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An analysis of skill-biased technical change across demographic groups

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by

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Abstract

I adopt a measure of task-based routineness from Autor and Dorn (2013) to investigate the effects of routineness on various demographic groups. I analyze data from the Current Population Surveys between 1976 and 2017 to determine which groups, separated by race, gender, and age, are most strongly affected by routine-biased technological change. My findings suggest that women are most negatively affected by occupational routineness. Further, both women's concentration in highly routine occupations and women's educational attainment trends from 1976 to 2017 could explain women's increasing susceptibility to changes in routineness.

Introduction

Recent estimates suggest that up to 47% of jobs could be at risk for automation in the near future (Frey and Osborne 2013). While other results indicate that this estimate is unreasonably high (Nedelkoska and Quintini 2018), there is in any case substantial evidence that the implementation of new technologies affects the wages and employment of certain types of occupations. Less research has been conducted on the types of *people* who have been most adversely affected by technological developments. The effects of automation on different demographic groups offers insight into the future income distributions for various groups. Naturally, such insights have critical implications for policy; to reduce the adverse effects of automation, policies could target skill-development in specific groups to mitigate those effects. In order to determine whether men or women, or older or younger workers are more strongly affected by automation, we first need to explore what personal characteristics make a worker more likely to see a wage decrease or loss of employment due to the implementation of new technologies.

Automation has certainly replaced some jobs–but clearly it has not made the whole of human labor obsolete. So why does mankind continue to have any jobs at all? David Autor (2015) explores why so many jobs have actually remained in spite of technological developments. He cites the complementary nature of technology to some types of labor; implementation of some technologies can actually increase the marginal revenue product of some types of labor if that technology makes a worker more productive. For example, programmers could work much more efficiently once they no longer had to rely on punch cards.

The implications of the notion that technology benefits workers with some skill sets and harms workers with other skill sets are vast. Studying the factors involved in skill-biased technical changes has vast implications for the income distribution. If workers who tend to do more routine tasks are more likely to be replaced and these workers are more likely to earn less, then technological developments will shift income to higher-skilled workers. Brynjolfsson and McAfee (2012) highlight the stagnation of real median household income and voice fears about the shrinking of the middle class. Understanding which industries and skills are most susceptible to replacement can help predict which jobs are most likely to be affected by widespread implementation of artificial intelligence. Since economic growth relies on a balance of production factors, many economists argue that the unprecedented acceleration of technological innovation could ultimately impair growth and drastically alter the labor markets for occupations and for different demographic groups in the near future.

A second reason Autor (2015) notes is the capacity of technology to create unprecedented forms of jobs. For example, the existence of large tech-based firms, including Apple, Google, Facebook, and Amazon, could not have been imagined with the limitations of twentieth century technology– a fact which does an excellent job of demonstrating the difficulty of predicting the effects of future technological developments. The much more recent widespread implementation of computer technology and artificial intelligence has revived the very fears inspired by the Industrial Revolution. About half of the recent decline in the labor share can be explained by decreasing prices of investment goods like new technologies (Karabarbounis and Neiman), but not all types of workers are impacted equally in terms of their wages and employment.

Workers' susceptibility to replacement and relative decreases in wages depends on the skill set of a worker. The size of the intersection between the tasks that machines can accomplish and the tasks that workers can accomplish effectively measures the degree of substitutability of this capital for labor. The more *routine* a worker's set of tasks are, the more easily that worker can be replaced by a machine. An example of a particularly routine job is bank telling.

For other sets of tasks, a machine can complement a worker's skill set, so implementation of those machines increases the wages and employment of that kind of worker. The more inherently creative, or *abstract*, a worker's task set is, the more likely it is that a machine will act as a complement for that worker. We can conceptualize a third set of workers who tend to do more *manual* tasks that are difficult to automate and who tend not to rely on much technological capital to do their work. For these workers, machines do not strongly act as a substitute or a complement.

Autor, Levy, and Murnane (2003) establish an aggregate measure of routineness that scores each occupation based on how abstract, manual, and routine the tasks associated with that occupation are. They rely on the *Dictionary of Occupational Titles* from 1977, which lists occupations and the tasks that a worker in each occupation does. They combine these individual measures into one single measure that denotes the relative routineness of any given occupation, called Routine Task Intensity (RTI). Their calculations match to 330 distinct occupations.

Autor, Levy, and Murnane control for occupations, industries, and education groups, and find that the effects of automation specifically using computer capital fits the theory; both routine manual and routine cognitive tasks saw a decrease in the input of labor, and nonroutine cognitive tasks saw an increase in labor input.

Green (2012) criticizes the model set forth by Autor, Levy, and Murnane (ALM). He asserts that the ALM model does not adequately account for changes in the tasks associated with an occupation change as management structures change. For instance, due to increasing use of computer capital, workers are more informed about their employers and are more involved in decision-making. Additionally, employees are increasingly involved in profit-sharing, which increases worker efficiency. This increase in employee involvement further places a premium on higher-level skills, such as those involving communication and collaboration.

Technology could possibly change the tasks involved in the jobs themselves, further skewing positions in favor of higher skilled workers, though evidence from case studies suggests contrarily that new technology is not necessarily an essential or deciding factor in facilitating these changes. To account for changes in employees' tasks, Green includes a measure of employee involvement in his model to measure the relative effects of computerization and organizational change. He additionally runs empirical tests that highlight the inherent subjectivity of assigning tasks to "routine" or "non-routine" domains. Intuitive reasoning for this challenge is that some tasks that were once considered "non-routine" have been automated to some degree, such as the task of making sales. The RTI measure is not perfect, but it has been utilized often.

Autor and Dorn (2013) computed the percentiles of "skill level" across occupations, where low-skilled jobs are more manual, and high-skilled jobs are more abstract. They observed that both employment growth and wage growth were higher for the very low-skilled and the high-skilled jobs, and that in particular, the lower-middle-skilled jobs faced the lowest (and sometimes negative) wage and employment growth. They theorized that this is because the occupations with the very lowest skill sets occur in the services sector, and the occupations with lower-middle skill sets were in the goods sector.

To test this theory, they modeled the goods and services sectors separately, noting that difficulty in replacing low-skilled labor with capital in the services sector could account for some of the unexpectedly high growth in some low-skilled wages and employment.[1] Technology has a much lower tendency to replace jobs that require interpersonal interactions, regardless of skill level, but low-skilled routine jobs are highly replaceable. Even some relatively high-skilled positions that involve routine tasks, like the jobs of radiologists, could very well be replaced by artificial intelligence technology in the near future ("Automation" 2016).

