Are Robots Replacing Routine Jobs

I. Introduction

With each iteration of technological progress comes the periodic warning that new technologies will lead to large-scale job replacement. Centuries of technological progress, however, hasn't rendered human labor obsolete—as new technology automates certain tasks traditionally performed by humans, it also frees the human laborer to accomplish other productive tasks that machines cannot perform. In short, technology has complemented labor rather than substituted for it.

Recent technological change, however, has renewed fears that millions of jobs stand to be imminently automated and replaced by machines and software. Frey and Osborne (2017), for instance, classifies the degree to which 702 occupations are susceptible to automation and predicts that over 47 percent of US workers risk replacement by machines over the next 20 years. A similar study by McKinsey Global Institute estimates that between 39 to 72 million jobs are to be automated in the US by 2030. These concerns stem from the profound progress in automating technologies that fundamentally sets recent automation apart from previous generations of technologies. The rapid adoption and advancement of new technologies have provoked discussions of their economic effects. For instance, mounting evidence suggests that the growing usage of computers and computer-assisted machinery has substantially substituted for medium-skill routine labor while complementing high and low-skilled labor. The vast literature of skill-biased technological change (SBTC) linked recent automation to the increasing polarization of jobs and rising wage inequality. (Autor et al. 2003; Acemoglu and Autor, 2011; Autor, 2013; Autor and Dorn, 2013; Goos et al. 2014)

The industrial robot, or robot, has garnered immense attention for its potential to automate a variety of production tasks. The International Federation of Robotics (IFR) defines a robot as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes" (IFR, 2016) Unlike traditional capital equipment or software, robots are versatile, reprogrammable, and able to simulate human movements and perform a variety of tasks that traditionally required human finesse and judgment. Robot usage has grown rapidly, especially in manufacturing industries such as motor vehicles and electronics production. Average robot intensity in the US, as measured in units per thousand workers, doubled since 2004 and is projected to rise in the coming decades.

Implied by skill-biased technological change, an increase in task replacing technology lowers demand for "routine" occupations. Robots, in theory, should also substitute human labor in executing "routine" tasks. An occupation's "routineness" can be defined as the extent to which its tasks are automatable. Figure 1 investigates this possibility by showing the average annual employment share of production and non-supervisory workers in manufacturing industries since 1990, a period which coincides with the rise in industrial robot usage. Production share of employment rose during the early nineties and declined over the following decade. Figure 2 shows a steadily increasing wage premium of supervisory versus production/non-supervisory occupations since 2006. This preliminary evidence suggest that robots may have played a role in shifting employment composition and wages within manufacturing.

Recent literature has begun to study and estimate labor market impact of robots with recently available data from IFR. (Acemoglu and Restrepo, 2017; Dauth et al. 2017; Graetz and Michaels, 2015) However, little attention has been given to studying how robots differentially impact routine-intense occupations. Many occupations can be feasibly automated, but economic incentives and other underlying conditions impacts which occupations are replaced. This thesis aims to empirically test if recent increases in robotization have indeed substituted for routine employment.

To test these hypothetical impacts, I construct industry-level robot intensities in the US since 2004 by matching robot stock from IFR to cross-sectional household data from the Current Population Survey (CPS). To measure occupational "routineness," I draw information from the Occupational Information Network (O*NET) and construct occupational routine task intensities. Using fixed effects to control for industry trends, I estimate that a unit increase in robot intensity in an industry decreases overall occupational wages by about 0.2 percent, and have little effect on employment levels. I also fail to find that a rise in robot intensity differentially impacts more routine occupations.

I first address a concern that the constructed measure of routineness is imperfect when applied to nonproduction workers. I restrict my sample to production and material moving occupations and find that increases in robot intensity negatively impact, in real wage and employment, more routine intensive occupations within production. Production occupations with low routine intensity, in turn, experience an increase in employment. I obtain similar results when restricting my sample by education/skill groups, and find robot substitution of tasks to be most prevalent among high school graduates and high school dropouts. However, I find no significant impact on highly educated workers. These results suggest that rising robot intensity impacts lower-skilled workers and production workers, while other workers are relatively insular from robot automation. The results are robust to alternate specifications such as controlling for regional trends and firm size.

The rest of the paper is structured as follows. Section II summarizes the existing literature on automation and skill/task biased technological change. Section III describes the data sources and methods for measuring robot and routine intensity. Section IV describes the empirical approach. Section V studies the impact of IR on individual workers and across occupations. Section VI concludes.

II. Literature Review

A growing body of literature has tried to explain recent changes in the labor market, rising wage inequality, with skill-biased technological change. SBTC posits that recent technological change is biased in favor of skilled workers against unskilled workers. (Katz and Autor, 1999) This explanation, however, doesn't entirely conform to empirical evidence—employment shares in the US have increased in both high and low skilled workers, while employment of medium-skilled occupations declined. (Autor et al. 2006; Autor, 2010; Goos and Manning, 2007) Evidence of "job polarization" demanded a more nuanced view of SBTC.

Most studies on changes in the wage structure focus on explaining wage in terms of returns to skill using measures such as education and experience. (Katz and Murphy, 1992, for example) Until recently, little attention has been put into explaining wage determination in terms of occupations and the tasks they perform. This view is not entirely new— Beyer and Knight (1989) provide evidence that a worker's occupation is a significant determinant of wage.

Autor, Levy, and Murnane (ALM) (2003) pioneered the task-based approach to SBTC. ALM argues that computer technology has depressed returns on a variety of "routine" tasks, which computer-assisted technology can adequately perform. ALM provides a convincing explanation for US job polarization—medium-skilled workers concentrated in occupations that execute "routine" tasks are facing automation. Using empirical evidence from computer usage since 1960, ALM demonstrates how automation shifts tasks from "routine" to "non-routine." Many subsequent studies confirm the results in ALM, including Goos and Manning (2007) and Autor, Katz, and Kearney (2006). The "task approach" by ALM and subsequently Acemoglu and Autor (2011) serves as a theoretical foundation for this paper.

Industrial robots provide a useful channel to investigate the implications of automation. Unlike computers, Industrial robots execute a well-defined, consistent set of tasks (such as moving and handling objects, palletizing, and assembling.) As such, robot automation can be matched precisely to occupational tasks. Studying robot automation can potentially push the boundaries of our understanding of SBTC.

Many recent studies estimate the impact of robots, and results vary significantly across countries and time periods. Acemoglu and Restrepo (2017) use variations in regional robot exposures from 1993 to 2007 and find significant and negative effects of robots on employment and wages across commuting zones. Their results suggest that one additional robot per thousand workers reduces employment to population ratio by 0.18-0.34 percentage points and wages by 0.25-0.5 percentage points. Dauth et al. (2017) replicate Acemoglu and Restrepo's methods on local labor market outcomes in Germany and find no evidence for negative employment effects. Dauth et al.'s findings suggest that workers in more robot-exposed industries have a higher probability to remain employed. Graetz and Michaels (2015) estimate robot impact contributed roughly 0.36 percentage points to annual labor productivity growth using a cross-country panel dataset.

Few, however, have taken advantage of well-defined robot applications to test the impact of robots on routine occupations. While existing studies on industrial robots focus on the general equilibrium effects of rising robot exposure, I attempt to address how robots interact with routine and nonroutine occupations using variations in occupational task intensities. I hypothesize that when an industry experiences growth in robot exposure, robots tend to automate routine tasks, which depresses earnings and employment for routine occupations. Furthermore, since robots are also complemented of "non-routine" tasks, they, in theory, increase relative demand for non-routine occupations.

Data

A. Data Sources and Descriptive Statistics

Industrial Robots/ CPS ASEC March Files

My main dataset is an annual series of the operational stock of industrial robots in the US drawn from the IFR Handbook. IFR data collects the stock of industrial robots for over 40 countries from annual surveys of major robot suppliers and covers over ninety percent of the global market. Data on the operational stock of robots is broken down by broad industry groups outside manufacturing, and detailed industry within manufacturing.

For the United States, IFR covers the stock of operational robots, in units, for the 1993-2016 period. However, data broken down by industry is only available for 2004-2016. Industrial robots are concentrated heavily in manufacturing, and specifically in the manufacturing of motor vehicles and electronics. I match operational stock of robots by industry from 2004 to 2016 to cross-sectional labor market data obtained from the

Current Population Survey's Annual Social and Economic Supplement (ASEC) files for odd years from 2005-2017. All CPS files are from the Census Public Use Micro-series (PUMS) database. The ASEC survey is a supplement to the larger CPS, a monthly survey of US households that yields nationally-representative labor market data. ASEC is conducted each March and follows a larger set of households. ASEC estimates wages and employment of the previous calendar year. I use all observations for full-time, non-military workers between ages 16 and 65. To maintain time-consistent and comparable occupation and industries over the period, I use consistent industry and occupational classifications (OCC10 and IND90, for 2010 equivalent occupation and 1990 equivalent industry) provided by the Census.

To measure the intensity of robots on each worker, I follow Dauth *et al.* (2017) and divide the stock of robots in each industry by its employment (measured by summing across ASEC sampling weights), multiplied by one thousand. A detailed description of data construction is provided in the Appendix. The robot intensity measures of the number of units of robots per one thousand workers in an industry in each year, and measures the per worker exposure to robots in an industry.

