Top Social and Non Top Math
	(reference category: Non Top Social and Non Top Math)		
All	$0.779^{\ddagger}$	$0.226^{\dagger}$	$0.604^{\ddagger}$
	(0.069)	(0.090)	(0.070)
Women	$0.865^{\ddagger}$	$0.220^{\ddagger}$	$0.591^{\ddagger}$
	(0.075)	(0.071)	(0.100)
Men	$0.737^{\ddagger}$	$0.394^{\ddagger}$	$0.593^{\ddagger}$
	(0.092)	(0.129)	(0.106)
C. Changes in the Gender Pay Gap			
	Coefficient on Pred share of Routine Occ in1980 × 2017 × Female		
All	$0.328^{\ddagger}$		
	(0.087)		

Notes: Each row presents coefficients from one pooled OLS reduced form regression with N between 6,652,127 and 14,044,245. Observations are drawn from the 1980 Census and the 2017 (2015-2017) ACS three-year aggregates and exclude self-employed and workers in farming and mining occupations. The independent variable of interest (i.e., the instrument) is the share of routine occupations in 1980 predicted by industry structure in 1950 ($\widehat{RSH_j}$) interacted with a dummy for 2017. Models in Panel A include an intercept, CZ × education FE, education × year FE, CZ × year FE, quartic in potential experience, dummies for married, gender, nonwhite and foreign-born, all interacted with year FE. Models in Panel B include an intercept, CZ × occupation group FE, occupation group × year FE, CZ × year FE, quartic in potential experience, education dummies, dummies for married, gender, nonwhite and foreign-born, all interacted with year FE. Models in Panel C include an intercept, CZ × gender FE, gender × year FE, CZ × year FE, quartic in potential experience, education dummies, dummies for married, nonwhite and foreign-born, all interacted with year FE. Hourly wages are defined as yearly wage and salary income divided by the product of weeks worked time usual weekly hours. Robust clustered at the CZ level are reported in brackets. Observations are weighted by each worker's share in total labor supply in a given year. *p< 0.10, †p< 0.05, ‡p< 0.01.

A Data Appendix

Employment and Occupational Distribution. We use data drawn from the 1980, 1990, and 2000 US Census, the three-year aggregates of the 2010 (2008, 2009, 2010), and the 2017 (2015, 2016 and 2017) ACS. The Census samples for 1980, 1990 and 2000 include 5 percent of the US population, and the 2010 and 2017 ACS aggregate samples include 3 percent of the population.

The sample of workers used consists of individuals between the ages of 25 and 64. Residents of institutional group quarters are dropped along with unpaid family workers. We adopt Autor and Dorn (2013)'s definition of local labor markets based on the concept of Commuting Zones (CZs) and implement their geographic matching process (see Online Appendix of Autor and Dorn (2013) and Dorn (2009) for details on the construction of CZs). Our analysis includes the 722 CZs that cover the mainland of the United States. All calculations are weighted by the Census sampling weight multiplied by a weight derived from the geographic matching process.

To create a balanced panel of occupations from 1980 to 2017 for use in our analysis, we use Dorn (2009)'s occupational classification up to 2010 and extend the crosswalk using Deming (2017)'s crosswalk from 2010 onward. The measures of an occupation's routine, abstract, and manual task inputs are derived from Autor and Dorn (2013).

Offshoring. We follow Autor and Dorn (2013) who measure the potential for offshoring job tasks instead of the actual offshoring that takes place. To compute the offshoring potential ("offshorability"), they combine the two variables *Face-to-Face Contact* and *On-Site Job* derived from O*NET database by Firpo et al. (2011). We use this measure of offshoring potential for each occupation and compute the commuting zone level offshorability index as the employment weighted average offshorability score in each commuting zone and year.

Import Exposure. To compute a measure of import exposure at the commuting zone level, we follow a similar approach as Autor et al. (2013). Our measure of local labor market exposure to import competition takes the following form,

$$\Delta IPW_{jt}^{US} = \sum_{k} \frac{L_{jkt}}{L_{kt}} \frac{\Delta M_{kt}}{L_{jt}} \tag{12}$$

where L_{jkt} is the employment in CZ j and industry k at year t, L_{kt} is the national employment in industry k, L_{jt} the employment level in CZ j, and ΔM_{kt} is the change in total US imports in industry k between t and $t+1$. Notice that the only difference in our measure of import exposure relative to Autor et al. (2013) resides in the use of total US imports, instead of US imports from China. This is because our sample period starts in 1980, decade in which US spending on Chinese goods represented less than 0.6 percent of total imports (Autor et al., 2013).

Similarly, we instrument the import exposure measure in (12) with a non-US exposure variable constructed as follows,

$$\Delta IPW_{jt}^{OTH} = \sum_k \frac{L_{jkt-1}}{L_{kt-1}} \frac{\Delta M_{okt}}{L_{jt-1}} \tag{13}$$

where ΔM_{okt} is the change in imports from Germany and Japan (for the period 1980-1990) and from China (for the period 1990-2017) to other high-income countries (Australia, Denmark, Finland, New Zealand, Spain, and Switzerland). Additionally, the measure in (13) uses employment levels from the prior decade.

To construct the variables in (12) and (13) we combine data from the UN Comtrade Database and the US Census. Furthermore, we use the industry classification provided by Autor et al. (2019). Comtrade Database provides import data for five-digit Standard International Trade Classification (SITC2) industry codes. Using the NBER-CES Manufacturing Industry Database (www.nber.org/research/data/nber-ces-manufacturing-industry-database), we construct a crosswalk between SITC2 and SIC87 industry codes, following a similar procedure as Autor et al. (2013). Finally, crosswalks between SIC87 and the classification used by Autor et al. (2019) are available at David Dorn's Webpage (www.ddorn.net/data). Employment at the CZ level is constructed using US Census data described previously.

B Model Appendix - Proofs

Proof of Proposition 1. The result is clear from equation (8) in the text. With automation, routine wage decreases driven by a decline in ψ, and total output Y increases. Assuming the share of educated workers stays constant (X_H is fixed), the value of the right-hand side of (8) increases. To restore the indifference condition, the education cost threshold must increase. Therefore, the shares of female and male educated workers increase in equilibrium. Q.E.D.

Proof of Proposition 2. This result is obatined by combining Proposition 1 and equation (9). As $\Gamma(a^{*i})$ increases with automation, routine labor shares have to decrease such that the labor market clears for both genders. Q.E.D.

