



Are Robots Stealing Our Jobs?

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Abstract

The media and popular business press often invoke narratives that reflect widespread anxiety that robots may be rendering humans obsolete in the workplace. However, upon closer examination, many argue that automation, including robotics and artificial intelligence, is spreading unevenly throughout the labor market, such that middle-skill occupations that do not require a college degree are more likely to be affected adversely because they are easier to automate than high-skill occupations. In this article, the author examines the effect of industrial robots on occupations in the United States in 2010 and 2015. Results from regression models indicate that an increase in industrial robots is associated with increases in high-skill and some middle-skill occupations but not for other types of occupations. These findings may indicate the ushering in of a new era in which robots are more technologically advanced and able to collaborate better with human employees.

Keywords

employment, robots, automation, technology

A *Washington Post* article asks, “Will robots steal all our jobs?” (Samuelson 2017). An online CNN article raises a similar question: “Robots: Is your job at risk?” (McFarland 2017). “Robots will destroy our jobs,” declares another headline in an article in *The Guardian* (Shewan 2017). Media outlets use provocative headlines to communicate widespread anxiety about robots replacing humans in the workforce. No doubt these headlines are intended to incite interest and attract readership. However, as technological advances expand the capabilities of robots, headlines exploit the fears that emotionless robots stand ready to do our paid work more efficiently and cheaply, thereby rendering human employees obsolete.¹ Nevertheless, a closer read reveals that most of these articles take a more measured view by suggesting that automation is spreading unevenly through the labor market, destroying employment prospects in some occupations characterized by simple and routine tasks such as bookkeeping and assembly-line work, while leaving other occupations characterized by abstract and complex tasks relatively unaffected.

The term *robot* refers to a programmable machine that operates with some element of autonomy and can move

around its environment (International Organization for Standardization 2012). Although robots have been around for a long time, a small empirical literature exists on the topic because of the dearth of data on robots operating in the workplace, with few studies investigating the direct effect of robots on jobs. However, a vast literature does exist in which scholars have examined the impact of automation more generally and employment (cf. Acemoglu and Autor 2011; Autor, Katz, and Kearney 2006; Autor, Levy, and Murnane 2003; Goos and Manning, 2007). *Automation* refers to replacing of human activity with machines (Satchell 1998) and may include a wide range of technologies from accounting software to scanners used in self-serve grocery lines. Because empirical scholarship on robots and employment is scant, the literature on automation and employment is instructive. It provides conceptual and empirical tools, however imperfect, for examining the impact of different types of automated technologies on employment.

The few studies that have examined the relationship between robots and jobs directly have yield mixed results. Acemoglu and Restrepo (2017) found that a negative

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¹It should be noted that, in contrast, some news articles suggest optimistically that humans are adept at adapting to new technologies and that automation will in fact create new types of jobs in the future (Smith 2018).



relationship existed between robots and total employment in the United States between 1990 and 2007. These findings provide support for the displacement view, the view that robots are replacing employees. Another study, conducted by Autor and Salomons (2018), observed a positive effect for robots on employment in 18 Organisation for Economic Co-operation and Development countries from 1970 through 2007. These findings support the complementary view, that tasks undertaken by robots in the workplace complement employee labor, thus providing additional value for human labor in the workplace. A third possibility exists as well, which is seldom discussed. Robots that are integrated into the workplace may have no effect on employment. Indeed, findings from a study limited to manufacturing firms in seven European countries in 2012 indicate that there is no statistically significant relationship between the use of robots and employment in a given firm (Jäger et al. 2015). But the debate about the relationship between robots and employment is almost singularly organized around the concepts of displacement and complementarity.

I add to this burgeoning research stream by investigating the influence of robots on employment and different types of occupations in metropolitan areas in the United States in 2010 and 2015. Results from the regression models reported in my study indicate that robots have a positive effect on employment in high-skill jobs characterized by nonroutine and cognitive labor and in middle-skill jobs characterized by routine and manual labor. Thus, the fear that robots are replacing paid workers on a large scale seems to insufficiently capture important technological changes that may be generating some complementarity between industrial robots for these types of occupations. Consequently, in the conclusion of this article, I call for the development of new perspectives that account for these complementarities and also anticipate the evolution of new occupations that are likely to occur as employees adapt to the novel technologies that are introduced continually into the workplace.