Figure 3 shows employment-weighted means of robot intensities in six occupational sectors from 2004 to 2016. Occupational sectors are grouped according to the Census occupational classification scheme. All occupational sectors experienced increases in robot intensity since 2004. As expected, robots are overwhelmingly concentrated in production, transportation, and material moving occupations. The relative concentration of robots in production is mostly due to manufacturing industries, which employ most of production and material moving workers. Over the 12-year period, robot intensity overall has increased rapidly. Robot prices have dropped significantly since 1995, which can partially explain the increase in robot usage. (IFR, 2016)

Industry robot intensities cannot, however, capture differential impact within occupation. Intuitively, robots substitute for workers whose tasks significantly match robot applications. Using only the industry robot exposure prevents separating complementary versus substitution between robots and occupations with different routineness. To test this hypothesis, I need to construct a measure of the occupation intensity of robot replaceable, or routine tasks.

*O*NET Occupational Task Measures*

Occupational tasks cannot be directly measured. However, I draw comparable information from the Occupational Information Network (O*NET) database. O*NET provides scores for a variety of occupational characteristics (such as abilities, work activities, and work context) of over 900 detailed occupations. For each variable, O*NET specifies both importance and level scores, evaluated on a 0-5 scale by either incumbent workers or special occupational analysts. O*NET data is available from 1998 and is updated periodically. I use O*NET measures from 2002 and 2016 to capture occupational task variations before and at the end of my observation period.

I aggregate O*NET data for detailed occupations to 547 consistent census occupations and matched the occupational characteristics to the main dataset by Census occupation codes. The 2002 O*NET data follows the 2000 Standard Occupational Classification (SOC) scheme, whereas 2016 O*NET uses updated 2010 SOC codes. I use a crosswalk provided by the BLS to map all O*NET SOC codes to the 2010 SOC equivalent, and subsequently aggregated the 2010 SOC codes to match the Census 2010 occupational classification.

I face two major limitations when studying occupational task change using data from O*NET. As Autor (2013) notes, O*NET has an overwhelming number of variables that capture different aspects of occupational characteristics. Since only a small fraction of variables can realistically be used, a researcher has a considerable amount discretion when choosing which variables to include. O*NET values do not directly correspond to occupational tasks, and using different variables as a proxy can lead to deviations in results. Second, O*NET's values are assigned according to an arbitrary scale, which makes interpreting task values difficult. Both concerns are addressed prominently in the previous studies that make use of O*NET task measures. (Autor *et al.* 2003; Deming, 2017)

Based on the definitions provided by O*NET, I choose the variable "Handling and Moving Objects," which approximate routine tasks performable by a robot.[1] The variable is defined as "Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things." (O*NET, 2017) Since industrial robots' primary application is to move object precisely using a multi-axle manipulator arm, this variable should measure the extent to which an occupation perform routine tasks automatable by a robot.

Since O*NET measures do not have a tangible scale, I follow Autor et al. (2003) and Deming (2017) and transform task measures of all 547 census occupations into values that reflects their respective percentile ranks on an employment-weighted task distribution. I use 1990 as a base period reflects task distribution during a time when industries are still relatively unexposed to robots. Therefore task measures directly compare to the period when robots were far less prevalent in the workforce. I apply the

[1] Since O*NET doesn't include a variable that directly captures occupational task overlap with robots, I use a related variable, "Handling and Moving Objects." Though the definition of this task variable isn't routine, per se, it adequately reflects occupational intensity in routine applications of industrial robots. See Table 10.

inverted 1990 task distribution to all subsequent O*NET routine measures. To ease interpretation, I further divide the routine measures by 100 such that all routine task measures scale from zero to one.

Table 1 shows the summary statistics for six occupational sectors. Routine measures are highest among farmers, construction workers, and production workers. Robot intensity, as expected, concentrates in routine occupational sectors. Management occupations experienced a 6 percent growth in employment share, whereas production occupation employment experienced a 1 percent decline in the share of total employment.

Empirical Approach

Previous studies on the impact of robots focus on regional variations in robot intensity within a country. (Acemoglu and Restrepo, 2017) Since IFR data isn't available at the regional level, measuring robot intensities of local labor markets requires assumptions about robot distribution within an industry. My paper instead focuses on the industry variations in robot exposure. Many recent studies have pointed out how long-run trends of industries well before the introduction of robots may bias the estimates of robot impact. (Dauth et al.,2016; Acemoglu and Restrepo, 2017) Since industries could be already on a growing or declining path before our observation period, increases in robot usage is potentially a response to pre-existing industry-specific trajectories. As such, rising robot intensities is potentially a symptom, rather than the causal force behind labor market changes. To address this concern, I identify effects *within* industry groups via industry fixed effects, thereby purging some of the confounding long-run trends across industries.

Using only industry robot intensities, however, cannot account for differences in occupational exposure to robots within an industry. The occupational task intensity, which proxies for the replaceability of robots, capture within-industry variations of robot exposure. By exploring the variation of routine task intensities across occupations, I can approximate how increasing robot exposure affect workers with varying task content.

A. Cross-sectional Analysis of Robot Impact

I first estimate the within-industry impact of robots, without task terms, on a constructed panel of gender-education-occupational-industry cells over the 12-year period. The main independent variable is the robot intensity in industry j, measured in robots per thousand workers. I aggregate all worker-level data such as hourly wage and age using census provided sampling weights. I choose to use aggregate worker-level outcomes because the studied variables, robot intensity, and routine task measure, are invariant within occupation-industry pairs and cannot explain worker level variations. However, CPS microlevel data allow me to separate occupations by demographic characteristics such as gender and education. This is helpful for studying the impact on specific subsets of the larger sample.

To analyze aggregate effects on real wage and labor supply over time, I regress annual labor outcome, $Y_{i,j,t}$, measured in log wage and log employment, on robot intensity, controlling for a variety of covariates:

$$\mathrm{Y}_{i,j,s,e,t} = \alpha_{i,j,s,e} + \beta_1 \cdot RobInt_{j,t} + \beta_2 \cdot Age_{i,j.s.e,t} + \lambda_i + \delta_j + \psi_t + \gamma_s + \tau_e + \epsilon_{i,j,t} \qquad (4.1)$$

Where *RobInt* measures robot intensity of occupation i, industry j, sex s, and education e, in year t. $Age_{i,j,t}$ controls for the mean age of occupation i in industry j during year t, and proxies an occupation's average level of experience. I also control for linear time trends and other worker characteristics using year dummies ψ_t, sex dummies γ_s , and controls for industry δ_j and occupation λ_i. I cluster standard errors by industry.

The coefficient of interest is the measure of robot intensity. Since the model above cannot differentiate complement and substitution effects of different types of workers, it captures the aggregate effect of robot intensity.

A. Routine Intensity and Tasks

To test if robots are more substitutable for routine labor, I extend the above model to include constructed occupational routine task measures, measured in percentile scores on the 1990 task distribution, adjusted to a 0-1 scale. Since O*NET values are only periodically updated, and each update revises values for a small portion of available occupations (roughly 100 occupations per year), using different versions of O*NET leads inevitably to inconsistent task measures over time. I fix the task values to only 2002 O*NET task measures to provide a consistent comparison between occupations.

Fixing the routine task measures assumes that task contents, and relative task intensities, within nominally identical occupation, haven't changed significantly over the 14-year period. Intuitively, since occupations are tied to the tasks they perform, the assumption that task changes are stagnant is reasonable. Even when task intensity changes within an occupation, these shifts would occur slowly.[2] Using 2002 occupational task measures, I test the following model,

$$Y_{i,s,e,j,t} = \alpha_{i,s,e,j} + \beta_1 \cdot RobInt_j + \beta_2 \cdot T_i + \beta_3 \cdot RobInt_j \times T_i + \beta_4 \cdot Age_{i,s,e,j,t} + \lambda_i + \delta_j + \psi_t + \tau_e + \epsilon_{i,s,e,j,t} \quad (4.2)$$

Where *RobInt* measures robot intensity of occupation i, industry j, sex s, and education e, in year t. T_i is the routine task intensity of occupation i, measured in percentiles on the 1990 distribution. β_1 estimates the effects purely attributable to levels in robot intensity, whereas the coefficient β_2 for the main task term. Coefficient β_3 estimates the impact from of robots given the level of routine task intensities in an occupation i. My hypothesis suggests that robots are more substitutable in performing routine tasks than non-routine tasks, hence the coefficient for robot routineness interaction should appear negative. An increase in robot intensity should more negatively impact routine-intense occupation. If robots complement non-routine labor, then the coefficient $\beta_1$should be positive. The overall effect of robots on labor outcomes of a given occupation-industry pair is some combination of the magnitudes of the two coefficients.