Proof of Proposition 3. The first-order conditions for wages for a representative firm of a given region imply:

$$w_R = \gamma \left[\frac{A_H X_H}{C + L_R}\right]^{1-\gamma}, \tag{14}$$

$$w_H^m = (1-\gamma) A_H^{1-\gamma} \left[\frac{C + L_R}{X_H}\right]^{\gamma}, \tag{15}$$

$$w_H^f = (1-\tau)(1-\gamma) A_H^{1-\gamma} \left[\frac{C + L_R}{X_H}\right]^{\gamma}. \tag{16}$$

Replacing $w_R = \psi$, we use equation (14) to determine the level of computer capital utilized by the representative firm:

$$C = \left(\frac{\gamma}{\psi}\right)^{1/(1-\gamma)} A_H X_H - L_R. \tag{17}$$

Substituting equation (17) into equations (15) and (16) we obtain:

$$w_H^m = (1-\gamma)A_H \left(\frac{\gamma}{\psi}\right)^{\gamma/(1-\gamma)},$$
$$w_H^f = (1-\tau)(1-\gamma)A_H \left(\frac{\gamma}{\psi}\right)^{\gamma/(1-\gamma)}.$$

We can then solve for the threshold levels of education cost at a given level of social skill:

$$a^{*i}(s) = (1-\tau\mathcal{D}^f)(1-\gamma)A_H \left(\frac{\gamma}{\psi}\right)^{\gamma/(1-\gamma)} s - \psi, \tag{18}$$

where $\mathcal{D}^f = 1$ if the agent is female and 0 otherwise. The number of routine workers by gender is, therefore, as follows:

$$L_R^m = \frac{1}{N}\left[N + \psi - (1-\gamma)A_H \left(\frac{\gamma}{\psi}\right)^{\gamma/(1-\gamma)} \mathbb{E}_m s\right] \tag{19}$$

$$L_R^f = \frac{1}{\mu N}\left[\mu N + \psi - (1-\tau)(1-\gamma)A_H \left(\frac{\gamma}{\psi}\right)^{\gamma/(1-\gamma)} \mathbb{E}_f s\right] \tag{20}$$

The partial and cross-partial derivatives of (19) are given by:

$$\frac{\partial L_R^m}{\partial \psi} = \frac{1}{N} + \frac{A_H}{N}\left(\frac{\gamma}{\psi}\right)^{\frac{1}{1-\gamma}} \mathbb{E}_m s > 0 \tag{21}$$

$$\frac{\partial^2 L_R^m}{\partial \psi \partial \gamma} = \frac{A_H}{N} \frac{\left(\frac{\gamma}{\psi}\right)^{\frac{1}{1-\gamma}} (\gamma \log(\gamma/\psi) - \gamma + 1)}{(1-\gamma)^2 \gamma} \mathbb{E}_m s > 0. \tag{22}$$

Similarly, the cross-partial term for females is also positive:

$$\frac{\partial^2 L_R^f}{\partial \psi \partial \gamma} = \frac{A_H}{N} \frac{\left(\frac{\gamma}{\psi}\right)^{\frac{1}{1-\gamma}} (\gamma \log(\gamma/\psi) - \gamma + 1)}{(1-\gamma)^2 \gamma} \frac{1-\tau}{\mu} \mathbb{E}_f s > 0. \tag{23}$$

Q.E.D.

Proof of Proposition 4. According to the proof of Proposition 3, the gender routine labor gap in a region with routine labor intensity γ is given by:

$$L_R^f - L_R^m = \frac{\psi}{N}\frac{1-\mu}{\mu} + \frac{(1-\gamma)A_H\left(\frac{\gamma}{\psi}\right)^{\gamma/(1-\gamma)}}{N}\left[\mathbb{E}_m s - \frac{1-\tau}{\mu}\mathbb{E}_f s\right]. \tag{24}$$

The partial and cross-partial derivatives of the gender labor routine gap are given by:

$$\frac{\partial(L_R^f - L_R^m)}{\partial\psi} = \frac{1-\mu}{\mu N} + \frac{A_H}{N}\left(\frac{\gamma}{\psi}\right)^{\frac{1}{1-\gamma}}\left[\frac{1-\tau}{\mu}\mathbb{E}_f s - \mathbb{E}_m s\right] \tag{25}$$

$$\frac{\partial^2(L_R^f - L_R^m)}{\partial\psi\partial\gamma} = \frac{A_H}{N}\left[\frac{\left(\frac{\gamma}{\psi}\right)^{\frac{1}{1-\gamma}}(\gamma\log(\gamma/\psi) - \gamma + 1)}{(1-\gamma)^2\gamma}\right]\left[\frac{1-\tau}{\mu}\mathbb{E}_f s - \mathbb{E}_m s\right]. \tag{26}$$

Derivatives (25) and (26) are positive if and only if $\left[\frac{1-\tau}{\mu}\mathbb{E}_f s - \mathbb{E}_m s\right] > 0$. Q.E.D.

C Appendix Tables and Figures

Appendix Table 1: RTI and Other Occupational Characteristics

A. Cross-occupation correlations between RTI in 1980 and other characteristics by gender		
	Women	Men
	Correlation RTI in 1980 and:	
Share Unionized in 1993	-0.2666‡	-0.0945
Share College in 1980	-0.4259‡	-0.0488
Hourly Wage in 1980	-0.2672‡	-0.1457‡

B. Changes in Occupational Distribution by gender between 1980-2017: RTI vs other characteristics			
	Dep Var: 1980-2017 Change in employment share of specific occupation for a given gender		
	(1)	(2)	(3)
Female	0.340	0.324	-0.538
	(0.298)	(0.299)	(1.126)
RTI	-0.003	-0.004	-0.004
	(0.055)	(0.053)	(0.048)
RTI × Female	-0.463†	-0.447†	-0484†
	(0.188)	(0.198)	(0.210)
Controls:			
Share Unionized, Share College, Hourly Wage	No	Yes	Yes
Share Unionized, Share College, Hourly Wage interacted with Female	No	No	Yes

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The number of observations is 276 for Panel A and 552 for Panel B. Variables are calculated using both men and women. Correlations in Panel A are weighted by the share of gender specific employment in 1980. In Panel B, the unit of analysis is at the occupation × gender level and each column represents a different regression. Robust standard errors in parenthesis. *$p< 0.10$, †$p< 0.05$, ‡$p< 0.01$.

Appendix Table 2: Descriptive Statistics at the CZ and Decade Level

	Men		Women	
	Mean	Std. Dev	Mean	Std. Dev
RSH	0.238	0.032	0.422	0.041
RSH (combined)	0.322	0.029	0.322	0.029
10 × Annual Change in Employment in:				
Top RTI Occupations	-0.005	0.018	-0.028	0.026
Professional and Technical Occupations	0.011	0.020	0.048	0.030
Clerical and Retail Sales	-0.005	0.013	-0.008	0.027
Production/Craft/Machine Operators	-0.017	0.019	-0.010	0.016
Service Occupations	0.009	0.010	0.009	0.013
Transport/Construction/Mech/Mining	-0.015	0.023	-0.001	0.006
Top Social Skills Occupations	0.006	0.019	0.040	0.026
Top Social and Top Math	0.005	0.017	0.022	0.020
Top Social and Non Top Math	0.001	0.010	0.019	0.011
Non Top Social and Top Math	-0.005	0.010	0.002	0.011
Non Top Social and Non Top Math	-0.018	0.033	-0.005	0.030
10 × Annual Change in Share of with College (25-34)	0.016	0.045	0.049	0.041
		Mean	Std. Dev	
10 × Annual Change in Segregation Index		-0.022	0.032	
10 × Annual Change in College Gap (25-35)		-0.033	0.037	

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 64. Statistics are weighted by 1980 commuting zone share of national population. The number of observations is 2,888 (722 CZ × 4 periods).