Lake and Millimet (2017) test the theory that trade could account for some of the observed

[1] Autor and Dorn (2013) model the production of goods as a function of capital K, abstract (high-skilled) labor L_a, and routine (low-skilled) labor L_r, and they model the production of services solely as a function of manual (low-skilled) labor L_m. Specifically, they define output

$$y = \begin{cases} L_a^{1-\beta}\left((\alpha_r L_r)^{\mu} + (\alpha_K K)^{\mu}\right)^{\frac{\beta}{\mu}} & \text{for the goods sector} \\ \alpha_s L_m & \text{for the services sector} \end{cases}$$

where the α terms measure the productivity of each factor of production. They use this model to explore job polarization and its relation to technological development.

changes in wages and employment for more routine jobs. While more routine jobs are more likely to be automated, they are also more likely to be offshored. Lake and Millimet isolate those effects by analyzing commuting zones data in conjunction with Census data, and they additionally use trade data between the US and China, where routine US jobs are likely to be offshored. They find that job polarization does occur, but it is due to routine-biased technological change and not due to exposure to trade. They additionally find that local exposure to imports actually has more of a negative effect on the extremes of the skill spectrum.

More routine *occupations* are more likely to see wage decreases or utter replacement by machines—but which groups of *people* are most likely to be negatively affected by this bias against routineness? Autor and Dorn (2009) evaluate RTI as a function of routine task input R and manual task input M. Specifically, RTI $= \ln \frac{R_{1980}}{M_{1980}}$, where both R and M are evaluated by using the *Dictionary of Occupational Titles*. They use these measures to evaluate whether older workers fall disproportionately into the category of low-skilled routine jobs; their empirical study supports the notion that technological developments are particularly detrimental to older workers.

However, a sampling of empirical studies on this subject reveals a lack of consensus. Using a 1997 French employer-employee survey that includes questions on computer training in the manufacturing industry, Behaghel and Greenan (2010) analyze the implementation of technology and workers in their twenties, thirties, forties, and fifties, and they find that low-skill older workers suffer a comparative disadvantage in technology-heavy firms. Aubert et. al. (2006) utilizes the same survey and additionally accounts for gender, finding that older men are more negatively impacted than older women. On the other hand, Schøne (2009) made use of an employer-employee panel data survey that was repeated in 1997 and 2003 found no evidence of age bias. The author cited difficulty of divorcing older workers' *higher* experience-based skills from *lower* technological skills as a potential reason for this result. Card and DiNardo (2002) report evidence that older US workers experienced age bias in the 1980s but find little evidence of bias in the 1990s.

Models and Data

Model 1

I obtained personal demographic data from the March Current Population Surveys (CPS), which have been collected annually from 1976 to 2017. The Annual Social and Economic Supplement provides wage and work data for the same individuals, their including occupation and industry. See Table A0 and Table A1 in the Appendix for the descriptive statistics.

To test for job polarization, I regressed on the percent change in employment by occupation over each decade, beginning in 1976 and ending in 2016. The model is

$$\%\Delta e_{it} = \beta_0 + \beta_1 w_{it} + \beta_2 w_{it}^2 + \upsilon_{it}$$

where e is employment, w_{it} is the median wage of occupation i in year t, υ is the error term, and the β terms represent the coefficients. I followed Lake and Millimet (2017), who similarly used percent change in employment as their dependent variable and regressed on a quality measure that was a function of median wage and median education level. Since they made use of Census data, they had access to geographic locations, and they found that their coefficients were insignificant until they added the geographic variables (a spatial analysis of commuting zones) to their model.

Model 2

To analyze skill-biased technical change, I relied on the same CPS data, in addition to the routineness measures set forth in ALM. I merged the datasets, using a 1990 census bridge for occupations. The routineness variable is computed as follows: each task is ranked on three scales, one for *abstract*, *routine*, and *manual*. Those tasks are weighted according to their importance, and for each occupation, the sum of the task scores over all tasks in that occupation is calculated. Autor, Levy, and Murnane create a variable that unites these three measures, the Routine Task Intensity (RTI) of an occupation. RTI is defined as $\ln(T_r) - \ln(T_m) - \ln(T_a)$, where T_r, T_m, and T_a are the routine, manual, and abstract task scores, respectively. This is equivalent to the natural log of the ratio of task-routineness to task-non-routineness—or $\ln\left(\frac{T_r}{T_m T_a}\right)$. The three scores for T_r, T_m, and T_a were all standardized in 1980 and are constant for each occupation over the 1976 to 2017 time frame.

I collapsed the dataset by occupation and year so that each observation is an occupation in a given year. The dependent variable is the natural log of median hourly wage, and the model is

$$\ln(w_{it}) = \beta_0 + \beta_1 \text{ RTI}_{it} + \beta_2 \text{ sex binary}_{it} + \beta_3 \text{ age}_{it} + \beta_4 \text{ race}_{it} + \beta_5 \text{ children}_{it} + \beta_6 \text{ married}_{it} + v_{it}$$

where wage is the median wage for the occupation i in year t, the sex binary is a mean over the individuals in the occupation-year where 1 is female and 0 is male, age is the median age, and race is broken down by the percentage of people who are Black, White, or Hispanic. The children variable is the median number of children a worker has, and the married variable is the mean of a binary that has a value of 1 if the individual is married and zero if he or she is not. The occupations were standardized in 1990. I then regress on men and women separately, to see whether the factors that explain the variation in their wages vary substantially–and particularly whether occupational routineness affects men and women differently. See Tables A2 and A3 in the Appendix for descriptive statistics.

Lake and Millimet (2017) control for similar variables, and also rely on the same RTI measure in their local regressions. Acemoglu (2003) uses a somewhat similar conceptual model, using $\ln w_{it}$ as the dependent variable, where w_{it} is the weekly wage of individual i in year t, and collecting data from the March CPS. He analyzes the differences between the 90th and 10th wage percentiles and the differences between the 50th and 10th percentiles and finds that wage inequality of white men has risen. Acemoglu does not analyze the wages of women or non-white men.

It is important to note the absence of a measure of education in this model. In theory, education should explain some variation in wage—even variation that is independent of actual skill. Notably, there is an important distinction between a worker's skill set and the set of tasks that a worker does in his or her occupation. A skill set belongs to the worker; the task set belongs to an occupation. The assumption that Autor, Levy, and Murnane make is that workers choose occupations that match their skill sets, and that their skill sets and task sets are equivalent.

For instance, if a worker is overqualified for a job, then the worker's skill set is a superset of the skill set required by the tasks of the job. But that skill set could make a worker more efficient in certain aspects of a job, and that efficiency could be reflected in wages. Controlling for education does account for this discrepancy to some degree, as Autor, Levy, and Murnane do. This model does not account for skill-task mismatches, since education and the abstractness of a task are highly correlated; inclusion of both variables makes at least one insignificant. As a result, over- or underqualification for jobs could introduce variation since education and other measures of skill level are not included in the model.