Results

A. Baseline results

Table 1 reports the results for robot impact on mean wages of each cell. When controlling for occupations and industries, robot intensity is significantly and negatively correlated with wage. One additional robot within and industry directly correlates to roughly a 0.25 percentage points decrease in real wage. The coefficient is robust under different controls and is consistent even when including measures of occupational routineness. These coefficients agree with the results from Acemoglu and Restrepo (2017), which estimates a unit increase robot intensity to lower wages by 0.25-0.5 percentage points within local labor markets. Column (4) includes routine measures for each occupation. As expected, routine occupations have lower wages. An occupation with task measures of 10 percentile points lower than another earns, on average, 2.6 percent less.

The effects of the interaction term between robot intensity and routine intensity, however, is statistically insignificant. This suggests that robot impact on an occupational wage is largely independent of the routine intensity of the occupation.

[2] Autor, Levy, and Murnane (2003) explores in depth intensive margin shifts in task intensities over time. Their study finds that in fact, task value shifts within occupation accounts for over 30 percent of all task change over the 1970-1998 period. So, this assumption doesn't hold true for long periods.

This result is surprising as we'd expect routine occupations in robotized industries to exhibit a greater decline in wage over time.

Table 2 reports the result when regressing robot intensity on the level of employment of occupation-industry cells. Column (1) reports the coefficient on robot intensity under a simple specification, where I omit industry and occupation controls. The value is significantly negative. However, when controlling for occupation and industry, the effect of robots vanishes. Column (4) and (5) includes routine intensity and the interaction between routine and robot intensities among regressors. The coefficients on all variables of interest are statistically insignificant.

These results show that an increase in robot intensity does not on average lead to lower occupational employment levels, even when adjusting for occupational differences in routine task intensities. No substitution effects are found in either wage or employment levels. This suggests that robot automation does not lower labor outcomes of routine occupations.

The impact of robots on employment estimated here is significantly smaller than that in Acemoglu and Restropo (2017). A potential explanation for this inconsistency is the focus on within industry rather than within region changes in labor outcomes. Studies such as Autor, Dorn, and Hanson (2013) suggest that most labor adjustment takes place within local labor markets, and my results cannot capture within region changes in labor market outcomes. Another potentially confounding element is the period of observation— significant growth in robot intensities coincides with the Great Recession, which had an immense impact on employment levels and labor structure in the US. Acemoglu and Restrepo (2017), for instance, restrict their observations to pre-2008 labor market outcomes.

Several characteristics of my study could also be affecting the estimates of robot intensity, especially regarding robot impact on routine occupations. For instance, the routine task intensity measure may not reflect robot replaceability outside production occupations. Table 7 lists the work activities measured in the task intensity variable. While most activities do in align with robot applications, few such as "direct vehicle traffic" or "train animals" are not routine tasks automatable by a robot. The limitation of the constructed task measures is that they do not exclusively apply to applications of a robot, but a large set of manual tasks. To address this issue, I repeat the analysis conditioning on production workers and material movers, which experienced the most significant increases in robot intensity among all occupational sectors over the observation period. Restricting my sample to production occupations also contains the task measures to the most relevant set of activities.

B. Impact of Robot Intensity on Production and Material Moving Occupations

Table 3 reports regression on wage when restricting our sample to production and material moving workers, as defined by the census occupational classification scheme. When not including the interaction term, robot intensity is negative and significant. Each additional unit of robot per thousand workers correlates with a 0.2 percent points decrease in wage. However, when adding the interaction term, we see substantial differences from the baseline results. The effect of the main robot intensity term becomes positive and insignificant, whereas the interaction term is significantly negative.

These results are consistent with the hypothesis that robot negatively impacts wages of more routine-intense workers. A production worker in an occupation that has a routine intensity measured at the 90th percentile (average in production occupation around 80) of the 1990 task distribution experiences, on average, experiences 0.35 percentage points decline in real wage given a unit increase in robot intensity. Whereas an additional unit of robot per thousand workers may not impact an occupation that is not as routine-intensive. Restricting the observation to production occupations yields results consistent with the hypothesis that robots substitute for human labor substantially in performing routine tasks.

Table 4 repeats the regression for employment levels within production and material moving workers. Column (1) excludes occupational task measures, whereas columns (2) – (3) includes task intensity and the interaction term. The coefficient on robot intensity increases when controlling for variations in occupational task measures. As column (3) suggests, occupations with low routine task intensities experience an increase in employment with a contemporaneous increase in robot intensity. Increased robot usage significantly and negatively impacts employment in occupations with high routine task scores. These findings suggest that when an industry increases its robot intensity, employment shifts away from occupations that perform routine tasks to non-routine occupations within the production occupation sector.

Intuitively, as more routine intense production occupations are automated, displaced workers sort into related occupations that are relatively insulated from automation, namely production occupations involving tasks that robots cannot perform. The estimates lend support to this explanation, as we see increases in employment of production occupations with low routine intensities, but no significant increases in wage.

C. Impact of Robot Intensity by Educational Attainment

Heterogeneous impact of robots may also exist across skill groups. Low skilled and medium-skilled workers may sort into occupations that are either substitutable to robots or relatively insular to robot substitution. (e.g., production worker or service workers) Whereas high skilled workers sort into occupations that are insulated from automation. Robots should affect workers differently according to skill level. To measure skill levels, I use the highest level educational attainment categorized into four groups: high school dropouts, high school graduates, some college, and college graduates.

Table 5 summarizes results for log real wage after conditioning on worker's educational attainment. Robot intensity most notably affects high school graduates as seen in column (2). Increases in robot intensity most directly impact workers in this category, as the main effect from robot intensity is significantly negative. Column (3) and (4) reports estimates for high skilled workers with at least some college education. Surprisingly, increases in robot intensity do not impact high skilled workers. These results suggest that rising robot use does not augment high-skilled labor.

Evidence for robot substitution, however, can be found in the low skilled group. The main effect for robot intensity remains negligible for high school dropouts. However, the interaction between robot intensity and routine task measure is significantly negative. A negative interaction term suggests that routine workers in the low skill category experiences decrease in wages when robot intensity increases.

Table 6 reports the results on employment level, conditioning on worker's educational level. Similarly, the coefficient for the interaction term significantly negative for high school dropouts and graduates. Robots negatively impact the employment of routine workers in the low and medium-skill categories. The main effect of robot intensity is positive for high school dropouts and graduates, suggesting that non-routine occupations experienced an increase in employment when experienced an increase in robot intensity.

For low skilled workers/ high school dropouts whose occupation is at the 100th percentile, employment levels decline by roughly 0.6 percentage points. For high school graduates, however, the negative interaction effect is smaller than the overall increase in employment from rising robot intensity.

For high skilled workers with above college education, however, robots negatively impact employment for non-routine occupations, whereas routine occupations experience an increase in employment. The results for high skilled workers are puzzling, suggesting that employment shifts towards more routine occupations with increases in robot intensities.

Results from separating the workers into skill groups suggest that robot substitution of routine occupations exist among low skilled workers. However, I find no significant offsetting or complementary effect among high-skilled workers. Acemoglu and Restrepo (2017) similarly find no employment gains in higher educational groups.

A possible explanation for these observations is that the effects of automation localize around tasks that are currently being automated. Rather than complementing all non-routine occupations, automation positively affects workers whose skill requirements and task contents are immediately outside the automation frontier. Initial employment shifts occur laterally within certain occupational and skill groups where robots affect most directly, shifting from routine intense to non-routine occupations. As a result, other occupational and skill groups are initially insular to the effects of rising robot intensity. Exploring these possibilities would require longer periods of observation.

D. Regional Variations and Other Controls

Finally, I also consider the possibility that confounding regional trends can impact my previous estimates. Using unaggregated CPS samples, I add additional controls for state, metropolitan status (urban or rural), and firm-size. Table 9 shows that adding regional fixed effects doesn't impact our results when already controlling for industry and occupation. The results from adding regional effects are consistent with our previous estimates, with robots overall having a negative impact on wage. The addition of routine-robot interaction doesn't change the coefficients on robot intensity. I find no substitution effects between robots and occupational routineness.

Table 10 restricts the sample to production workers. I again find that robots negatively impact wages without controls of occupational routineness. However, after adding routine intensity and the interaction term, the main effect on robot intensity loses significance. The interaction term has a negative coefficient and suggests that robot intensity decreases the most routine occupations by around 0.2 percentage points. When controlling for occupations, there is a clear substitution-complementary relation between robots and occupational routineness. Occupations with low routine scores experience increases in wage from robots, and occupations with the highest routine scores experience roughly 0.3 percentage points decrease in real wage. These results are consistent with our previous estimates. Within production occupations, routine workers are differentially impacted by robot exposure, even after controlling for regional trends. I repeat the analysis without using census weights and find statistically identical results.

Conclusion

The results of this paper show that overall impact of increasing robot usage negatively impacts wages overall but have little impact on employment levels. Overall, the constructed routineness measure fails to have substantial explanatory power over routine-biased shifts in either employment or wages. The baseline results show that there is little to no task-biased shifts in wage or employment. A potential reason for this result is a flawed routineness measure.

I address this issue by restricting the sample to production workers, and find that increases in robot intensity depress wage and employment in routine occupations. These results are consistent with predictions of task-biased technological change and previous studies on robot automation. (Acemoglu and Restrepo, 2017). When separating the sample into educational groups, I also find robots impact to be greater on routine workers with low and medium skill, as opposed to high skilled. Surprisingly, we do not find any offsetting employment gains by other occupational or skill groups.