Appendix Table 3: First Stage Regressions

	Dep. Variable: Routine Occupation Share (RSH)			
	Men		Women	
	(1)	(2)	(3)	(4)
Predicted Routine Share × 1980	$0.719^{\ddagger}$	$0.680^{\ddagger}$	$0.715^{\ddagger}$	$0.731^{\ddagger}$
	(0.037)	(0.039)	(0.038)	(0.037)
Predicted Routine Share × 1990	$0.487^{\ddagger}$	$0.438^{\ddagger}$	$0.485^{\ddagger}$	$0.503^{\ddagger}$
	(0.032)	(0.039)	(0.033)	(0.032)
Predicted Routine Share × 2000	$0.352^{\ddagger}$	$0.317^{\ddagger}$	$0.352^{\ddagger}$	$0.359^{\ddagger}$
	(0.032)	(0.046)	(0.032)	(0.034)
Predicted Routine Share × 2010	$0.266^{\ddagger}$	$0.216^{\ddagger}$	$0.266^{\ddagger}$	$0.257^{\ddagger}$
	(0.030)	(0.044)	(0.031)	(0.035)
F-stat on instruments	224.859	111.293	215.186	223.066
Controls	None	Levels	None	Levels
Observations	2,888			

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The unit of analysis is at the CZ × decade level (4 time periods × 722 commuting zones). All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. $^{*}p< 0.10$, $^{\dagger}p< 0.05$, $^{\ddagger}p< 0.01$.

Appendix Table 4: Social and Math Skills Composition of Main Occupational Groups, 1980

	Share Top RTI	Share Top Social	Share Top Math	Share Top Social & Top Math
Professional and Technical Occ.	0.19	0.822	0.732	0.624
Clerical and Retail Sales	0.74	0.08	0.278	0.048
Production/Craft/Machine Operators	0.5	0.182	0.238	0.182
Service Occupations	0.28	0.105	0.000	0.000
Transport/Construction/Mech/Mining	0.07	0.076	0.027	0.027

Notes: The shares are calculated using labor supply weights (weeks worked times usual weekly hours in prior year) derived from the 1980 U.S. Census. The sample is restricted to non-institutionalized individuals aged 25 to 64. See Data Appendix for a list of the occupations included in each category. Top RTI is the set of occupations that are in the top employment-weighted third of routine task-intensity in 1980, following Autor and Dorn (2013). Top social skill occupations are defined as those in the top employment-weighted third of the social skill distribution in 1980, and top math skill occupations are defined as those in the top employment-weighted third of the math skill distribution in 1980 (using 1988 O*NET database).

Appendix Table 5: Robustness Tests

	I. Baseline		II. Alternative Definitions of Routine Intensity						II. Alternative Measurements of RSH					
	Ln(R)-Ln(M) -Ln(A) Empl. in 33% occ w/high RTI		Ln(R)-Ln(M) Empl. in 33% occ w/high RTI		Ln(R^{sts})-Ln(M) -Ln(A) Empl. in 33% occ w/high RTI		Ln(R^{fdex})-Ln(M) -Ln(A) Empl. in 33% occ w/high RTI		Ln(R)-Ln(M) -Ln(A) Empl. in 25% occ w/high RTI		Ln(R)-Ln(M) -Ln(A) Empl. in 40% occ w/high RTI		Ln(R)-Ln(M) -Ln(A) Gender Specific Empl. in 33% occ w/high RTI	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
I. Top RTI Occupations. Dep. Var.: 10 × Annual Change in Employment Share in Top RTI Occupations														
RSH_{-1}	-0.221‡	-0.370‡	-0.185‡	-0.309‡	-0.188‡	-0.321‡	-0.214‡	-0.337‡	-0.292‡	-0.485‡	-0.204‡	-0.331‡	-0.221‡	-0.477‡
	(0.026)	(0.040)	(0.023)	(0.035)	(0.025)	(0.034)	(0.028)	(0.032)	(0.034)	(0.052)	(0.026)	(0.039)	(0.027)	(0.051)
II. Occupational Distribution. Dep. Var.: 10 × Annual Change in Employment Share in Specific Occupation Groups														
A. Professional and Technical														
RSH_{-1}	0.177‡	0.320‡	0.153‡	0.270‡	0.173‡	0.263‡	0.167‡	0.287‡	0.271‡	0.435‡	0.142‡	0.262‡	0.144‡	0.460‡
	(0.042)	(0.050)	(0.041)	(0.040)	(0.042)	(0.046)	(0.037)	(0.044)	(0.057)	(0.061)	(0.034)	(0.043)	(0.041)	(0.085)
B. Clerical and Retail														
RSH_{-1}	-0.042†	-0.232‡	-0.037†	-0.211‡	-0.039†	-0.227‡	-0.036†	-0.214‡	-0.060*	-0.316‡	-0.041‡	-0.196‡	-0.048‡	-0.160†
	(0.018)	(0.048)	(0.017)	(0.038)	(0.020)	(0.042)	(0.015)	(0.038)	(0.034)	(0.065)	(0.014)	(0.039)	(0.015)	(0.074)
C. Production/Craft/Machine Operators														
	-0.399‡	-0.159‡	-0.350‡	-0.125‡	-0.388‡	-0.137‡	-0.400‡	-0.145‡	-0.545‡	-0.229‡	-0.308‡	-0.121‡	-0.370‡	-0.238‡
	(0.032)	(0.025)	(0.029)	(0.023)	(0.033)	(0.021)	(0.037)	(0.024)	(0.051)	(0.034)	(0.032)	(0.020)	(0.034)	(0.056)
D. Service Occupations														
RSH_{-1}	-0.001	-0.098‡	0.006	-0.083‡	0.003	-0.092‡	0.007	-0.085‡	-0.014	-0.138‡	-0.013	-0.054‡	0.002	-0.088*
	(0.020)	(0.026)	(0.019)	(0.021)	(0.020)	(0.023)	(0.018)	(0.024)	(0.030)	(0.033)	(0.012)	(0.020)	(0.016)	(0.053)
E. Transport/Construction/Mech/Mining														
RSH_{-1}	0.157‡	-0.020†	0.123‡	-0.015†	0.107‡	-0.017†	0.140‡	-0.020†	0.196‡	-0.028†	0.193‡	-0.010	0.168‡	-0.034‡
	(0.035)	(0.009)	(0.032)	(0.007)	(0.035)	(0.008)	(0.030)	(0.008)	(0.052)	(0.012)	(0.026)	(0.009)	(0.026)	(0.013)
F. Not in the Labor Force														
RSH_{-1}	0.108‡	0.190‡	0.104‡	0.164‡	0.145‡	0.210‡	0.122‡	0.178‡	0.152‡	0.276‡	0.026	0.119†	0.103‡	0.061
	(0.036)	(0.053)	(0.034)	(0.043)	(0.033)	(0.044)	(0.037)	(0.043)	(0.049)	(0.073)	(0.030)	(0.047)	(0.032)	(0.088)
III. Skill Investments. Dep. Var.: 10 × Annual Change in Share of Population Aged 25 to 34 With College Education														
RSH_{-1}	0.165‡	0.355‡	0.138‡	0.313‡	0.161‡	0.347‡	0.170‡	0.347‡	0.208‡	0.460‡	0.143‡	0.313‡	0.162‡	0.228†
	(0.054)	(0.062)	(0.051)	(0.050)	(0.051)	(0.055)	(0.049)	(0.057)	(0.075)	(0.075)	(0.040)	(0.042)	(0.046)	(0.109)

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 64, born and residing in the same state. Each number comes from a separate regression and corresponds to the coefficient on RSH in equation (3), instrumenting for RSH with interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. The number of observations is 2,888 (722 CZ × 4 time periods). Column (3) excludes routine cognitive tasks from the Routine Task Measure while Column (4) excludes routine-physical tasks. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. $^{*}p<0.10$, $^{\dagger}p<0.05$, $^{\ddagger}p<0.01$.