Model 3

To explore the nature of the interaction between education and RTI, I relied on another model, this time regressing on individuals rather than occupations in the collapsed data set. I split the sample into four groups: women with a four-year degree, men with a four-year degree, women with no college education, and men with no college education. I broke down each group by decade and ran the following model on each of the four groups separately:

$$\ln(w_i) = \beta_0 + \beta_1 \text{ RTI}_i + \beta_2 \text{ age}_i + \beta_3 \text{ children}_i + \beta_4 \text{ married}_i + \beta_5 \text{ race}_i + \beta_6 \text{ year}_i$$
$$+\beta_7 \text{ industry}_i + \upsilon_i$$

where w_i is median hourly real wage of individual i, “children” is the number of children i has, “married” is a binary that is equal to 1 if i is married, and “race” is a set of dummies representing White, Black, or Hispanic. I additionally controlled for effects with sets of year and industry binary variables. Industry denotes the 1990 Census industry classification, which matches the 1990 classification for occupations.

Model 4

I tested one final model for evidence of skill bias against older workers. This model is similar to Model 2, and is of the form:

$$\ln(w_{it}) = \beta_0 + \beta_1 \text{ RTI}_{it} + \beta_2 \text{ sex binary}_{it} + \beta_3 \text{ race}_{it} + \beta_4 \text{ children}_{it} + \beta_5 \text{ married}_{it} + \upsilon_{it}$$

where i is an occupation rather than an individual. I regressed on two separate age categories: 30 to 39 years of age, and 50 to 59 years of age. People in their twenties are somewhat likely to be in school, or at least to have recently attended school, so their years of employment is not reflected by age in the way that it is for people who did not attend college. Analysis of the 30 to 39 age group avoids this problem.

Results

Model 1

The results of this regression, in addition to a detailed description of the variables, are listed below in Table 1. Unlike Lake and Millimet's findings, the coefficients were significant, but wage and wage squared offered very little explanatory power for the variation in the decennial percent change in employment. Without meaningful geographic data from the CPS, further regressions on job polarization for demographic groups are not especially telling.

Table 1: Percent Change* in Employment Over 10 Years

Variable	β
Wage	-0.0799^{*}
	(0.0464)
$(\text{Wage})^2$	0.0027^{***}
	(0.0009)
Intercept	0.9216^{*}
	(0.4796)
N	1,331
R^2	0.0129
Adj. R^2	0.0115

$^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$

*Percent change in employment was computed by collapsing the dataset by occupation and year, and dividing the sum of the weights of the individuals who are employed in a given occupation by the weights of the total number of individuals in the labor force in that same year. Wage is the hourly real wage in 1999 dollars.

The results imply that a one-dollar increase in the median hourly wage of an occupation corresponds to a 0.0799% decrease in the employment share of an occupation. These results are similar to Lake and Millimet's results for their first local model, in which the sole independent variables were job quality and its square. Without geographic data, I am regressing on the national level. Lake and Millimet's results for their national-level regression were not significant.

Model 2

Five separate regressions by decade track the changes in these variables over time. The decades are: 1976 – 1985, 1986 – 1995, 1996 – 2005, and 2006 – 2017. I ran an additional regression over the period from 2012 to 2017. Table 2 shows the results from the data that includes both men and women.

Table 2: Men and Women, Dependent Variable: ln(wage)

Variable	1976–1985	1986–1995	1996–2005	2006–2017	2012–2017
RTI	-0.005	-0.008^{**}	-0.022^{***}	-0.025^{***}	-0.029^{***}
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
Sex Binary	-0.411^{***}	-0.226^{***}	-0.156^{***}	-0.081^{***}	-0.046
	(0.025)	(0.023)	(0.023)	(0.020)	(0.031)
Age	0.006^{***}	0.012^{***}	0.008^{***}	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Percent Black	-0.531^{***}	-0.304^{***}	-0.430^{***}	-0.317^{***}	-0.434^{***}
	(0.074)	(0.073)	(0.069)	(0.071)	(0.114)
Percent Hispanic	-1.297^{***}	-1.488^{***}	-1.260^{***}	-1.214^{***}	-1.239^{***}
	(0.095)	(0.075)	(0.059)	(0.048)	(0.069)
# Children	-0.011	-0.032^{**}	0.039^{***}	0.029^{**}	0.012
	(0.014)	(0.013)	(0.013)	(0.013)	(0.018)
Married	0.478^{***}	0.562^{***}	0.703^{***}	1.104^{***}	1.142^{***}
	(0.070)	(0.060)	(0.063)	(0.060)	(0.089)
Intercept	2.352^{***}	2.013^{***}	2.160^{***}	2.375^{***}	2.382^{***}
	(0.054)	(0.052)	(0.058)	(0.053)	(0.079)
R^2	0.2772	0.2765	0.3278	0.4039	0.4414
Adj. R^2	0.2756	0.2751	0.3265	0.4028	0.4388
N	3,057	3,595	3,455	3,727	1,504
df	7	7	7	7	7

$^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$

Both the significance and the magnitude of the routineness measure increase over time. This is consistent with the theory that the implementation of technology over time reduces the demand for routine jobs. The coefficient on RTI is highly significant and makes a large jump in magnitude from the 1986–1995 decade to the 1996–2005 decade.

There are also demographic changes that are apparent in Table 2. Note that the coefficient on the sex binary (which is 1 for women and 0 for men) decreases in magnitude and loses significance in the final regression. Additionally, the coefficient on age is no longer significant in the post-2005 and post-2012 regressions. Finally, the positive coefficient on marriage increases fairly substantially over the decades.

Table 3 shows the same regression (without the sex binary) for women.