The results present some evidence for robot-induced task biased technological change. I find that the most apparent evidence of robot-task complementarity takes place *within* the production occupational sector and low-skilled category. High skilled workers experience little employment or earning gains from increasing robot intensity. The localized impact has potentially important implications on the possible mechanisms of skill and task-biased technological change—automation increases demand for occupations immediately related to occupations being replaced. A possible explanation for this phenomenon is that automating existing tasks of one occupation immediately increases the productivity of similar occupations, and therefore increases demand for these related occupations.

More evidence is needed, however, to confirm this hypothesis. Many variables which I do not control for, may impact my results. Investments in information and communication technology, exposure to trade and offshoring, and increases in capital investment all have important implications on occupational labor outcomes. (Autor, Dorn, and Hanson, 2013)

Further research can certainly clarify some confounding findings in this paper. The routine task measures derived from O*NET is at best an adequate measure of robot replaceability within production occupations. There is also little consensus in the literature of standard sets of task measures used to study the effects of automation. Improving the standard of measuring occupational tasks requires experimenting with various task variables, and maybe the first step towards furthering research on the economic impacts of automation.

Appendix

A. Measuring Outcome Variables

The sample of workers in this study consists of individuals of working age, defined as between age 16 and 64, who worked full-time in the year prior to the CPS survey. Full-time workers are selected according to the indicator variable FULLPART included in CPS ASEC data, where a FULLPART value of 1 indicates that a worker was a full-time employee in his/her main occupation last year. I also restrict my analysis to non-military workers as O*NET task values are not available for military occupations. All occupational and industry aggregates are weighted by the Census-provided sampling weights. To calculate estimates for occupation and industry employment, I sum census sampling weights across observations over each occupation/industry.

For wage calculations, I exclude observations with zero or missing wages. The wage income reflects the worker's wage earned in the previous calendar year, and are in nominal terms. To construct a consistent wage variable comparable across samples, I first convert all wages to 1999 US dollar equivalent using the census conversion variable CPI99. These values are then converted into 2010 US dollar values using conversion rates provided by the census. Hourly wages are calculated by dividing real adjusted wage income by the individual labor supply. All aggregated measurements of mean wage and total labor supply are weighted by the census sampling weights.

B. Constructing Industry-level Robot Intensity

Different industry classification schemes prevent direct matching between IFR industrial robot data and the CPS. IFR uses a variant of the International Standard Industrial Classification, Revision 4 (ISIC, rev.4), whereas the CPS uses census standard industry codes, OCC10. Since both classifications offer consistent coding of industries, I needed only to match IFR industries to its corresponding census industry. IFR data is only available for six broad industry sectors outside manufacturing and 19 2/3-digit industries within Manufacturing, which is a higher-level aggregation of detailed census industry codes. To match IFR industries to equivalent census codes, I only use the most detailed industry classification available in the IFR data. Since no crosswalk was available, I assign census industry codes (using definitions of its aggregates) to its equivalent IFR industries using industry descriptions provided in the IFR handbook. Due to the difference of the two classification schemes, many census industry codes are assigned the same IFR industry.

Since employment and robot stock varies significantly across IFR industries and over time, I divide robot stock by employment in each IFR industry to obtain the units of robots per worker in each industry in each year. I multiply this value by 1000 to obtain measures in units per thousand workers within each IFR industry-year pair.

C. Selecting O*NET Task Variables

The data on occupational task requirements are from O*NET's vast library of occupational characteristics. The O*NET provides detailed series of work abilities, work context abilities, and knowledge of over 900 occupations. O*NET measures are surveyed and updated annually by incumbent workers and occupational experts, who assign a level and importance value to each variable. For my analyses, I need to identify variables that best approximate industrial robot applications. O*NET data contains a series of a set of general work activities (GWA), defined as "a set of similar actions that are performed together in many different occupations." (Peterson, et al., 1999) GWA variables contain measures of the importance of tasks performed within an occupation and can be further broken down into detailed work activities. Based on the textual definitions of the detailed work activities, I chose to use the GWA variable "Handling and Moving Objects" as it matches most closely IFR robot applications.

Table 10 shows a comparison between detailed work activity contained in the variable "Handing and Moving Objects" and robot applications from the IFR handbook. Panel A and B share a large portion of similar and comparable tasks, such as assembly and disassembly, welding, coating, and cutting.

Occupational information for each GWA variable is further divided into two ratings, importance and level. The importance of each of an occupation's GWA has a 1-5 scale, with one being not important, and five being extremely important. For this study, I use only IM values to determine task intensity, as importance anchors are consistent across occupations and GWAs. Using either measure shouldn't hinder the outcome of our results as importance, and level ratings are highly correlated. (Tsacoumis and Willison, 2010)

D. Constructing Task Measures by Census Occupation

I assign task scores to each worker based on reported census occupation codes. The challenge in doing so is that occupation classifications are substantially different between O*NET and the CPS ASEC march files. This section explains how I measured mean task inputs for each census occupation.

O*NET occupations exclusively adopt the standard occupational classification (SOC) scheme but go even further in detail. O*NET data is available for over 900 occupations. I first convert all O*NET SOC codes to the more commonly used 6-digit

SOC classification by simply aggregating SOC measures to the 6-digit levels. This aggregation produces mean task values for 547 SOC occupations, which is then matched to CPS occupations using a crosswalk provided by the Bureau of Labor Statistics website.

Following Autor *et al.*, I construct task means of 1990 industry-sex-education cells. The four education groups are based on CPS education codes: below high school, high school diploma, some college, and college and higher degrees. 1990 task measures are aggregated by cell and weighted by the CPS sampling weights. Using the 1990 task measures, I generate an empirical cumulative task distribution weighted by 1990 employment. (Fig. 7) This distribution is inverted and applied it to all occupational task values of subsequent years, measured in their percentile rank on the 1990 task distribution.

E. Stagnation in Task Trends

A puzzling aspect of the routine task intensity is the fact that it remained relatively constant over the 12-year period, across all occupational sectors (Table 1). Aggregate task means are weighted by sampling weights. If employment shifts from more routine to less routine there should also be significant shifts in the weighted task intensities over time. A potential explanation is that the 12-year observation window is too short to observe long-term task shifts.

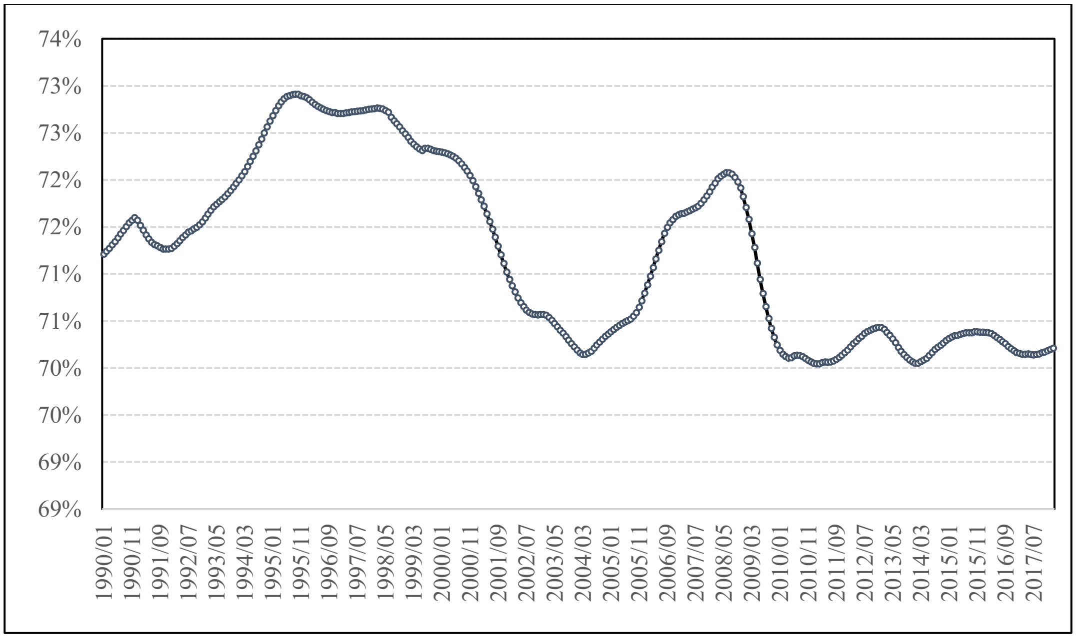
Replicating Autor, Levy, and Murnane (2003), Figure 4 shows the aggregate task trends for routine tasks, measured by O*NET's "Handling and Moving Objects" variable, in the U.S. economy and the manufacturing sector since 1990, and reflects the changes in employment-weighted task intensities over a longer period. 1990, by construction, has a weighted mean of 50. Each subsequent value depicts the employment-weighted mean of the cell percentiles ranks. Consistent with our expectations, routine task measures have fallen significantly since 1990, both in manufacturing and overall. The most significant decline occurred before our observation period. Changes in task measures were stagnant since 2004.