Background

Two views primarily animate discussions about the impact of robots, in particular, and automation, more generally, on employment. The first view, which I call the displacement view, is more familiar, prominent, and reflected in the headlines mentioned above. Not unlike the Luddites in England in the early 1800s who sought to destroy textile machines for fear that this automation would threaten weavers' jobs, the displacement view raises concerns about robots making employees obsolete. This view supposes that employees who perform routine tasks in particular are most likely to be affected adversely, while those who engage in cognitively complex and abstract tasks will remain relatively immune. For instance, a worker on an assembly line is more likely to be replaced by a robot than a marketing executive whose task is to develop creative and emotionally compelling advertisements. An extreme version of

this view raises the possibility that, with the improvement of artificial intelligence, robots will render humans completely superfluous in the workplace. What was once thought to be the realm of science fiction is ostensibly becoming a reality in some settings. Artificial intelligence already undertakes tasks such as driving, engaging in conversation, and diagnosing medical conditions (Brynjolfsson and McAfee 2014). Some even raise the possibility that it is only a matter of time before robots will "rule the earth" (e.g., Hanson 2016).

The rise of robots that can perform tasks better than humans does not necessarily precipitate employee displacement. Sometimes a robot, and automation more generally, will displace an employee, but sometimes it will not. Tasks that are marked by manual dexterity or creative, intuitive, and emotional labor are particularly difficult to automate. Jobs with these characteristics are primed for complementarity between humans and robots, with humans performing cognitively or physically complex tasks and robots carrying out tasks that are routine and easily automated. Some have argued that new technologies can create complementarities between humans and robots, and these interdependencies will make human labor more valued, not less valued (Bessen 2015a; Daugherty and Wilson 2018; Davenport and Kirby 2016; Mindell 2015). I call the process of robots and employees engaging in work tasks that are interdependent the complementary view. This alternative to the displacement view is the minority view, but it is gaining traction among scholars and industry experts.

The complementary view suggests that new robots may increase demand for human labor and enable job growth. One example of complementarity between humans and robots can be found in SEW-Eurodrive, an industrial engineering firm. In an SEW-Eurodrive factory, assembly-line employees work alongside robots. The robots restock workstations or retrieve parts for use by workers who assemble drive engines. Another example is a Nissan plant in Tennessee that uses autonomous vehicles on the factory floor to work with employees and has not laid off a single employee. Likewise, Airbus uses robots to help assemble passenger planes by drilling thousands of holes for the purpose of joining two parts of a fuselage (Hollinger 2016). What is notable about each of these anecdotes is that they illustrate manufacturing settings in which collaboration between robots and employees occurs, the settings in which employee are supposed to be the most vulnerable to displacement by robots.

Because of the lack of empirical studies on robots, it is instructive to look to the scholarship on automation for guidance about how changes in automation can affect employment. Shestakofsky (2017) identified three ways that the emergence and diffusion of automated technologies can create complementarities between humans and machines to boost job growth. Although automation is a much more inclusive concept than robots (i.e., it includes more types of technology than robots), Shestakofsky's insights are still informative. Each of the ways Shestakofsky identified is

applicable potentially to the use of robots in the workplace and provides rationale for why complementarities between robot and human behavior may also occur. First, new technologies may “increase the demand for other types of work” (p. 378). Shestakofsky remarked that the industrial revolution that gave rise to large manufacturing firms and the concomitant expansion of a managerial workforce composed of supervisors, accountants, and other administrators. Bessen (2015b) pointed to more contemporary examples of ways technology (i.e., computers) can complement employees:

Although computers can pick stock portfolios, financial advisors provide reassurance when markets are down. Although computers can recommend which products to buy, salespeople understand consumer needs and inspire confidence that unforeseen contingencies will be handled fairly. Although computers can make accurate medical prognoses, they don't yet have the bedside manner to guide patients through difficult medical choices. (p. 18)

Second, automation can also complement human labor by generating entirely new sectors of employment. Shestakofsky cited computer technologies that have given rise to an extensive list of occupations related to hardware, software, and networking products and services. Additional economic sectors that have grown out of technological advances and created a wide range of jobs include biotechnology, renewable energy, and mobile technologies. Third, automation that reduces labor costs may increase product supply and customer demand. In the late 1700s and early 1800s, power looms were developed that automated most of the tasks required to weave textiles. Weaving jobs increased because lower labor costs meant that prices fell and demand for fabrics and clothing increased (Bessen 2015b).