Table 3: Women, Dependent Variable: ln(wage)

Variable	1976–1985	1986–1995	1996–2005	2006–2017	2012–2017
RTI	-0.017^{***}	-0.023^{***}	-0.039^{***}	-0.047^{***}	-0.052^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
Age	0.004^{***}	0.002^{*}	0.004^{***}	0.001	0.003^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Percent Black	-0.164	-0.122^{*}	-0.174^{***}	0.015	0.014
	(0.067)	(0.064)	(0.063)	(0.060)	(0.097)
Percent Hispanic	-0.247^{***}	-0.500^{***}	-0.737^{***}	-0.742^{***}	-0.510^{***}
	(0.082)	(0.072)	(0.064)	(0.051)	(0.075)
# Children	-0.105^{***}	-0.114^{***}	-0.054^{***}	0.007	-0.059^{***}
	(0.015)	(0.016)	(0.015)	(0.015)	(0.022)
Married	-0.219^{***}	0.014	0.233^{***}	0.357^{***}	0.432^{***}
	(0.046)	(0.046)	(0.048)	(0.045)	(0.070)
Intercept	2.401^{***}	2.394^{***}	2.358^{***}	2.408^{***}	2.334^{***}
	(0.053)	(0.060)	(0.066)	(0.061)	(0.090)
R^2	0.0467	0.0469	0.0852	0.1136	0.1146
Adj. R^2	0.0446	0.0451	0.0835	0.1120	0.1107
N	2,681	3,227	3,132	3,454	1,400
df	6	6	6	6	6

$^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$

The coefficients on the routineness measure increase substantially over decades, and are all larger in magnitude than those for the combined-sex regression. This implies that the routineness of the women's occupations accounts for greater variation in women's wages. Several factors could explain this outcome; the concentration of women in particular jobs, educational attainment patterns, or changes in social structure could account for the discrepancy.

The social factors that cause the coefficient for the marriage binary to move from negative, to zero, to positive and growing in magnitude over the decades could play a role in women's wages.

Note additionally that the coefficient for the median number of children a worker in occupation i has is negative for women, and relatively large in magnitude, particularly for the earlier decades. In contrast, the coefficients from Table 2 are largely positive.

Table 4 shows the men's regressions for the same model.

Table 4: Men, Dependent Variable: ln(wage)

Variable	**1976–1985**	**1986–1995**	**1996–2005**	**2006–2017**	**2012–2017**
RTI	-0.006	-0.001	-0.013^{***}	-0.016^{***}	-0.023^{***}
	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)
Age	0.004^{***}	0.012^{***}	0.007^{***}	0.003^{**}	0.003^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Percent Black	-0.522^{***}	-0.370^{***}	-0.414^{***}	-0.301^{***}	-0.362^{***}
	(0.076)	(0.065)	(0.063)	(0.064)	(0.103)
Percent Hispanic	-0.838^{***}	-0.944^{***}	-0.964^{***}	-0.999^{***}	-0.981^{***}
	(0.085)	(0.063)	(0.051)	(0.045)	(0.071)
# Children	0.036^{**}	0.038^{**}	0.039^{***}	0.024^{*}	-0.019
	(0.016)	(0.015)	(0.014)	(0.013)	(0.021)
Married	0.574^{***}	0.361^{***}	0.617^{***}	0.860^{***}	0.885^{***}
	(0.061)	(0.054)	(0.055)	(0.054)	(0.085)
Intercept	2.223^{***}	2.057^{***}	2.198^{***}	2.336^{***}	2.382^{***}
	(0.048)	(0.048)	(0.049)	(0.047)	(0.074)
R^2	0.1918	0.2025	2925	0.3534	0.3429
Adj. R^2	0.1902	0.2011	0.2913	0.3523	0.3402
N	3,030	3,563	3,434	3,715	1,500
df	6	6	6	6	6

$^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$

The coefficients on the routineness measure further illustrate their difference from the women's coefficients. The changes in the magnitudes of women's RTI coefficients are also more dramatic than the changes over time for men. What could be the root cause of this discrepancy? It is possible that women could be more highly concentrated in occupations that are more routine. Over this period, women have grown considerably more likely to attain higher education relative to men.

Holding post-secondary education constant, if people's wages are more susceptible to having a higher RTI, then education could account for this discrepancy.

Model 3

See Tables 5 through 8 for the regression results on women and men with a four-year degree, and women and men with less than a college education.

Table 5: Women with a Four-Year Degree

Variable	1976–1985	1986–1995	1996–2005	2006–2017	2012–2017
RTI	-0.0324^{***}	-0.0502^{***}	-0.0451^{***}	-0.0393^{***}	-0.0440^{***}
	(0.0027)	(0.0021)	(0.0019)	(0.0015)	(0.0024)
Age	0.0034^{***}	0.0026^{***}	0.0031^{***}	0.0036^{***}	0.0039^{***}
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
# Children	-0.0686^{***}	-0.0478^{***}	-0.0153^{***}	-0.0004	0.0042
	(0.0045)	(0.0038)	(0.0032)	(0.0026)	(0.0040)
Married	-0.0280^{***}	0.0036	0.0272^{***}	0.0424^{***}	0.0520^{***}
	(0.0106)	(0.0085)	(0.0077)	(0.0063)	(0.0098)
Black	0.0581^{***}	0.0347^{**}	0.0179	-0.0267^{***}	-0.0580^{***}
	(0.0184)	(0.0148)	(0.0119)	(0.0093)	(0.0145)
Hispanic	-0.0318	-0.0217	-0.0433^{***}	-0.0808^{***}	-0.1083^{***}
	(0.0214)	(0.0160)	(0.0127)	(0.0091)	(0.0137)
Intercept	1.0744^{***}	1.1221^{***}	1.2230^{***}	1.0842^{***}	1.2028^{***}
	(0.0618)	(0.0643)	(0.0614)	(0.0510)	(0.0738)
N	30,309	44,939	67,185	106,121	43,831
df	232	245	246	237	274
R^2	0.1785	0.1994	0.1518	0.1366	0.1339
Adj. R^2	0.1722	0.195	0.1487	0.1346	0.1294

$^{*} = p < 0.1, ^{**} = p < 0.05, ^{***} = p < 0.01$

Table 6: Women with Less Than College Education

Variable	1976–1985	1986–1995	1996–2005	2006–2017	2012–2017
RTI	0.0159^{***}	-0.0013	-0.0041^{***}	-0.0029^{***}	-0.0010
	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0018)
Age	0.0038^{***}	0.0042^{***}	0.0066^{***}	0.0078^{***}	0.0076^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
# Children	-0.0227^{***}	-0.0237^{***}	-0.0041^{***}	0.0020^{***}	-0.0004^{***}
	(0.0015)	(0.0018)	(0.0018)	(0.0017)	(0.0029)
Married	-0.0441^{***}	-0.0057	0.0315^{***}	0.0518^{***}	0.0647^{***}
	(0.0043)	(0.0043)	(0.0045)	(0.0045)	(0.0076)
Black	-0.0601^{***}	-0.0697^{***}	-0.0736^{***}	-0.0762^{***}	-0.0836^{***}
	(0.0065)	(0.0065)	(0.0064)	(0.0062)	(0.0104)
Hispanic	-0.0326^{***}	-0.0791^{***}	-0.1010^{***}	-0.0807^{***}	-0.0632^{***}
	(0.0061)	(0.0058)	(0.0055)	(0.0051)	(0.0082)
Intercept	0.6811^{***}	1.1187^{***}	1.0307^{***}	1.0702^{***}	1.0893^{***}
	(0.0186)	(0.0249)	(0.0253)	(0.0255)	(0.0393)
N	187,278	165,520	150,797	165,092	60,372
df	239	248	248	237	229
R^2	0.1821	0.1954	0.1651	0.1361	0.1244
Adj.R^2	0.181	0.1942	0.1637	0.1349	0.121