It is important to note that task change can be driven by either occupational employment shifts from routine occupations to non-routine occupations, or by changes in the task values over time in nominally identical occupations. Autor *et al.* (2003) refer to these separate effects as the extensive and intensive margins.

To better grasp the extent of task change since 1990, I use 2016 O*NET task values to measure the most up-to-date task intensities. Figure 4 and 5 depict the smoothed change in the density of routine task measure since 1990 in the US economy and manufacturing. The density is calculated as the employment share of the total full-time-workers in the sample each year. The horizontal axis is the change in the density of workers for each percentile on the 1990 task distribution. By construction, the 1990 density distribution is uniform. Evident from the figure is a general decline in the density of highly routine workers and an increase in density for workers at the bottom of the routine task distribution since 1990. The gap between the two 2009 series is the intensive margin task shift over the 2002-2016 period. Task shifts in the intensive margin are opposite to extensive margin shifts and are relatively small. Consistent with the previous figure, changes in task intensities are stagnant since 2009.

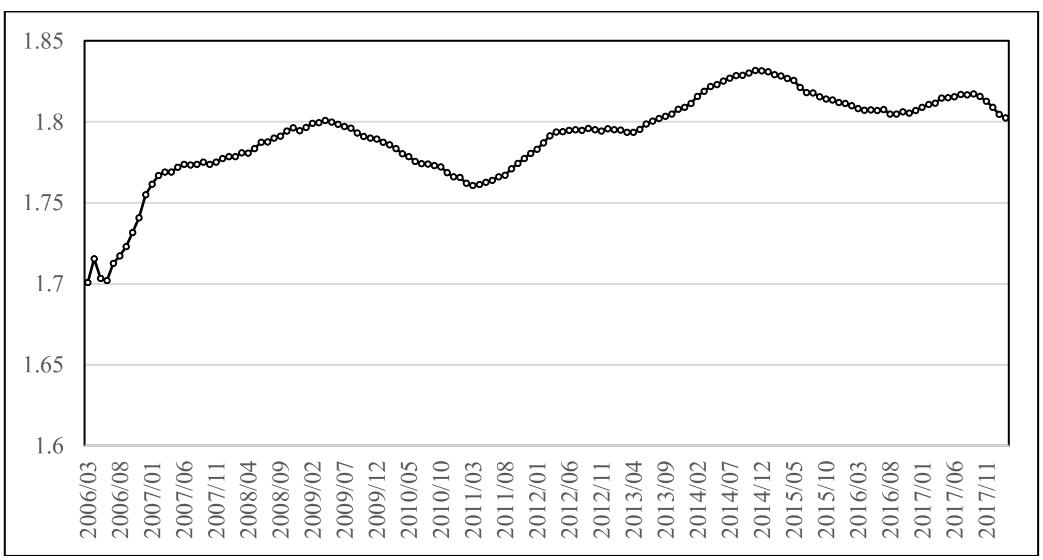
Observed task shifts have been stagnant since the mid-2000s, even when automating technologies have experienced tremendous growth. This is a puzzling phenomenon as we would expect new technologies further shift employment away from routine occupations and depress routine task values within existing occupations over time.

FIGURE 1. Production Employment as Share of total Manufacturing Employment, 1990-2017.



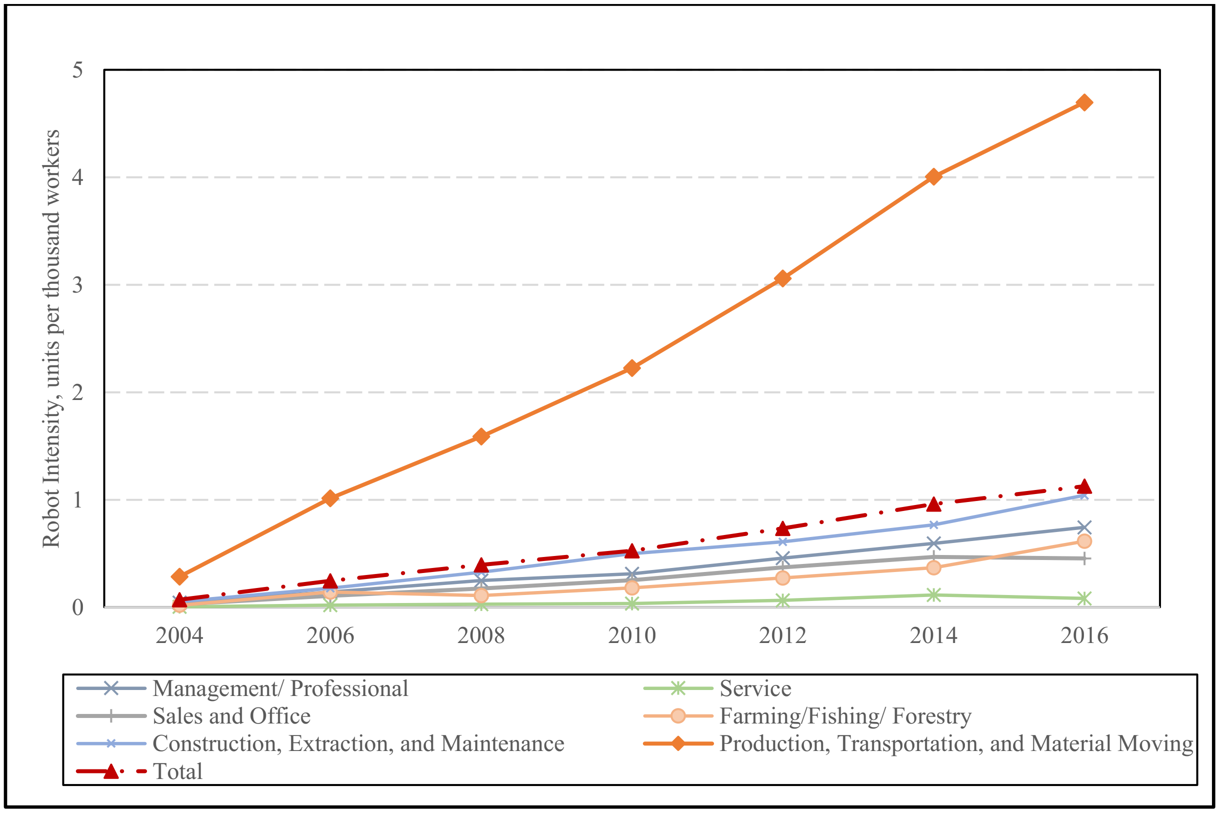
Sources: Current Employment Statistics.
Notes: Employment shares as the employment of production and non-supervisory workers as a percentage of total workers in Manufacturing. Displayed values are 12-month running averages.

FIGURE 2. Wage Premium between Supervisory workers and production workers in Manufacturing, 2006-2017.



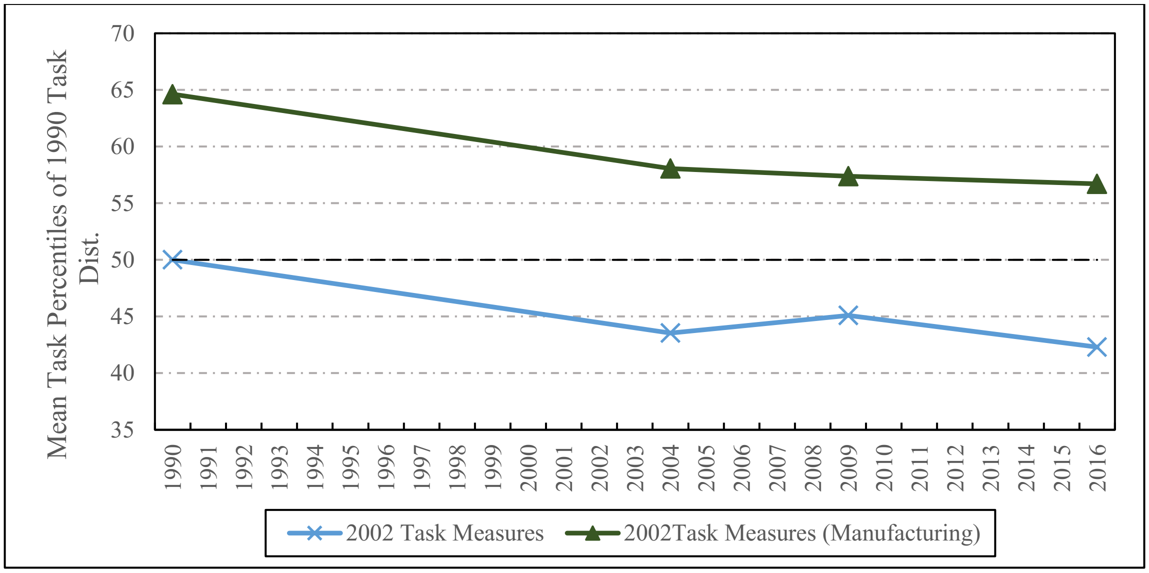
Sources: Current Employment Statistics.
Notes: Wage premium calculated by dividing hourly wage of supervisory workers by hourly wages of production and non-supervisory workers. Displayed values are 12-month running averages.