Appendix Table 6: Placebo Regressions – Routine Occupation Share and Changes in Occupational Segregation Pre-1980

	1980–2017 Panel			1950–1980 Panel		
	OLS	2SLS		OLS	2SLS	
	A. Dep. Var: Change in Segregation Index					
Routine	-0.161‡	-0.266‡	-0.127‡	0.060	0.038	0.163‡
Occ Share$_{-1}$	(0.027)	(0.029)	(0.042)	(0.036)	(0.036)	(0.044)
	B. Dep. Var: Change in the College Gap (Men-Women)					
Routine	-0.132‡	-0.137‡	-0.105*	0.033	0.031	0.107
Occ Share$_{-1}$	(0.023)	(0.033)	(0.057)	(0.026)	(0.026)	(0.068)
Controls	None	None	Levels	None	None	Levels
Observations		2,888			1,444	

Notes: The data are from the 1950, 1970, 1980, 1990, 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals aged 25 to 64, born and residing in the same state. The unit of analysis is at the CZ × decade level. Each coefficient is from a separate regression. The 1980–2017 panel (first three columns) reproduce the estimates from Table 2 and Table 3. The 1950–1980 panel (last three columns) re-estimate equation (3) using data from 1950 to 1980 (we use the 1950 to 1970 and 1970 to 1980 changes since data limitations in the 1960 Census preclude the construction of comparable CZs. For the 2SLS specifications, the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p$<$ 0.10, †p$<$ 0.05, ‡p$<$ 0.01.

Appendix Table 7: Robustness to Import Exposure and Offshorabilty

	Panel A: Dep Var: 10 × Annual Change in Employment Share in Specific Occupation Groups															
	Top RTI Occupations				Professional and Technical Occupations				Clerical and Retail Sales				Production/Craft/ Machine Operators			
	Men		Women		Men		Women		Men		Women		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(10)	(11)	(12)	(13)	(15)	(16)	(17)	(18)
RSH$_{-1}$	-0.221‡	-0.254‡	-0.370‡	-0.397‡	0.177‡	0.198‡	0.320‡	0.408‡	-0.042†	-0.038	-0.232‡	-0.115*	-0.399‡	-0.496‡	-0.159‡	-0.234‡
	(0.026)	(0.038)	(0.040)	(0.064)	(0.042)	(0.049)	(0.050)	(0.059)	(0.018)	(0.028)	(0.048)	(0.066)	(0.032)	(0.042)	(0.025)	(0.043)
Import Exposure$_{-1}$		-0.063†		-0.055*		0.019		0.320‡		-0.030*		0.071†		-0.087‡		-0.158‡
		(0.028)		(0.033)		(0.024)		(0.090)		(0.017)		(0.031)		(0.031)		(0.031)
Offshorability$_{-1}$		0.028†		0.005		0.004		-0.022		-0.002		-0.071‡		0.084‡		0.030†
		(0.014)		(0.013)		(0.016)		(0.017)		(0.008)		(0.009)		(0.016)		(0.013)
	Panel A (cont.): Dep Var: 10 × Annual Change in Employment Share in Specific Occupation Groups												*Panel B: Dep Var: 10 × Annual Change in Share of Population Aged 25 to 34 with College Education*			
	Service Occupations				Transport/Construct/Mech Mining/Farm				Not in Labor Force							
	Men		Women		Men		Women		Men		Women		Men		Women	
RSH$_{-1}$	-0.001	-0.004	-0.098‡	-0.127‡	0.157‡	0.172‡	-0.020†	-0.053‡	0.108‡	0.169‡	0.190‡	0.121	0.165‡	0.096	0.355‡	0.203†
	(0.020)	(0.028)	(0.026)	(0.047)	(0.035)	(0.056)	(0.009)	(0.016)	(0.036)	(0.062)	(0.053)	(0.090)	(0.054)	(0.070)	(0.062)	(0.080)
Import Exposure$_{-1}$		-0.022		-0.008		-0.028		-0.025		0.147‡		-0.201†		-0.019		0.058
		(0.017)		(0.020)		(0.038)		(0.017)		(0.052)		(0.101)		(0.044)		(0.052)
Offshorability$_{-1}$		-0.006		0.001		0.003		0.015‡		-0.083‡		0.047†		0.054†		0.088‡
		(0.010)		(0.012)		(0.024)		(0.005)		(0.029)		(0.021)		(0.024)		(0.022)

Notes: See Data Appendix for a description of the data sources and the methods used to construct the variables. Results come from 2SLS regression models with population aged 25 to 64, born and residing in same state. Each column is a separate regression, where the share of routine occupations is instrumented by interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. The unit of analysis is at the CZ × decade level (4 times period × 722 commuting zones). All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p<0.10, †p<0.05, ‡p<0.01.