$^{*} = p < 0.1,^{**} = p < 0.05,\ ^{***} = p < 0.01$

Table 7: **Men with a Four-Year Degree**

Variable	**1976–1985**	**1986–1995**	**1996–2005**	**2006–2017**	**2012–2017**
RTI	-0.0248^{***}	-0.0424^{***}	-0.0508^{***}	-0.0480^{***}	-0.0491^{***}
	(0.0031)	(0.0029)	(0.0026)	(0.0022)	(0.0034)
Age	0.0053^{***}	0.0022^{***}	0.0015^{***}	0.0017^{***}	0.0032^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0004)
# Children	0.0404^{***}	0.0426^{***}	0.0544^{***}	0.0612^{***}	0.0622^{***}
	(0.0040)	(0.0040)	(0.0034)	(0.0029)	(0.0045)
Married	0.1443^{***}	0.1636^{***}	0.1937^{***}	0.2120^{***}	0.1928^{***}
	(0.0122)	(0.0108)	(0.0096)	(0.0081)	(0.0124)
Black	-0.0983^{***}	-0.1117^{***}	-0.0889^{***}	-0.1371^{***}	-0.1331^{***}
	(0.0247)	(0.0197)	(0.0155)	(0.0119)	(0.0180)
Hispanic	-0.0879^{***}	-0.1423^{***}	-0.1302^{***}	-0.1260^{***}	-0.1192^{***}
	(0.0211)	(0.0177)	(0.0141)	(0.0107)	(0.0156)
Intercept	0.4935^{***}	0.7124^{***}	0.8998^{***}	1.1185^{***}	1.2872^{***}
	(0.0398)	(0.0521)	(0.0509)	(0.0390)	(0.0579)
N	44,051	53,598	71,016	103,595	42,245
df	236	247	248	237	229
R^2	0.2160	0.1819	0.1479	0.1314	0.1249
Adj. R^2	0.2118	0.1781	0.1449	0.1294	0.1201

$^* = p < 0.1, ^{**} = p < 0.05, ^{***} = p < 0.01$

Table 8: Men with Less Than College Education

Variable	1976–1985	1986–1995	1996–2005	2006–2017	2012–2017
RTI	0.0433^{***}	0.0092^{***}	-0.0050^{***}	-0.0136^{***}	-0.0157^{***}
	(0.0016)	(0.0017)	(0.0018)	(0.0017)	(0.0027)
Age	0.0005^{***}	0.0020^{***}	0.0039^{***}	0.0048^{***}	0.0051^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
# Children	0.0212^{***}	0.0261^{***}	0.0280^{***}	0.0258^{***}	0.0199^{***}
	(0.0015)	(0.0020)	(0.0019)	(0.0018)	(0.0029)
Married	0.1989^{***}	0.1602^{***}	0.1701^{***}	0.1980^{***}	0.2001^{***}
	(0.0052)	(0.0054)	(0.0054)	(0.0049)	(0.0080)
Black	-0.1258^{***}	-0.1252^{***}	-0.1249^{***}	-0.1676^{***}	-0.1732^{***}
	(0.0068)	(0.0073)	(0.0074)	(0.0067)	(0.0109)
Hispanic	-0.0220^{***}	-0.0826^{***}	-0.0881^{***}	-0.0757^{***}	-0.0793^{***}
	(0.0056)	(0.0056)	(0.0052)	(0.0046)	(0.0074)
Intercept	0.7834^{***}	1.0232^{***}	1.2526^{***}	1.3412^{***}	1.3350^{***}
	(0.0123)	(0.0169)	(0.0193)	(0.0174)	(0.0264)
N	236,407	196,758	184,551	227,257	86,062
df	239	248	248	237	228
R^2	0.2403	0.2014	0.1373	0.1195	0.1169
Adj. R^2	0.2396	0.2004	0.1361	0.1185	0.1145

$^{*} = p < 0.1,^{**} = p < 0.05,\ ^{***} = p < 0.01$

The coefficients for the more educated groups have larger magnitude. This may at first be surprising, but recall the composition of the RTI variable: the measures for how abstract, manual, and routine a job is. Higher-educated workers have lower routine and manual scores, and a considerably higher abstract score.[2] So a 1% increase in the ratio of routine to non-routine tasks is mostly a change in the ratio of routine to abstract tasks; it is equivalent to a decrease in task-abstractness. Technology complements abstract, but *not* manual, tasks. So for higher-educated workers, the effects of a change in RTI on wage are two-fold; workers see both an increase in substitutability and a decrease in complementarity by machines. Workers with a lower education see primarily the

[2] See tables A4 and A5 in the Appendix for descriptive statistics, including the breakdown of the RTI score.

effects of the increase in substitutability.

The coefficients on RTI for less-educated workers are positive for the earlier decades, and particularly large in magnitude for men. The higher percentage of men in manufacturing during that decade could explain that coefficient. Occupations in the manufacturing industry have especially high RTI scores. It is widely known that the manufacturing industry declined rampantly in the later half of the twentieth century. Naturally, wages of workers in that industry also declined, so demographic groups that are more highly concentrated in manufacturing will see a similar decline. While only 7.8% of individuals worked in manufacturing industries between 1976 and 1985, 17.9% of men with no college education were in manufacturing, and only 2.3% of women worked in manufacturing.

The changes in the coefficients on RTI across decades for educated workers is relatively small and lacks a clear trend. So the effects of routineness seems to have a minimal effect on changes in wage over time. On the other hand, for men without college education, the coefficients on RTI change from positive to negative and then increase in magnitude. This implies that routineness explains some measure of the decline in men's wages over time.

While the decline of the manufacturing industry could the *change* in the RTI coefficients, unionization in the manufacturing industry could explain why the initial coefficient was large in magnitude and positive. For less-educated workers, RTI effectively measures the ratio of routine tasks to manual tasks. So unionization of the more routine occupations could raise the relative wages of routine-intensive to manual-intensive jobs. I have not empirically tested this hypothesis.

Model 4

Tables 9 and 10 show the regression results for workers aged 30 to 39, and for workers aged 50 to 59, respectively. The older workers tend to have slightly higher coefficients on the RTI variable. This could imply that older workers are more adversely affected by technological developments. Though education level does not vary much over these groups, experience level will inherently differ. The inability to separate experience from task routineness.