FIGURE 3 Mean Robot Intensity (Robots per 1000 workers) by Occupational Sector and Year



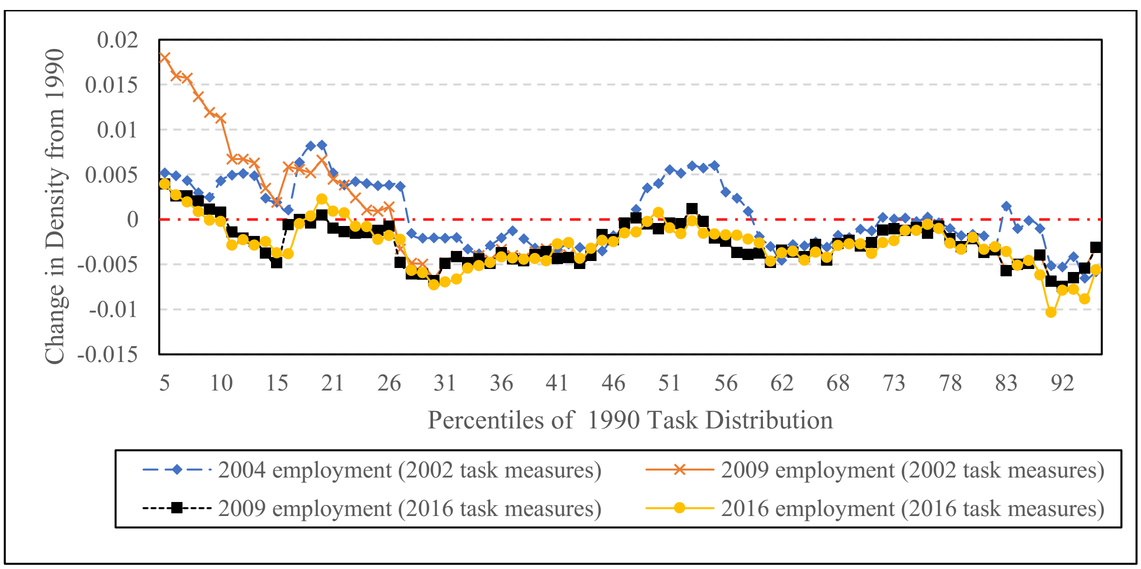
Sources: IFR Operational Stock of Industrial Robots. CPS/ASEC March files. Occupational sector aggregated by detailed Census occupations. Means are weighted by Census-provided individual sampling weights. Year denotes calendar year and not survey year.

FIGURE 4. Changes in Robot Replaceable Task Intensities in the US Economy 1990-2016. (Update on Autor, Levy, and Murnane (2003) Figure I)



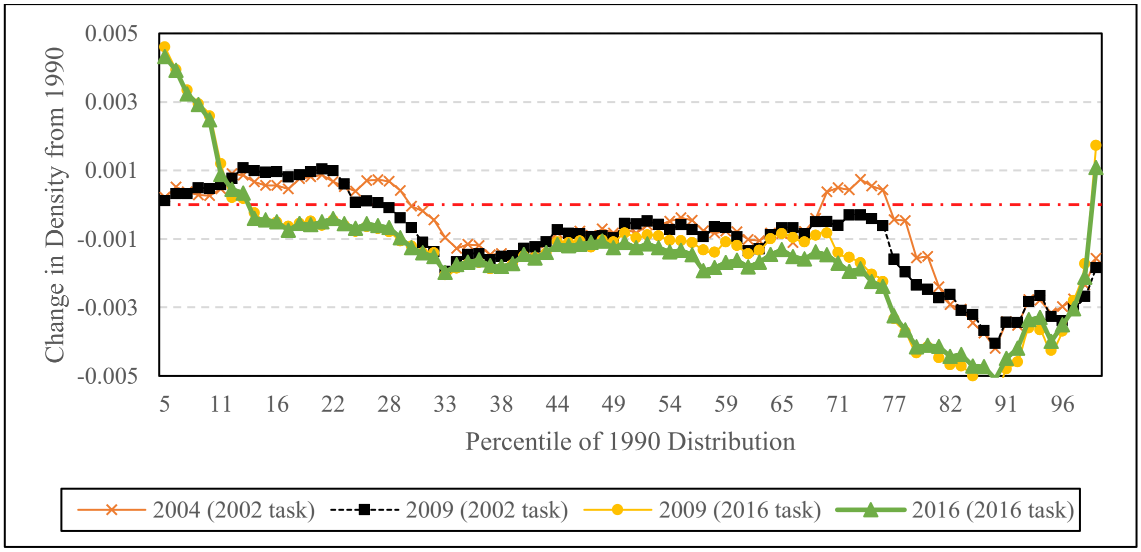
Sources: O*NET 2002 and 2016 Task measures. Data aggregated to industry-education-sex cells by year, and each cell is assigned a value according to its rank in the 1990 task distribution. Plotted values are employment-weighted means.

FIGURE 5. Smoothed Difference between the density of Routine Task Measures between 1990 and subsequent years. (Update on Autor, Levy, and Murnane (2003) Figure II)



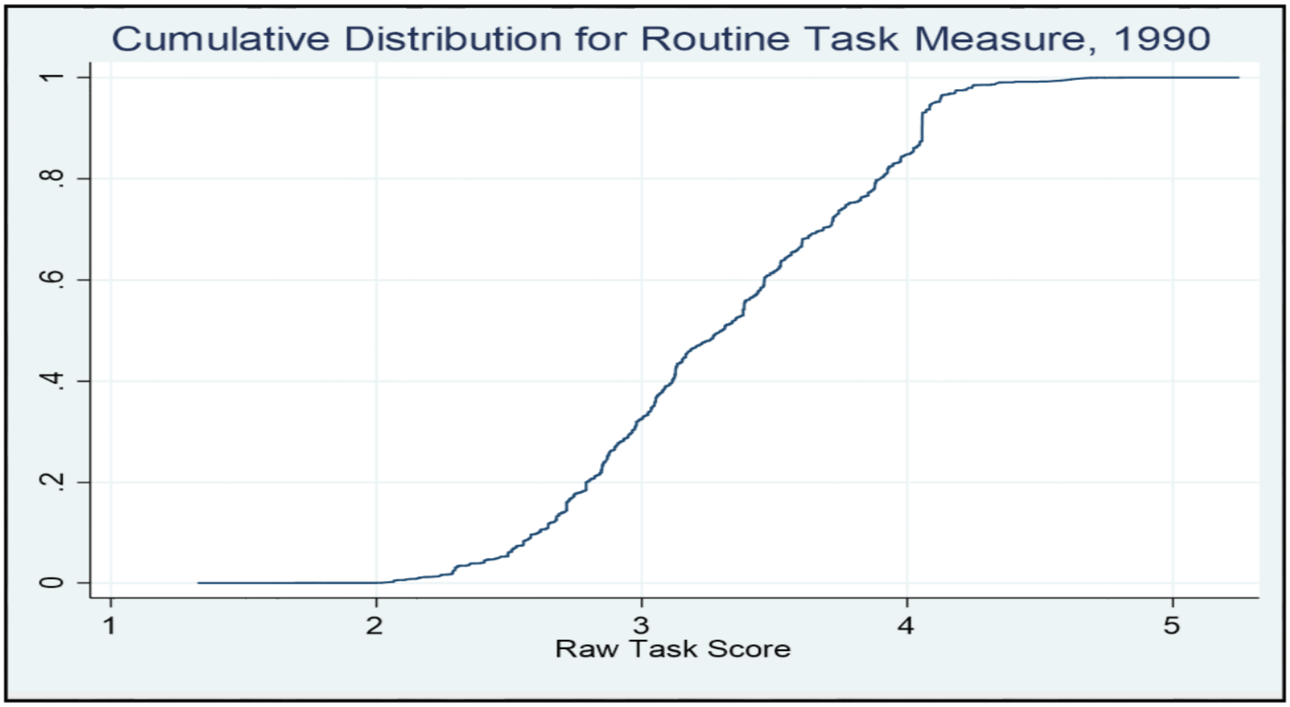
Sources: O*NET 2002 and 2016 Task measures. Data aggregated to industry-education-sex cells by year, and each cell is assigned a value according to its rank in the 1990 task distribution. Density measured as employment share.

FIGURE 6. Smoothed Difference between the density of Routine Task Measures in Manufacturing between 1990 and subsequent years.



Sources: O*NET 2002 and 2016 Task measures. Data aggregated to industry-education-sex cells by year, and each cell is assigned a value according to its rank in the 1990 task distribution. Density measured as employment share.

FIGURE 7. Cumulative Distribution for O*NET Task Measures.



Sources: 1990 CPS ASEC March file, O*NET 2002.

Notes: Employment-weighted Empirical Cumulative distribution of 2002 O*NET task measures. O*NET assigns each occupation a value on a 0-5 scale according to the importance of a given activity within the occupation. Employment-weighted task means assigned to 1990 industry-education-sex cells.