Although empirical research is scant and results are mixed with respect to the relationship between robots and overall employment, one study has received a lot of attention that provides empirical support for the displacement view. Acemoglu and Restrepo (2017) examined the association between the change in the incidence of industrial robots and overall employment between 1990 and 2007 in 722 commuting zones in the contiguous United States. A commuting zone represents a local labor market, which is similar conceptually to a metropolitan area, but commuting zones cover the entire United States, including rural areas. Results from their analysis indicate that each additional robot per thousand workers is associated with a decrease of 5.6 paid workers.

Another important study, conversely, showed that industrial robots influence employment positively and provided support for the complementary view. Although Autor and Salomons (2018) were concerned primarily with understanding the impact of total factor productivity² on employment

for a sample of Organisation for Economic Co-operation and Development countries from 1970 through 2007, a secondary finding from their study was that increases in industrial robots are associated positively and significantly with employment. Although total factor productivity provides an indirect measure of innovation, the variable for industrial robots that has a positive effect on employment is a direct measure. In contrast to Acemoglu and Restrepo (2017), Autor and Salomons's analysis illustrates that robots have a labor-enhancing effect for the countries in their sample. Autor and Salomons did not, however, offer a reconciliation of their findings (a positive effect for industrial robots on total employment) with those of Acemoglu and Restrepo (a negative effect for industrial robots on total employment).

Moving Forward

Research on robots and employment is relatively new because obtaining appropriate data to study is difficult. One weakness of work in this area to date, the exception being Acemoglu and Restrepo (2017), is that it does not examine the effect of robots on employment at the subnational level. Heterogeneity exists in the distribution of industry activities across geographic areas (Porter 1998; Rigby and Essletzbichler 2005), which could have a large effect on local labor markets. Consequently, the county-level analyses in the scholarship on robots and employment fail “to reflect [these] substantial sub-national variations that are apparent in the use production technologies” (Green Leigh and Kraft 2018:804). Another issue that has been previously overlooked is robots' influence on different types of occupations. A widespread presumption is that robots are more likely to affect some jobs than others. But research has yet to examine these differences; instead, analyses have been limited to examining robots' effects on aggregate levels of employment (e.g., Acemoglu and Restrepo 2017; Autor and Salomons 2018).

In the analysis provided in this article, I address the first issue by examining the impact of robots on employment at the metropolitan level of analysis. To address the second issue regarding presumptions about the extent to which robots impact different types of occupations, which is insufficiently examined in the robots literature, I draw from two perspectives in labor economics that examine the effects of automation on different occupations. One of these perspectives, the skill-biased technical change (SBTC) view, advances the notion that developments in technology, especially in information technology, increase the demand for more highly educated employees in “high-skill” occupations (employees with

(Cobb and Douglas 1928; Solow 1956). Presumably, an increase in total factor productivity is a result of developing better and novel ways to convert inputs into outputs, which represents an indirect measure of innovation (Autor and Salomons 2018).

²Total factor productivity describes how effectively inputs (such as capital and labor) are converted into outputs (such as products)

a college degree or higher) compared with “middle-skill” occupations (employees with a high-school degree but less than a college degree) or “low-skill” occupations (employees with a high-school degree or less).³ Proponents of this view point to the increase in labor market inequality as evidence and the concomitant expansion of personal computing technology, and technology more generally, that occurred in the 1980s (Katz and Murphy 1992; Levy and Murnane 1992). Computers may either complement or provide a substitute for employees, two plausible pathways on the basis of the SBTC approach. If computer use complements employees’ skills, they are likely to experience increased productivity, further opportunities for employment, and higher earnings. The SBTC approach presumes that highly skilled employees possess the requisite competencies and engage in more cognitive tasks that complement computer technology. Alternatively, the introduction of computers may substitute for labor, leaving particular employees, especially those who are low skilled, obsolete. In a 1993 study, Krueger used Current Population Survey data from 1984 to 1989 to demonstrate that college graduates were 22 percent more likely to use computers to work than high school graduates. Krueger also reported that “less than 5 percent of employees . . . use computers in the agricultural, construction, textile, lumber and personal services industries, whereas computer use is widespread (exceeding 60 percent of employees) in the banking, insurance, real estate, communications, and public administration industries” (p. 37). Krueger provided this evidence in support of SBTC’s view that highly skilled employees are more likely to use (and benefit from) computers in the workplace. Overall, the SBTC perspective that automation will benefit high-skill occupations resonates with the complementary view, and its expectation that automation will have deleterious effects on middle-skill occupations is consistent with the displacement view.