Table 9: Workers Ages 30–39

Variable	**1976–1985**	**1986–1995**	**1996–2005**	**2006–2017**	**2012–2017**
RTI	-0.0107^{**}	-0.0040	-0.0190^{***}	-0.0269^{***}	-0.0327^{***}
	(0.0050)	(0.0047)	(0.0049)	(0.0044)	(0.0066)
sexbinary	-0.4848^{***}	-0.2601^{***}	-0.1634^{***}	-0.1264^{***}	-0.1290^{***}
	(0.0277)	(0.0250)	(0.0258)	(0.0240)	(0.0360)
pcentblack	-0.2490^{***}	-0.2841^{***}	-0.2340^{***}	-0.3325^{***}	-0.4083^{***}
	(0.0672)	(0.0612)	(0.0598)	(0.0566)	(0.0862)
pcenthispanic	-0.7684^{***}	-0.9068^{***}	-0.6714^{***}	-0.7310^{***}	-0.7058^{***}
	(0.0721)	(0.0638)	(0.0490)	(0.0395)	(0.0580)
nchild	-0.0429^{***}	-0.0930^{***}	-0.0864^{***}	-0.0806^{***}	-0.0694^{***}
	(0.0133)	(0.0127)	(0.0124)	(0.0118)	(0.0172)
Married	0.1808^{***}	0.4848^{***}	0.6850^{***}	0.7054^{***}	0.6473^{***}
	(0.0585)	(0.0499)	(0.0475)	(0.0452)	(0.0666)
Intercept	2.8169^{***}	2.5687^{***}	2.5021^{***}	2.6145^{***}	2.6693^{***}
	(0.0442)	(0.0354)	(0.0346)	(0.0340)	(0.0498)
N	2,993	3,485	3,343	3,645	1,486
df	6	6	6	6	6
R^2	0.1741	0.1514	0.1681	0.2296	0.2446
Adj. R^2	0.1724	0.1500	0.1666	0.2283	0.2415

$^{*} = p < 0.1,^{**} = p < 0.05,\ ^{***} = p < 0.01$

Table 10: Workers Ages 50–59

Variable	**1976–1985**	**1986–1995**	**1996–2005**	**2006–2017**	**2012–2017**
RTI	-0.0106^{*}	-0.0103	-0.0349^{***}	-0.0372^{***}	-0.0438^{***}
	(0.0064)	(0.0063)	(0.0063)	(0.0049)	(0.0074)
Sex Binary	-0.4739^{***}	-0.4208^{***}	-0.2736^{***}	-0.1059^{***}	-0.0913^{**}
	(0.0358)	(0.0330)	(0.0331)	(0.0270)	(0.0407)
Percent Black	-0.5546^{***}	-0.2584^{***}	-0.3101^{***}	-0.2814^{***}	-0.3757^{***}
	(0.0798)	(0.0722)	(0.0711)	(0.0671)	(0.1065)
Percent Hispanic	-0.6374^{***}	-0.7733^{***}	-0.9186^{***}	-1.0345^{***}	-0.9805^{***}
	(0.1082)	(0.0771)	(0.0689)	(0.0552)	(0.0797)
# Children	0.0107	0.0076	0.0467^{**}	0.0788^{***}	0.0692^{***}
	(0.0179)	(0.0188)	(0.0197)	(0.0153)	(0.0233)
Married	0.0941	0.1430^{***}	0.2214^{***}	0.4938^{***}	0.5128^{***}
	(0.0681)	(0.0550)	(0.0555)	(0.0496)	(0.0747)
Intercept	2.8099^{***}	2.7217^{***}	2.7632^{***}	2.5999^{***}	2.6427^{***}
	(0.0622)	(0.0491)	(0.0486)	(0.0408)	(0.0613)
R^2	0.1235	0.1044	0.1172	0.1810	0.2036
Adj. R^2	0.1217	0.1028	0.1156	0.1797	0.2003
N	2,888	3,354	3,285	3,631	1,467
df	6	6	6	6	6

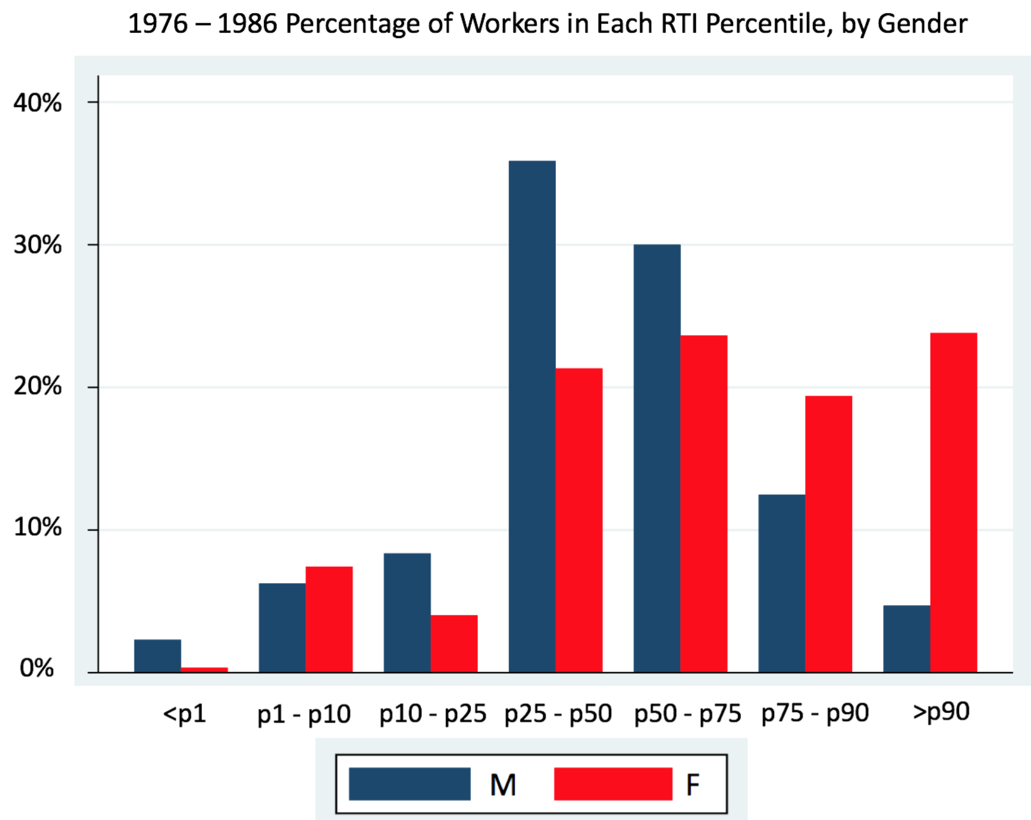
$^{*} = p < 0.1, ^{**} = p < 0.05, ^{***} = p < 0.01$

A notable jump in the magnitude of a coefficient on RTI is the difference between the 1986 to 1995 decade and the 1996 to 2005 decade. For workers aged 50 to 59, that jump was from zero to 0.0349, whereas the younger workers jumped only from zero to 0.0190. This could imply that technological developments in this period (possibly the introduction of the internet and widespread computerization) could have adversely affected older workers. The age group in their thirties is much more likely to have been exposed to computers in the course of their education than the age group in their fifties. As a result, the younger group may have better adapted to computerization, so that, as a result, the coefficient on their routineness variable changed by a lower magnitude.