TABLE 1. Summary Statistics

Occupational Sector		2004	2008	2012	2016
Management/ Professional	Wage	30.417	31.124	30.795	31.489
	Emp. Share	35.241	37.681	39.400	41.658
	Robot Intensity	0.043	0.250	0.456	0.743
	Routine	0.206	0.207	0.205	0.212
Service	Wage	13.792	13.824	14.256	14.470
	Emp. Share	13.761	13.878	14.324	14.450
	Robot Intensity	0.004	0.028	0.064	0.082
	Routine	0.610	0.603	0.606	0.607
Sales and Office	Wage	19.546	19.296	18.990	20.228
	Emp. Share	24.350	23.274	22.805	20.646
	Robot Intensity	0.027	0.175	0.372	0.453
	Routine	0.277	0.308	0.316	0.299
Farming/Fishi ng/ Forestry	Hrly. Wage	11.825	12.228	11.194	13.039
	Emp. Share	0.867	0.795	0.791	0.886
	Robot Intensity	0.018	0.108	0.271	0.614
	Routine	0.930	0.925	0.936	0.939
Construction, Extraction, and Maintenance	Wage	19.920	20.102	20.836	20.451
	Emp. Share	11.103	10.581	9.684	9.402
	Robot Intensity	0.052	0.327	0.609	1.042
	Routine	0.877	0.883	0.883	0.896
Production, Transportation , and Material Moving	Wage	17.821	17.206	17.082	17.677
	Emp. Share	14.686	13.788	13.033	12.932
	Robot Intensity	0.285	1.589	3.060	4.698
	Routine	0.811	0.808	0.813	0.808
Total	Emp. Share	100	100	100	100

Sources: IFR, O*NET, CPS ASEC

Notes: Mean wages, robot intensity, intensity, and employment share by broad occupational groups. Mean values are weighted by the ASEC sampling weights.

Table 2. *Robot Impact on Wage*

	(1)	(2)	(3)	(4)
Robot Intensity	-0.00227***	-0.00249***	-0.00254***	-0.00252**
	(0.000457)	(0.000513)	(0.000439)	(0.000996)
Age	0.0237***	0.0186***	0.0206***	0.0206***
	(0.00393)	(0.00276)	(0.00395)	(0.00395)
Female	-0.249***	-0.269***	-0.268***	-0.268***
	(0.00210)	(0.00280)	(0.00616)	(0.00616)
Routine			-0.262***	-0.262***
			(0.0219)	(0.0218)
Routine × Robot				-0.0000315
				(0.00118)
Constant	1.410***	1.899***	1.751***	1.751***
	(0.159)	(0.104)	(0.180)	(0.179)
IND FE	Yes	Yes	Yes	Yes
OCC FE	No	Yes	No	No
YEAR FE	Yes	Yes	Yes	Yes
Observations	48442	48442	48442	48442
Adjusted R^2	0.575	0.655	0.607	0.607

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Sources: CPS ASEC March files; IFR, O*NET.
Notes: Dependent variable = log real hourly wages in 2010 USD. Routine measures reflect percentile rank on the 1990 task distributions for "Handling and Moving Object." Robot intensity measured as units of robots per thousand full-time employees. Industry dummies control for time-invariant industry characteristics and identify *within* industry effects. All regressions weighted by employment within occupation-industry-sex-education cells. Standard errors clustered by IFR industry.

Table 3. *Robot Impact on Employment*

	(1)	(2)	(3)	(4)	(5)
Robot Intensity	-0.0964**	-0.000608	-0.000732	-0.000461	-0.0108
	(0.0378)	(0.00135)	(0.00127)	(0.00142)	(0.00951)
Routine				0.142	0.131
				(0.0967)	(0.0956)
Routine x Robot					0.0171
					(0.0146)
Constant	11.32***	10.14***	9.672***	9.952***	9.960***
	(0.547)	(0.457)	(0.566)	(0.334)	(0.336)
IND FE	No	Yes	Yes	Yes	Yes
OCC FE	No	No	Yes	No	No
YEAR FR	Yes	Yes	Yes	Yes	Yes
Observations	48442	48442	48442	48442	48442
Adjusted R^2	0.086	0.374	0.377	0.375	0.375

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable = log employment level. Unit of observation is occupation-industry-sex-education-year. Routine measures reflect percentile rank on the 1990 task distributions for "Handling and Moving Object." Robot intensity measured as units of robots per thousand full-time employees. All estimates control for sex, age, and education. Standard errors clustered by IFR industry

Table 4. *Robot Impact on Wage, Production and Material Moving Occupations*

	(1)	(2)	(3)
Robot Intensity	-0.00208**	-0.00221**	0.00149
	(0.000881)	(0.000906)	(0.00164)
Routine		-0.200***	-0.187***
		(0.0428)	(0.0401)
Routine x Robot			-0.00495***
			(0.00167)
Constant	1.931***	2.170***	2.156***
	(0.0649)	(0.0924)	(0.0912)
Observations	13068	13068	13068
Adjusted R^2	0.353	0.370	0.370

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Sources: CPS ASEC March files; IFR, O*NET.
Notes: Dependent variable = log real hourly wages in 2010 USD. Routine measures reflect percentile rank on the 1990 task distributions for "Handling and Moving Object." Robot intensity measured as units of robots per thousand full-time employees. All regressions weighted by employment. Estimates control for education, sex, age, and industry. Production worker as defined by census occupational classification. Standard errors clustered by IFR industry.

Table 5. *Robot Impact on Employment, Production and Material Moving Occupations*

	(1)	(2)	(3)
Robot Intensity	0.00178	0.00226*	0.0695***
	(0.00156)	(0.00127)	(0.0165)
Routine		0.719	0.953*
		(0.609)	(0.543)
Routine x Robot			-0.0900***
			(0.0225)
Constant	8.090***	7.229***	6.975***
	(0.357)	(1.150)	(1.103)
Observations	13068	13068	13068
Adjusted R^2	0.508	0.517	0.525

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Dependent variable = log employment level. Unit of observation is occupation-industry-sex-education-year cells. Routine measures reflect percentile rank on the 1990 task distributions for "Handling and Moving Object." Robot intensity measured as units of robots per thousand full-time employees. All estimates control for sex, age, industry, and education. Occupational categories based on census occupation classification. Standard errors clustered by IFR industry.

Table 6. *Robot Impact on Wage by Education*

	(1) High school dropouts	(2) High school graduates	(3) Some college	(4) College graduates
Robot Intensity	0.000925	-0.00209***	-0.00224	-0.000251
	(0.00248)	(0.000634)	(0.00154)	(0.00215)
Routine	-0.208***	-0.259***	-0.201***	-0.357***
	(0.0373)	(0.00834)	(0.0245)	(0.0514)
Routine x Robot	-0.00562**	0.000969	0.000736	-0.0115*
	(0.00235)	(0.00100)	(0.00160)	(0.00608)
Constant	1.920***	1.980***	1.865***	2.445***
	(0.106)	(0.157)	(0.214)	(0.146)
Observations	6599	14161	14356	13326
Adjusted R^2	0.328	0.417	0.398	0.274

Sources: CPS ASEC March files; IFR, O*NET.

Notes: Dependent variable = log real hourly wages in 2010 USD. Routine measures reflect percentile rank on the 1990 task distributions for "Handling and Moving Object." Robot intensity measured as units of robots per thousand full-time employees. All estimates control for sex, age, broad industry and occupational groups; coefficients for dummies and fixed effects excluded. Education categories based on reported census education codes. Regressions weighted by employment. Standard errors clustered by IFR industry.

Table 7. *Robot Impact on Employment, by Education*

	(1) High school dropouts	(2) High school graduates	(3) Some college	(4) College graduates
Robot Intensity	0.0489***	0.0189***	0.000899	-0.0248***
	(0.00596)	(0.00289)	(0.00623)	(0.00672)
Routine	0.883***	0.288**	0.346***	-0.157***
	(0.0665)	(0.123)	(0.100)	(0.0242)
Routine x Robot	-0.0541***	-0.0187**	0.00578	0.0570**
	(0.00562)	(0.00764)	(0.0110)	(0.0223)
Constant	8.786***	9.519***	9.096***	8.322***
	(0.758)	(0.375)	(0.290)	(0.497)
Observations	6599	14161	14356	13326
Adjusted R^2	0.443	0.425	0.435	0.483

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Sources: CPS ASEC March files; IFR, O*NET.

Notes: Dependent variable = log real hourly wages in 2010 USD. Routine measures reflect percentile rank on the 1990 task distributions. Robot intensity measured as units of robots per thousand full-time employees. All estimates control for sex, age, broad industry and occupational groups; coefficients for dummies and fixed effects excluded. Education categories based on reported census education codes. Regressions weighted by employment. Standard errors clustered by IFR industry.