Appendix Table 8: Robustness to Controlling for Social Norms

	I. Baseline		II. Controlling for Alternative Measures of Social Norms									
	No Norms Controls		Sexism Index		Kleven Index 1980		1980-2010 Change in Kleven Index		Kleven Index		Decadal Change in Kleven Index	
	(1)		(2)		(3)		(4)		(5)		(6)	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
I. Top RTI Occupations. Dep. Var.: 10 × Annual Change in Employment Share in Top RTI Occupations												
RSH_{-1}	-0.221‡	-0.370‡	-0.222‡	-0.361‡	-0.218‡	-0.358‡	-0.218‡	-0.369‡	-0.215‡	-0.364‡	-0.238‡	-0.386‡
	(0.026)	(0.040)	(0.029)	(0.037)	(0.029)	(0.036)	(0.026)	(0.039)	(0.027)	(0.040)	(0.032)	(0.047)
II. Occupational Distribution. Dep. Var.: 10 × Annual Change in Employment Share in Specific Occupation Groups												
A. Professional and Technical												
RSH_{-1}	0.177‡	0.320‡	0.164‡	0.292‡	0.151‡	0.282‡	0.158‡	0.307‡	0.167‡	0.320‡	0.175‡	0.342‡
	(0.042)	(0.050)	(0.041)	(0.045)	(0.038)	(0.043)	(0.041)	(0.050)	(0.041)	(0.051)	(0.038)	(0.052)
B. Clerical and Retail												
RSH_{-1}	-0.042†	-0.232‡	-0.039†	-0.238‡	-0.033†	-0.228‡	-0.041†	-0.225‡	-0.044†	-0.228‡	-0.020	-0.260‡
	(0.018)	(0.048)	(0.017)	(0.045)	(0.014)	(0.041)	(0.017)	(0.046)	(0.018)	(0.047)	(0.020)	(0.049)
C. Production/Craft/Machine Operators												
RSH_{-1}	-0.399‡	-0.159‡	-0.404‡	-0.140‡	-0.408‡	-0.149‡	-0.398‡	-0.159‡	-0.395‡	-0.159‡	-0.443‡	-0.186‡
	(0.032)	(0.025)	(0.036)	(0.026)	(0.034)	(0.027)	(0.034)	(0.028)	(0.035)	(0.027)	(0.037)	(0.034)
D. Service Occupations												
RSH_{-1}	-0.001	-0.098‡	0.014	-0.093‡	0.021	-0.084‡	0.013	-0.071‡	0.007	-0.086‡	-0.006	-0.070‡
	(0.020)	(0.026)	(0.018)	(0.026)	(0.018)	(0.025)	(0.018)	(0.024)	(0.019)	(0.025)	(0.017)	(0.022)
E. Transport/Construction/Mech/Mining												
RSH_{-1}	0.157‡	-0.020†	0.165‡	-0.018*	0.142‡	-0.016*	0.154‡	-0.014	0.165‡	-0.016*	0.174‡	-0.020*
	(0.035)	(0.009)	(0.037)	(0.010)	(0.038)	(0.010)	(0.033)	(0.009)	(0.036)	(0.010)	(0.047)	(0.011)
F. Not in the Labor Force												
RSH_{-1}	0.108‡	0.190‡	0.100‡	0.198‡	0.127‡	0.197‡	0.114‡	0.162‡	0.100‡	0.169‡	0.120*	0.194‡
	(0.036)	(0.053)	(0.033)	(0.056)	(0.037)	(0.058)	(0.036)	(0.057)	(0.038)	(0.055)	(0.064)	(0.060)
III. Skill Investments. Dep. Var.: 10 × Annual Change in Share of Population Age 25 to 34 With College Education												
RSH_{-1}	0.165‡	0.355‡	0.215‡	0.394‡	0.203‡	0.388‡	0.143‡	0.351‡	0.166‡	0.355‡	0.238‡	0.379‡
	(0.054)	(0.062)	(0.051)	(0.062)	(0.056)	(0.063)	(0.055)	(0.065)	(0.056)	(0.064)	(0.059)	(0.069)

Notes: The data are from the 1980 to 2000 U.S. Census and 2010 (2008-2010), 2017 (2015-2017) ACS three-year aggregates. The sample is restricted to non-institutionalized individuals age 25 to 64 who are residing in their state of birth. The unit of analysis is at the CZ × decade level (4 time periods × 722 commuting zones). Each number comes from a separate regression and corresponds to the coefficient on RSH in equation (3), instrumenting for RSH with interactions between the 1950 industry mix instrument ($\widehat{RSH_j}$) and time dummies. The Sexism Index is time-invariant and comes from Charles et al. (2022). The Kleven measure comes from Kleven (2023) and varies by decade. To include the Sexism Index, the Kleven Index measured at 1980, and the change in the Kleven Index between 1980 and 2010 as controls, we interact them with year fixed effects. All regressions include state and year fixed effects, and additional controls include the LFP of college educated married women, share of women in top paying occupations, share of non-college immigrants in the labor force, difference in marriage rates between college and non-college individuals, differences in family income between college and non-college individuals, the share of the population aged 65 and older, and the service sector share of employment. Regressions are weighted by the CZ share of the national population in 1980. Standard errors clustered at the state level are reported in parentheses. *p<0.10, †p<0.05, ‡p<0.01.