Discussion of Models 2 and 3

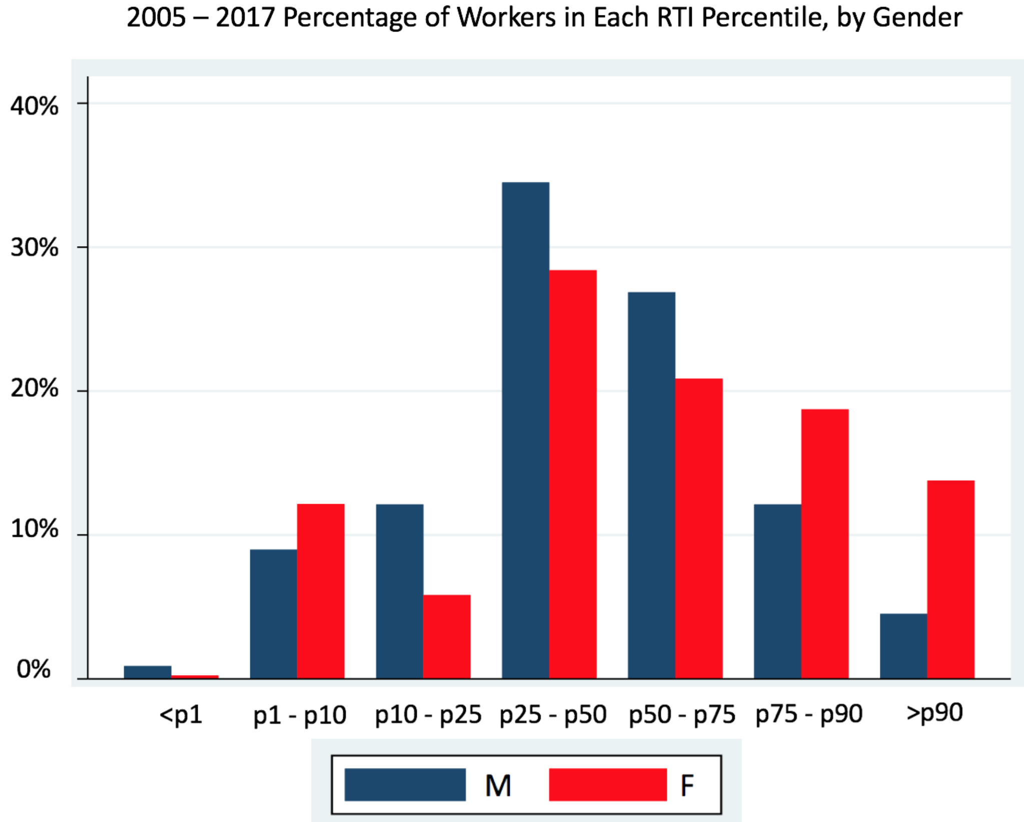
The change in the distributions of RTI over time for men and women is telling. Figure 1 (below) depicts the 1976 – 1985 percentages of men and women by RTI percentile. Women are clearly more concentrated in more routine work. For comparison, see Figure 2 (also below), which shows the same bar graph for the years 2006 – 2017. Clearly, the percentages of women in highly routine occupations has declined.

Figure 1



Each bar represents the percentage of workers of a given gender who are between two RTI percentiles. For instance, the bars above "p10 – p25" denote the percentages of workers between the 10th and 25th RTI percentiles.

Figure 2



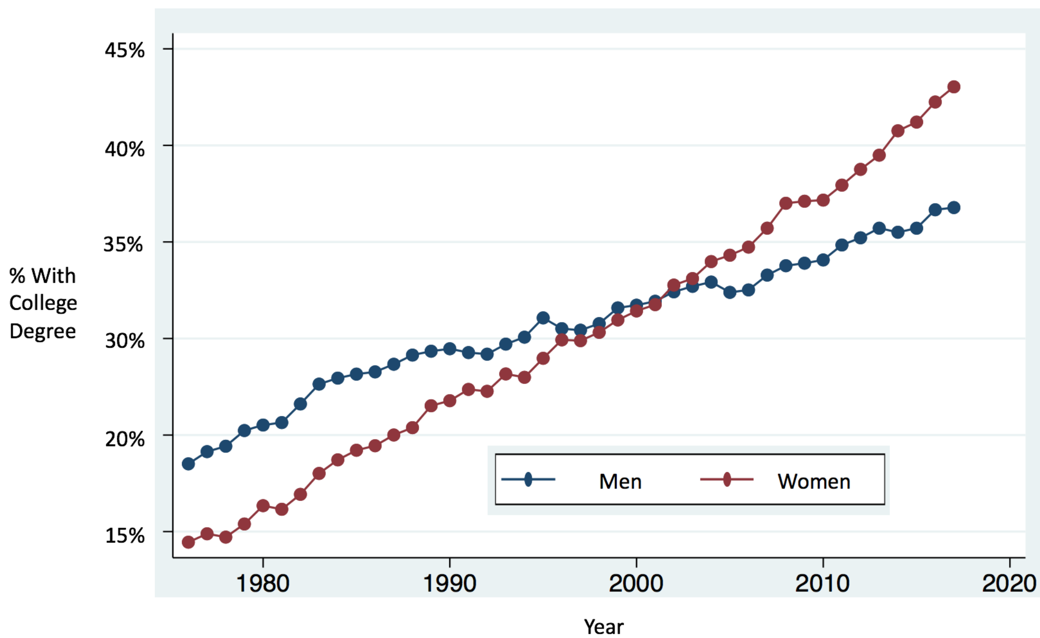
In particular, note the high percentage of women with routineness scores above the 90th percentile in 1976 to 1986. Workers like typists and secretaries have extremely high RTI scores, and these occupations composed a fairly large percentage of women's employment during that time. In contrast, that percentage of women above the 90th percentile decreased substantially from that decade to the post-2005 decade. While the women's bar is significantly higher than the men's, the women's bar dropped by nearly half, and the distance between the men's and women's bars has narrowed considerably.