Table 8. *Robot Impact, cross-sectional worker-level regressions on Log Wage*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Robot Intensity	0.00384**	-0.00204**	0.00149	-0.00188**	-0.00246***	-0.00214***	0.00000141	-0.000990	-0.00154
	(0.00144)	(0.000833)	(0.000932)	(0.000785)	(0.000720)	(0.000755)	(0.00185)	(0.00120)	(0.00120)
Routine						-0.242***	-0.240***		
						(0.0277)	(0.0266)		
Rob. × Rout.							-0.00354*	-0.00146	-0.00152
							(0.00198)	(0.000913)	(0.000992)
Constant	1.916***	1.655***	2.779***	2.583***	2.556***	1.814***	1.813***	2.582***	2.555***
	(0.0286)	(0.0495)	(0.0344)	(0.0298)	(0.0303)	(0.0196)	(0.0192)	(0.0300)	(0.0305)
IND FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
OCC FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes
STATE FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demo. /Sex dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ASEC weights	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Observations	517079	517079	517079	517079	517079	517079	517079	517079	517079
Adjusted R^2	0.257	0.331	0.378	0.399	0.405	0.350	0.350	0.399	0.405

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Sources: CPS ASEC March files; IFR, O*NET.

Notes: Dependent variable = log real hourly wages in 2010 USD. Routine measures reflect percentile rank on the 1990 task distributions. Robot intensity measured as units of robots per thousand full-time employees. Estimates also control for age, education, metro status (urban vs. rural), and firm size, which are excluded from this table. Columns (9) and (5) are unweighted regressions. Standard errors clustered by IFR industry.

Table 9. *Robot Impact on Production/Material Moving Workers, Log Wage*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Robot Int.	0.00324***	-0.00229***	0.00113	-0.00214***	-0.00257***	-0.00228***	-0.000540	0.00194**	-0.00100
	(0.00104)	(0.000692)	(0.000761)	(0.000652)	(0.000516)	(0.000672)	(0.000746)	(0.000810)	(0.000903)
Routine						-0.251***	-0.243***		-0.241***
						(0.0160)	(0.0152)		(0.0179)
Rob. × Rout.							-0.00231**	-0.00542***	-0.00218**
							(0.000965)	(0.00111)	(0.000961)
Constant	1.981***	1.865***	2.290***	2.231***	2.218***	2.104***	2.097***	2.215***	2.113***
	(0.0515)	(0.0448)	(0.0427)	(0.0578)	(0.0394)	(0.0592)	(0.0588)	(0.0582)	(0.0491)
IND FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
OCC FE	No	No	Yes	Yes	Yes	No	No	Yes	No
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
STATE FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Dem./sex dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Observations	70027	70027	70027	70027	70027	70027	70027	70027	70027
Adjusted R^2	0.140	0.219	0.223	0.258	0.263	0.231	0.231	0.258	0.239

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Sources: CPS ASEC March files; IFR, O*NET.

Notes: Dependent variable = log real hourly wages in 2010 USD. Routine measures reflect percentile rank on the 1990 task distributions. Robot intensity measured as units of robots per thousand full-time employees. Estimates also control for age, education, metro status (urban vs. rural), and firm size, which are excluded from this table. Columns (9) and (5) are unweighted regressions. Standard errors clustered by IFR industry.

Table 10. *Comparison between O*NET task content and Industrial Robot Applications*

Build structures.
Collect samples of products or materials.
Prepare foods or beverages.
Assemble equipment or components.
Sew garments or materials.
Position workpieces or materials on equipment.
Shape materials to create products.
Arrange displays or decorations.
Adjust equipment to ensure adequate performance.
Train animals.
Prepare medical equipment or work areas for use.
Cut materials.
Prepare industrial materials for processing or use.
Cut trees or other vegetation.
Smooth surfaces of objects or equipment.
Install energy or heating equipment.
Fabricate medical devices.
Direct vehicle traffic.
Disassemble equipment.
Install commercial or production equipment.
Apply hygienic or cosmetic agents to skin or hair.
Position tools or equipment.
Tend watercraft.
Adjust medical equipment to ensure adequate performance.
Engrave objects.
Embalm corpses.
Fabricate devices or components.
Create decorative objects or parts of objects.
Process animal carcasses.
Drill holes in earth or materials.
Groom or style hair.
Set up classrooms, facilities, educational materials, or equipment.
Apply protective solutions or coatings.
Connect components or supply lines to equipment or tools.
Join parts using soldering, welding, or brazing techniques.
Assemble products or work aids.
Stock supplies or products.
Collect environmental or biological samples.
Apply materials to fill gaps or imperfections.
Remove workpieces from production equipment.
Position materials or components for assembly.
Package objects.
Install plumbing or piping equipment or systems.
Hunt animals.
Apply decorative finishes.
Set up equipment.
Prepare specimens or materials for testing.

Panel A: Detailed Work Activity

110-Handling operations / Machine Tending
111-Metal casting
112-Plastic moulding
113-Stamping forging, bending
114-Handling operations at machine tools
115-Machine tending for other processes
116-Measurement, inspection, testing
117-Palletizing
118-Packaging, picking, placing
119-Material handling
120-Handling operations unspecified
160-Welding and soldering
161-Arc welding
162-Spot welding
163-Laser welding
164-other welding
165-Soldering
170-Dispensing
171-Painting and enameling
172-Application of adhesive, sealing material
179-Others dispensing/spraying
180-Dispensing unspecified
190-Processing
191-Laser cutting
192-Water jet cutting
193-Mechanical cutting/grinding/deburring....
198-Other processing
199-Processing unspecified
200-Assembling and disassembling
201-Fixing, press-fitting
202-Assembling, mounting, inserting
203-Disassembling
208-Other assembling
209-Assembling unspecified

Panel B: Robot Application

Source: O*NET, IFR.

Notes: Panel A lists detailed work activity within O*NET variable "Handling and Moving Objects". Panel B lists IFR detailed robot applications. Definition for "Handling and Moving Objects": "Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things." (Tsacoumis and Willison, 2010)

References

ACEMOGLU, D., AND D. AUTOR (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, 4(12): 1043–1171. Elsevier.

AUTOR, D. H. (2013): "The 'task approach' to labor markets: an overview," *Journal Labour Market Research*, 46(3): 185-199.

AUTOR, D.H. (2015): "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, 29(3): 3–30.

AUTOR, D. H., L. F. KATZ, AND A. B. KRUEGER (1998): "Computing Inequality: Have Computers Changed The Labor Market?," *The Quarterly Journal of Economics*, 113(4): 1169–1213.

AUTOR, D. H. AND D. DORN (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review*, 103(5): 1553–97.

AUTOR, D. H., D. DORN, AND G. H. HANSON (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121-68.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The Skill Content Of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118(4), 1279–1333.

AUTOR, D.H., L. F. KATZ, AND M. S. KEARNEY (2006): "The Polarization of the US Labor Market," *The American Economic Review*, 189-194.

AUTOR, D.H., L. F. KATZ, AND M. S. KEARNEY (2008): "Trends In U.S. Wage Inequality: Revising The Revisionists," *The Review of Economics and Statistics*, 90(2): 300-323.

DE BEYER, J. AND J. B. KNIGHT (1989): "The Role of Occupation In The Determination Of Wages," *Oxford Economic Papers*, 41: 595-618.

BRAINBRIDGE, L. (1983): "Ironies of Automation," *Automatica*, 19(6): 775-779.

BRYNJOLFSSON, E., AND A. MCAFEE (2014): "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies," W. W. Norton & Company.

DAUTH, W., S. FINDEISEN, J. SUDEKUM, N. WOBNER (2017): "German Robots – The Impact of Industrial Robots on Workers," *IAB Discussion Paper*, Articles on labour market issues.

DEMING, D (2017): "The Growing Importance Of Social Skills In The Labor Market," *NBER Working Paper Series*. .

FLOOD, S., M. KING, R. STEVEN, AND J. R. WARREN (2017): *Integrated Public Use Microdata Series, Current Population Survey*: Vers. 5.0 [dataset]. Minneapolis: University of Minnesota. https://doi.org/10.18128/D030.V5.0.

FREY, C. B., AND M. A. OSBORNE (2013): "The future of employment: how susceptible are jobs to computerisation?," Sept, 17, 2013.

GOOS, M., AND A. MANNING (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89(1): 118–133.

GOOS, M., A. MANNING, AND A. SALOMON (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104(8): 2509-2526.

GRAETZ, G. AND G. MICHAELS (2015): *CEP Discussion Paper*, No. 1335.

GOOS, M., A. MANNING, AND A. SALOMONS (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104(8), 2509–26.

INTERNATIONAL FEDERATION OF ROBOTICS (2016): "World Robotics Industrial Robots 2016," report.

KATZ, L. F., AND D. H. AUTOR (1999): "Changes In The Wage Structure And Earnings Inequality," *Handbook of Labor Economics*, 3(26): 1463-1555.

KATZ, L. F., AND K. M. MURPHY (1992): "Changes in Relative Wages, 1963- 1987: Supply and Demand Factors." *The Quarterly Journal of Economics*, 107(1): 35–78.

MANYIKA, J., S. LUND, M. CHUI, J. BUGHIN, J. WOETZEL, P. BATRA, R. KO, AND S. SANGHVI (2017): "What the future of work will mean for jobs, skills, and wages?", *McKinsey Global Institute Report.*

TSACOUMIS, S. AND S. WILLISON (2010): "O*NET Analyst Occupational Skill Ratings: Procedures," *Human Resource Research Organization*.