Appendix Table 9: Occupation Classification

Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
4	Chief executives, public administrators, and legislators	0.06%	No	Professional and Technical	Top Social - Top Math
7	Financial managers	0.54%	Yes	Professional and Technical	Top Social - Top Math
8	Human resources and labor relations managers	0.29%	No	Professional and Technical	Top Social - Top Math
13	Managers in marketing, advert., PR	1.12%	No	Professional and Technical	Top Social - Top Math
14	Managers in education and related fields	0.5%	No	Professional and Technical	Top Social - Top Math
15	Managers of medicine and health occupations	0.15%	No	Professional and Technical	Top Social - Top Math
18	Managers of properties and real estate	0.22%	No	Professional and Technical	Top Social - Top Math
19	Funeral directors	0.05%	Yes	Professional and Technical	Top Social - Non Top Math
22	Managers and administrators, n.e.c.	7.35%	No	Professional and Technical	Top Social - Top Math
23	Accountants and auditors	1.13%	Yes	Professional and Technical	Non Top Social - Top Math
24	Insurance underwriters	0.02%	Yes	Professional and Technical	Non Top Social - Top Math
25	Other financial specialists	0.47%	Yes	Professional and Technical	Top Social - Top Math
26	Management analysts	0.14%	No	Professional and Technical	Top Social - Top Math
27	Personnel, HR, training, and labor rel. specialists	0.51%	No	Professional and Technical	Top Social - Non Top Math
28	Purchasing agents and buyers of farm products	0.02%	Yes	Professional and Technical	Top Social - Top Math
29	Buyers, wholesale and retail trade	0.19%	No	Professional and Technical	Top Social - Top Math
33	Purchasing agents and buyers, n.e.c.	0.34%	No	Professional and Technical	Top Social - Top Math
34	Business and promotion agents	0.02%	No	Professional and Technical	Top Social - Top Math
35	Construction inspectors	0.06%	No	Professional and Technical	Non Top Social - Top Math
36	Inspectors and compliance officers, outside	0.19%	No	Professional and Technical	Non Top Social - Top Math
37	Management support occupations	0.04%	No	Professional and Technical	Top Social - Top Math
43	Architects	0.14%	Yes	Professional and Technical	Top Social - Top Math
44	Aerospace engineers	0.11%	No	Professional and Technical	Top Social - Top Math
45	Metallurgical and materials engineers	0.03%	No	Professional and Technical	Non Top Social - Top Math
47	Petroleum, mining, and geological engineers	0.05%	No	Professional and Technical	Top Social - Top Math
48	Chemical engineers	0.07%	No	Professional and Technical	Top Social - Top Math
53	Civil engineers	0.26%	No	Professional and Technical	Top Social - Top Math
55	Electrical engineers	0.42%	No	Professional and Technical	Top Social - Top Math
56	Industrial engineers	0.25%	No	Professional and Technical	Non Top Social - Top Math
57	Mechanical engineers	0.26%	No	Professional and Technical	Top Social - Top Math
59	Engineers and other professionals, n.e.c.	0.36%	No	Professional and Technical	Top Social - Top Math
64	Computer systems analysts and computer scientists	0.26%	No	Professional and Technical	Top Social - Top Math
65	Operations and systems researchers and analysts	0.1%	No	Professional and Technical	Top Social - Top Math
66	Actuaries	0.01%	Yes	Professional and Technical	Non Top Social - Top Math
68	Mathematicians and statisticians	0.04%	No	Professional and Technical	Non Top Social - Top Math
69	Physicists and astronomists	0.03%	Yes	Professional and Technical	Non Top Social - Top Math
73	Chemists	0.13%	No	Professional and Technical	Top Social - Top Math
74	Atmospheric and space scientists	0.01%	Yes	Professional and Technical	Non Top Social - Top Math
75	Geologists	0.06%	No	Professional and Technical	Non Top Social - Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
76	Physical scientists, n.e.c.	0.01%	Yes	Professional and Technical	Non Top Social - Top Math
77	Agricultural and food scientists	0.03%	No	Professional and Technical	Non Top Social - Top Math
78	Biological scientists	0.06%	No	Professional and Technical	Non Top Social - Top Math
79	Foresters and conservation scientists	0.04%	No	Professional and Technical	Non Top Social - Top Math
83	Medical scientists	0.03%	No	Professional and Technical	Top Social - Top Math
84	Physicians	0.72%	No	Professional and Technical	Top Social - Top Math
85	Dentists	0.15%	No	Professional and Technical	Non Top Social - Non Top Math
86	Veterinarians	0.05%	Yes	Professional and Technical	Top Social - Non Top Math
87	Optometrists	0.03%	Yes	Professional and Technical	Non Top Social - Top Math
88	Podiatrists	0.01%	No	Professional and Technical	Top Social - Non Top Math
89	Other health and therapy occupations	0.02%	No	Professional and Technical	Top Social - Non Top Math
95	Registered nurses	1.27%	No	Professional and Technical	Top Social - Non Top Math
96	Pharmacists	0.18%	Yes	Professional and Technical	Non Top Social - Top Math
97	Dieticians and nutritionists	0.06%	Yes	Professional and Technical	Top Social - Non Top Math
98	Respiratory therapists	0.05%	No	Professional and Technical	Non Top Social - Non Top Math
99	Occupational therapists	0.02%	No	Professional and Technical	Top Social - Non Top Math
103	Physical therapists	0.04%	No	Professional and Technical	Top Social - Non Top Math
104	Speech therapists	0.04%	No	Professional and Technical	Top Social - Non Top Math
105	Therapists, n.e.c.	0.04%	No	Professional and Technical	Top Social - Non Top Math
106	Physicians' assistants	0.03%	No	Professional and Technical	Top Social - Non Top Math
154	Subject instructors, college	0.67%	No	Professional and Technical	Top Social - Top Math
155	Kindergarten and earlier school teachers	0.12%	No	Professional and Technical	Non Top Social - Non Top Math
156	Primary school teachers	2.23%	No	Professional and Technical	Top Social - Top Math
157	Secondary school teachers	0.88%	No	Professional and Technical	Top Social - Top Math
158	Special education teachers	0.03%	No	Professional and Technical	Top Social - Non Top Math
159	Teachers, n.e.c.	0.24%	No	Professional and Technical	Top Social - Non Top Math
163	Vocational and educational counselors	0.19%	No	Professional and Technical	Top Social - Non Top Math
164	Librarians	0.17%	No	Professional and Technical	Non Top Social - Non Top Math
165	Archivists and curators	0.02%	No	Professional and Technical	Non Top Social - Non Top Math
166	Economists, market and survey researchers	0.12%	No	Professional and Technical	Top Social - Top Math
167	Psychologists	0.11%	No	Professional and Technical	Top Social - Top Math
169	Social scientists and sociologists, n.e.c.	0.02%	No	Professional and Technical	Non Top Social - Top Math
173	Urban and regional planners	0.02%	Yes	Professional and Technical	Top Social - Top Math
174	Social workers	0.5%	No	Professional and Technical	Top Social - Non Top Math
176	Clergy	0.45%	No	Professional and Technical	Top Social - Non Top Math
177	Welfare service workers	0.05%	No	Professional and Technical	Top Social - Non Top Math
178	Lawyers and judges	0.71%	Yes	Professional and Technical	Top Social - Non Top Math
183	Writersandauthors	0.04%	Yes	Professional and Technical	Non Top Social - Non Top Math
184	Technical writers	0.06%	No	Professional and Technical	Non Top Social - Non Top Math
185	Designers	0.34%	No	Professional and Technical	Top Social - Non Top Math
186	Musicians and composers	0.08%	No	Professional and Technical	Non Top Social - Non Top Math
187	Actors, directors, and producers	0.07%	No	Professional and Technical	Top Social - Non Top Math
188	Painters, sculptors, craft-artists, and print-makers	0.14%	Yes	Professional and Technical	Non Top Social - Non Top Math
189	Photographers	0.09%	Yes	Professional and Technical	Non Top Social - Non Top Math
193	Dancers	0.01%	No	Professional and Technical	Non Top Social - Non Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