Given the initial distribution, we expect that increasing automation should affect women more adversely than men since women's jobs are more easily substitutable by machines than men's are.

So as more and more technology that substitutes for routine tasks is implemented, the negative coefficients on RTI should grow in magnitude, as we see in the regressions from Model 2.

These distribution, in conjunction with the results from Model 3, can help explain the trend in the RTI coefficients for men versus women from Model 2. Since higher education is associated with a more negative effect of an increase in routineness, demographic groups that increase their percentage attainment of higher education relatively *more* than another demographic group will see a similar increase in the coefficients on routineness. See Figure 3 (below) for the percentages of women and men in the labor force by year who have a college degree. The trend in educational attainment for women is much more substantial than for men.

Figure 3: Percentage of Workers With a College Degree



Education, then, has the same predicted effect on the coefficients from Model 2 as automation does. These two factors, women's relative changes in education and women's concentration in highly routine jobs, could explain why the coefficients on women's routineness have increased so dramatically over the decades.

Conclusion

This analysis leads to several interesting questions for further study. For instance, what is the nature of the relationship between education and routineness? A distinction between tasks and skills might be needed in an analysis of that sort. Traditionally, we expect that skill development through education should decrease the adverse effects of task routineness. In these models, the effects of education and routineness are similar. A measurement of the effects of education on women and men's routineness and wages could help isolate the effects of education on wage from the effects of routineness on wage. This undertaking would paint a clearer picture of the role of routineness and its remedies.

How have recent developments both the tasks associated with an occupation? The concern noted by Green (2012) that the tasks of occupations change over time could be accounted for with an updated list of tasks. And how has the invention of new technologies changed how we define routineness? A new measure of routineness could update what exactly is deemed to be *routine*. Relatively newer technologies, like the internet, along with artificial intelligence technologies that are currently being developed, are not accounted for in the 1977 *Dictionary of Occupational Titles*. Autor, Levy, and Murnane (2003) highlight an example of how their measure of routineness could change. They list "Truck Driving" as an example of a manual, non-routine task. Truck drivers, then, would have a fairly low RTI score. But the recently developed potential for self-driving automobiles implies that some tasks like driving that were once "manual" may now be considered routine.

Of course, the potential for creating meaningful predictions is somewhat limited by our inability to know how technologies that haven't been invented yet could affect different occupations. This is the concern highlighted by Autor (2015), and this could account to some degree for the current variation in estimates for the percentages of jobs that will be made obsolete.

Another question is, how would conducting a spatial analysis with geographic data affect these results? Given Lake and Millimet's results, it seems probable that meaningful results concerning job polarization could be obtained. Do certain regions of the country respond to automation differently? Controlling for regional differences offers another way to break down demographic groups. More specifically, with regional data, an analysis of the implementation of one particular technology can be studied.

Ultimately, a clearer understanding of which groups of workers are most likely to be negatively affected by skill bias and job polarization can lead to enacting measures that reduce these effects. The higher concentration of women in routine jobs seems to imply that women are more adversely affected by automation, so development of more abstract skills—which has occurred in the past few decades through increased enrollment in post-secondary education institutions—could reduce the negative effects of automation.

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Appendix

Table A0: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Wage	3,139,230	14.6406	28.1744	0	9384.75
Year	3,139,230	1997.678	12.0690	1976	2017
RTI	3,139,230	1.0566	1.9503	-2.4110	7.9704
Task-Routine	3,139,230	4.0187	2.3650	1.1863	8.6420
Task-Manual	3,139,230	1.2437	1.3158	.0012	10
Task-Abstract	3,139,230	3.1778	2.3759	.0415	9.0020
Sex Binary	3,139,230	.4640	.4987	0	1
Age	3,139,230	39.0545	12.3202	18	66
# Children	3,139,230	1.0224	1.2136	0	9
Married	3,139,230	.6072	.4883	0	1
Education	3,139,230	1.7299	1.1625	0	4

Table A1: Descriptive Statistics, Collapsed by Year, Occupation

Variable	N	Mean	Std. Dev.	Min	Max
Wage	13,838	15.2666	7.6216	0	160.9305
Year	13,838	1996.455	11.7073	1976	2017
RTI	13,838	1.0877	1.7372	-2.4110	7.9704
Percent Black	13,838	.1054	.0965	0	1
Percent Hispanic	13,838	.1185	.1131	0	1
Sex Binary	13,838	.3687	.3075	0	1
# Children	13,838	.6361	.5664	0	5
Age	13,838	38.2026	5.8211	18	64
Married	13,838	.6164	.1540	0	1

Table A2: Descriptive Statistics: Men

Variable	N	Mean	Std. Dev.	Min	Max
Wage	13,742	16.5046	9.3587	0	361.2622
Year	13,742	1996.483	11.7095	1976	2017
RTI	13,742	1.0857	1.7363	-2.4110	7.9704
Percent Black	13,742	.1031	.1114	0	1
Percent Hispanic	13,742	.1291	.1356	0	1
# Children	13,742	.5709	.6119	0	5
Age	13,742	37.9452	6.9200	18	66
Married	13,742	.6195	.1951	0	1

Table A3: Descriptive Statistics: Women

Variable	N	Mean	Std. Dev.	Min	Max
Wage	12,494	13.1371	12.6085	0	832.3269
Year	12,494	1996.713	11.6883	1976	2017
RTI	12,494	1.1261	1.7698	-2.4110	7.9704
Percent Black	12,494	.1221	.1584	0	1
Percent Hispanic	12,494	.1121	.1575	0	1
# Children	12,494	.6904	.6692	0	7
Age	12,494	37.7419	6.9211	18	66
Married	12,494	.5358	.2274	0	1

Table A4: Descriptive Statistics: College-Educated

Variable	N	Mean	Std. Dev.	Min	Max
RTI	520,814	0.6410	1.8793	-2.4110	7.9704
Task-Routine	520,814	3.4744	2.2279	1.1863	8.6420
Task-Manual	520,814	0.9592	1.0966	0.0012	10
Task-Abstract	520,814	4.6271	2.3570	0.0415	9.0020

Table A5: Descriptive Statistics: Not College-Educated

Variable	N	Mean	Std. Dev.	Min	Max
RTI	1,513,660	1.2318	1.8789	-2.4110	7.9704
Task-Routine	1,513,660	4.3228	2.3463	1.1863	8.6420
Task-Manual	1,513,660	1.4655	1.4126	0.0012	10
Task-Abstract	1,513,660	2.2964	1.9785	0.0415	9.0020