194	Art/entertainment performers and related occs	0.04%	No	Professional and Technical	Non Top Social - Non Top Math
195	Editors and reporters	0.22%	Yes	Professional and Technical	Non Top Social - Non Top Math
198	Announcers	0.03%	Yes	Professional and Technical	Non Top Social - Non Top Math
199	Athletes, sports instructors, and officials	0.04%	No	Professional and Technical	Non Top Social - Non Top Math
203	Clinical laboratory technologies and technicians	0.24%	Yes	Professional and Technical	Non Top Social - Top Math
204	Dental hygienists	0.03%	Yes	Professional and Technical	Non Top Social - Non Top Math
205	Health record technologists and technicians	0.02%	Yes	Professional and Technical	Non Top Social - Top Math
206	Radiologic technologists and technicians	0.09%	No	Professional and Technical	Non Top Social - Non Top Math
207	Licensed practical nurses	0.41%	No	Professional and Technical	Non Top Social - Non Top Math
208	Health technologists and technicians, n.e.c.	0.14%	No	Professional and Technical	Non Top Social - Non Top Math
214	Engineering and science technicians	0.62%	No	Professional and Technical	Non Top Social - Top Math
217	Drafters	0.32%	Yes	Professional and Technical	Non Top Social - Top Math
218	Surveryors, cartographers, mapping scientists/techs	0.1%	No	Professional and Technical	Non Top Social - Top Math
223	Biological technicians	0.04%	No	Professional and Technical	Non Top Social - Non Top Math
224	Chemical technicians	0.08%	No	Professional and Technical	Non Top Social - Top Math
225	Other science technicians	0.07%	No	Professional and Technical	Non Top Social - Top Math
226	Airplane pilots and navigators	0.09%	No	Professional and Technical	Non Top Social - Top Math
227	Air traffic controllers	0.05%	Yes	Professional and Technical	Non Top Social - Non Top Math
228	Broadcast equipment operators	0.07%	No	Professional and Technical	Non Top Social - Non Top Math
229	Computer programmers	0.33%	No	Professional and Technical	Top Social - Top Math
233	Programmers of numerically controlled machine tools	0.01%	No	Professional and Technical	Non Top Social - Top Math
234	Legal assistants and paralegals	0.07%	Yes	Professional and Technical	Top Social - Non Top Math
235	Technicians, n.e.c.	0.35%	No	Professional and Technical	Non Top Social - Non Top Math
243	Sales supervisors and proprietors	2.05%	No	Professional and Technical	Top Social - Top Math
253	Insurance sales occupations	0.71%	Yes	Professional and Technical	Top Social - Non Top Math
254	Real estate sales occupations	0.77%	Yes	Professional and Technical	Top Social - Top Math
255	Financial service sales occupations	0.16%	Yes	Professional and Technical	Top Social - Top Math
256	Advertising and related sales jobs	0.12%	Yes	Professional and Technical	Top Social - Non Top Math
258	Sales engineers	0.06%	No	Professional and Technical	Top Social - Top Math
274	Sales occupations and sales representatives	1.96%	No	Clerical and Retail Sales	Non Top Social - Top Math
275	Sales counter clerks	2.35%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
276	Cashiers	0.91%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
277	Door-to-door sales, street sales, and news vendors	0.17%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
283	Sales demonstrators, promoters, and models	0.01%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
303	Office supervisors	1%	Yes	Clerical and Retail Sales	Top Social - Top Math
308	Computer and peripheral equipment operators	0.44%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
313	Secretaries and administrative assistants	3.6%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
315	Typists	0.51%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
316	Interviewers, enumerators, and surveyors	0.09%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
317	Hotel clerks	0.04%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
318	Transportation ticket and reservation agents	0.11%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
319	Receptionists and other information clerks	0.41%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
326	Correspondence and order clerks	0.31%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
328	Human resources clerks, excl payroll and timekeeping	0.07%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
329	Libraryassistants	0.07%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
335	File clerks	0.18%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
336	Records clerks	0.13%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
337	Bookkeepers and accounting and auditing clerks	1.69%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
338	Payroll and timekeeping clerks	0.17%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
344	Billing clerks and related financial records processing	0.24%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
346	Mail and paper handlers	0.01%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
347	Office machine operators, n.e.c.	0.04%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
348	Telephone operators	0.36%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
349	Other telecom operators	0.02%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
354	Postal clerks, exluding mail carriers	0.32%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
355	Mail carriers for postal service	0.33%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
356	Mail clerks, outside of post office	0.11%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
357	Messengers	0.05%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
359	Dispatchers	0.12%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
364	Shipping and receiving clerks	0.68%	Yes	Clerical and Retail Sales	Top Social - Non Top Math
365	Stock and inventory clerks	0.51%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
366	Meter readers	0.04%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
368	Weighers, measurers, and checkers	0.07%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
373	Material recording, sched., prod., plan., expediting cl.	0.4%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
375	Insurance adjusters, examiners, and investigators	0.17%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
376	Customer service reps, invest., adjusters, excl. insur.	0.26%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
377	Eligibility clerks for government prog., social welfare	0.03%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
378	Bill and account collectors	0.08%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
379	General office clerks	1.35%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
383	Bank tellers	0.35%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
384	Proofreaders	0.02%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
385	Data entry keyers	0.33%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
386	Statistical clerks	0.14%	Yes	Clerical and Retail Sales	Non Top Social - Top Math
387	Teacher's aides	0.13%	No	Clerical and Retail Sales	Non Top Social - Non Top Math
389	Administrative support jobs, n.e.c.	0.44%	Yes	Clerical and Retail Sales	Non Top Social - Non Top Math
405	Housekeepers, maids, butlers, and cleaners	0.77%	No	Service	Non Top Social - Non Top Math
408	Laundry and dry cleaning workers	0.16%	Yes	Service	Non Top Social - Non Top Math
415	Supervisors of guards	0.03%	No	Service	Non Top Social - Non Top Math
417	Fire inspection, fire fighting, and fire prevention occupations	0.38%	No	Professional and Technical	Top Social - Non Top Math
418	Police and detectives, public service	0.67%	No	Professional and Technical	Top Social - Non Top Math
423	Sheriffs, bailiffs, correctional institution officers	0.18%	No	Professional and Technical	Top Social - Non Top Math
425	Crossing guards	0.02%	No	Service	Non Top Social - Non Top Math

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Appendix Table 9 – continued from previous page

Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
426	Guards and police, except public service	0.48%	Yes	Service	Top Social - Non Top Math
427	Protective service, n.e.c.	0.01%	No	Service	Top Social - Non Top Math
433	Supervisors of food preparation and service	0.2%	No	Service	Top Social - Non Top Math
434	Bartenders	0.26%	Yes	Service	Non Top Social - Non Top Math
435	Waiters and waitresses	0.67%	No	Service	Non Top Social - Non Top Math
436	Cooks	0.84%	Yes	Service	Non Top Social - Non Top Math
439	Food preparation workers	0.05%	No	Service	Non Top Social - Non Top Math
444	Miscellanious food preparation and service workers	0.38%	No	Service	Non Top Social - Non Top Math
445	Dental Assistants	0.09%	Yes	Service	Non Top Social - Non Top Math
447	Health and nursing aides	1.31%	No	Service	Non Top Social - Non Top Math
448	Supervisors of cleaning and building service	0.14%	No	Service	Top Social - Non Top Math
450	Superv. of landscaping, lawn service, groundskeeping	0.02%	No	Service	Top Social - Non Top Math
451	Gardeners and groundskeepers	0.27%	No	Service	Non Top Social - Non Top Math
453	Janitors	1.64%	No	Service	Non Top Social - Non Top Math
455	Pest control occupations	0.04%	No	Service	Non Top Social - Non Top Math
457	Barbers	0.11%	Yes	Service	Non Top Social - Non Top Math
458	Hairdressers and cosmetologists	0.46%	Yes	Service	Non Top Social - Non Top Math
459	Recreation facility attendants	0.06%	No	Service	Non Top Social - Non Top Math
461	Guides	0.02%	No	Service	Non Top Social - Non Top Math
462	Ushers	0%	No	Service	Non Top Social - Non Top Math
464	Baggage porters, bellhops and concierges	0.01%	No	Service	Non Top Social - Non Top Math
466	Recreation and fitness workers	0.03%	No	Service	Top Social - Non Top Math
467	Motion picture projectionists	0.01%	Yes	Service	Non Top Social - Non Top Math
468	Childcareworkers	0.43%	No	Service	Non Top Social - Non Top Math
469	Personal service occupations, n.e.c	0.14%	No	Service	Non Top Social - Non Top Math
470	Supervisors of personal service jobs, n.e.c	0.03%	No	Service	Top Social - Non Top Math
471	Public transportation attendants	0.06%	No	Service	Non Top Social - Non Top Math
472	Animal caretakers, except farm	0.04%	No	Service	Non Top Social - Non Top Math
473	Farmers, ranchers, and other agricultural managers	1.75%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
475	Farm managers	0.21%	No	Transport/Construct/Mech/ Mining/Farm	Top Social - Top Math
479	Farm workers, incl. nursery farming, and marine life cultivation workers	0.61%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
488	Graders and sorters of agricultural products	0.01%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
489	Inspectors of agricultural products	0%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
496	Timber, logging, and forestry workers	0.13%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
498	Fishing and hunting workers	0.06%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
503	Supervisors of mechanics and repairers	0.23%	No	Transport/Construct/Mech/ Mining/Farm	Top Social - Top Math
505	Automobile mechanics and repairers	0.97%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
507	Bus, truck, and stationary engine mechanics	0.17%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
508	Aircraft mechanics	0.13%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
509	Small engine repairers	0.03%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
514	Auto body repairers	0.2%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
516	Heavy equipement and farm equipment mechanics	0.23%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
518	Industrial machinery repairers	0.58%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
519	Machinery maintenance occupations	0.05%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
523	Repairers of industrial electrical equipment	0.18%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
525	Repairers of data processing equipment	0.05%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
526	Repairers of household appliances and power tools	0.09%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
527	Telecom and line installers and repairers	0.41%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
533	Repairers of electrical equipment, n.e.c.	0.08%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
534	Heating, air conditioning, and refrigeration mechanics	0.16%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
535	Precision instrument and equipment repairers	0.08%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
536	Locksmiths and safe repairers	0.02%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
539	Repairers of mechanical controls and valves	0.03%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
543	Elevator installers and repairers	0.02%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
544	Millwrights	0.17%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
549	Mechanics and repairers, n.e.c.	0.59%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
558	Supervisors of construction work	1.02%	No	Transport/Construct/Mech/ Mining/Farm	Top Social - Non Top Math
563	Masons, tilers, and carpet installers	0.28%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
567	Carpenters	1.13%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
573	Drywall installers	0.08%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
575	Electricians	0.7%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
577	Electric power installers and repairers	0.13%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
579	Painters, construction and maintenance	0.34%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
583	Paperhangers	0.02%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
584	Plasterers	0.03%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
585	Plumbers, pipe fitters, and steamfitters	0.53%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
588	Concrete and cement workers	0.06%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
589	Glaziers	0.03%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
593	Insulation workers	0.05%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
594	Paving, surfacing, and tamping equipment operators	0.1%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
595	Roofers	0.08%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
597	Structural metal workers	0.09%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
598	Drillers of earth	0.02%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
599	Misc. construction and related occupations	0.15%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
614	Drillers of oil wells	0.07%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
615	Explosives workers	0.01%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
616	Miners	0.1%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
617	Other mining occupations	0.06%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
628	Production supervisors or foremen	2.67%	No	Production/Craft/Machine Operators	Top Social - Top Math
634	Tool and die makers and die setters	0.25%	Yes	Production/Craft/Machine Operators	Non Top Social - Top Math
637	Machinists	0.57%	Yes	Production/Craft/Machine Operators	Non Top Social - Top Math
643	Boilermakers	0.04%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
644	Precision grinders and fitters	0.02%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
645	Patternmakers and model makers, metal and plastic	0.04%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
649	Engravers	0.01%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
653	Sheet metal workers	0.17%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
657	Cabinetmakers and bench carpeters	0.07%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
658	Furniture and wood finishers	0.03%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
666	Tailors, dressmakers, and sewers	0.15%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
668	Upholsterers	0.07%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
669	Shoe and leather workers and repairers	0.04%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
675	Hand molders, shapers, and casters, except jewelers	0.09%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
677	Optical goods workers	0.05%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
678	Dental laboratory and medical applicance technicians	0.05%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
679	Bookbinders	0.03%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
684	Miscellaneous precision workers, n.e.c.	0.04%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
686	Butchers and meat cutters	0.3%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
687	Bakers	0.1%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
688	Batch food makers	0.02%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
694	Water and sewage treatment plant operators	0.04%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
695	Power plant operators	0.04%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
696	Plant and system operators, stationary engineers	0.17%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
699	Other plant and system operators	0.06%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
703	Lathe and turning machine operatives	0.21%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
706	Punching and stamping press operatives	0.17%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
707	Rollers, roll hands, and finishers of metal	0.02%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
708	Drilling and boring machine operators	0.07%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
709	Grinding, abrading, buffing, and polishing workers	0.27%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
713	Forge and hammer operators	0.02%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
719	Molders and casting machine operators	0.15%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
723	Metal platers	0.04%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
724	Heat treating equipment operators	0.03%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
727	Sawing machine operators and sawyers	0.09%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
729	Nail, tacking, shaping and joining mach ops (wood)	0.01%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
733	Misc. woodworking machine operators	0.04%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
734	Bookbinders and printing machine operators, n.e.c.	0.35%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
736	Typesetters and compositors	0.07%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
738	Winding and twisting textile and apparel operatives	0.11%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
739	Knitters, loopers, and toppers textile operatives	0.07%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
743	Textile cutting and dyeing machine operators	0.01%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
744	Textile sewing machine operators	0.81%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
745	Shoemaking machine operators	0.07%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
747	Clothing pressing machine operators	0.09%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
749	Miscellanious textile machine operators	0.14%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
753	Cementing and gluing machne operators	0.03%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math

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Appendix Table 9 – continued from previous page

Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
754	Packers, fillers, and wrappers	0.1%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
755	Extruding and forming machine operators	0.05%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
756	Mixing and blending machine operators	0.11%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
757	Separating, filtering, and clarifying machine operators	0.08%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
763	Food roasting and baking machine operators	0.01%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
764	Washing, cleaning, and pickling machine operators	0.01%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
765	Paper folding machine operators	0.03%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
766	Furnance, kiln, and oven operators, apart from food	0.18%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
769	Slicing and cutting machine operators	0.24%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
774	Photographic process machine operators	0.07%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
779	Machine operators, n.e.c.	2.29%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
783	Welders, solderers, and metal cutters	0.8%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
785	Assemblers of electrical equipment	1.62%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
789	Painting and decoration occupations	0.04%	No	Production/Craft/Machine Operators	Non Top Social - Non Top Math
799	Production checkers, graders, and sorters in manufacturing	1.07%	Yes	Production/Craft/Machine Operators	Non Top Social - Non Top Math
803	Supervisors of motor vehicle transportation	0.05%	No	Transport/Construct/Mech/ Mining/Farm	Top Social - Top Math
804	Driver/sales workers and truck Drivers	3.41%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
808	Bus drivers	0.33%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
809	Taxi drivers and chauffeurs	0.19%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
813	Parking lot attendants	0.02%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
823	Railroad conductors and yardmasters	0.07%	No	Transport/Construct/Mech/ Mining/Farm	Top Social - Top Math
824	Locomotive operators: engineers and firemen	0.12%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
825	Railroad brake, coupler, and switch operators	0.1%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
829	Sailors and deckhands, ship/marine engineers	0.09%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
834	Miscellanious transportation occupations	0.01%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
844	Operating engineers of construction equipment	0.26%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
848	Hoist and winch operators	0.19%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
853	Excavating and loading machine operators	0.09%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
859	Misc. material moving equipment operators	0.26%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math

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Occupation Code	Occupation Title	Percentage Employment in 1980	Top RTI	Occupation Group	Social and Analytical Skills
865	Helpers, constructions	0.06%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
866	Helpers, surveyors	0.01%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
869	Construction laborers	0.61%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
873	Production helpers	0.08%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
875	Garbage and recyclable material collectors	0.07%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
878	Machine feeders and offbearers	0.09%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
885	Garage and service station related occupations	0.15%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
887	Vehicle washers and equipment cleaners	0.08%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
888	Packers and packagers by hand	0.5%	Yes	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math
889	Laborers, freight, stock, and material handlers, n.e.c.	1.65%	No	Transport/Construct/Mech/ Mining/Farm	Non Top Social - Non Top Math