Another perspective, the job polarization view, extends the SBTC view. Proponents of the job polarization approach suggest that technological advances have accompanied employment growth for those in both high- and low-skill occupations, whereas middle-skill occupations have declined. As with the SBTC view, job growth has occurred for highly educated occupational groups possessing the skills to learn and adapt to new technological advancements (Greenwood and Yorukoglut 1997). But job growth also

occurs for those in lower skill occupations, as technological change pushes those who do not have the necessary technical skills from middle-skill jobs into low-skill or service sector jobs. Similar to arguments about robot displacement of human labor, the presumption here is that occupations that engage in the routine tasks and limited manual dexterity found in middle-skill jobs are susceptible to replacement by automation, especially computers. Middle-skill jobs characterized by cognitively and manually routine tasks—manufacturing, record keeping, and office staff, among others—are readily automated because they follow precise, well-defined procedures that can be carried out by new technologies. The decline in these types of middle-skill jobs drives the employees who inhabited these jobs to low-skill jobs in the service sector that require relatively little training but more manual dexterity. Low-skill jobs include food services workers, retail workers, security guards, janitors, care workers, and personal care workers. Empirical research confirms the job polarization view’s expectation of the hollowing out of middle-skill occupations (Acemoglu and Autor 2011; Autor and Dorn 2013; Autor et al. 2006; Goos and Manning 2007). Specifically, a study by Tüzemen and Willis (2013) showed that middle-skill occupations declined from 60 percent of total occupations in 1979 to 43 percent in 2016, even as low-skill jobs increased from 14 percent in 1979 to 18 percent in 2016.⁴ As with the SBTC view, the job polarization perspective supports both the displacement and complementary perspectives. Assuming technology advances over time, the hollowing out of the middle supports the displacement view, while the expansion of high- and low-skill occupations confirms the complementary view.

Although the majority of literature on the SBTC and job polarization perspectives focuses on the broad impacts of automation, rather than robots, on employment, these arguments are still instructive. These perspectives inform the scholarship on robots by focusing on the types of occupations that are most likely to be affected. Applying the broad lessons learned from these perspectives to the possible effects of robots, we would expect robots to affect differentially high-, middle-, and low-skill occupations. Proponents of these views would expect robots to have a positive effect on high-skill occupations given that such technologies are more likely to be present in these workplaces and complement nonroutine work tasks, or because employees in high-skill occupations such as computer scientists and engineers are the ones who are working to create and develop robots. Proponents of the job polarization view also would expect industrial robots to have a negative effect on middle-skill jobs, especially routine middle-skill jobs, and no effect necessarily on low-skill jobs such as a line cook or a hotel

³Sociologists such as Fernandez (2001) and Avent-Holt and Tomaskovic-Devey (2014) have criticized the SBTC view on various fronts. Fernandez pointed out that many SBTC studies examine occupational titles or job requirements, but they provide no direct examination of employee skills or technology use. Moreover, Fernandez demonstrated that wages are more likely to depend on organizational processes than employee skill or technology use. Avent-Holt and Tomaskovic-Devey cited social relationships in organizational settings as the primary drivers of inequality in employee wages rather than a skill differentiation among employees.

⁴To calculate the decline of middle-skill jobs through 2016, Tüzemen and Willis provided me with a version of the data they used in their 2013 publication, which they have updated for the years through 2016.

housekeeper because these jobs involve variable manual tasks that are difficult to automate.

In sum, two perspectives animate debates about the impact of robots on employment. The displacement view supposes that robots will take jobs, beginning with occupations characterized by routine tasks, while the complementary view is optimistic that robots will supplement and increase the value of human labor, thereby generating overall job growth, even if some occupations become obsolete. The scant research on robots and jobs, however, does not examine robots' impacts on different types of occupations characterized by tasks that may be either routine or nonroutine. Nevertheless, the labor economics scholarship provides conceptual frameworks for examining the impact of technology more generally on different types of occupations and it provides a set of expectations about which types of jobs are more likely to be affected adversely or favorably.

Data and Method

In this study, I examine the effects of robots on different types of occupations at the subnational level in the United States. The data I use consist of industrial robots and are available for U.S. states and metropolitan areas.⁵ I choose to examine metropolitan-level data because metropolitan areas constitute geographically confined areas that contain “a recognized population nucleus and adjacent communities that have a high degree of integration with that nucleus” (Spotila 2000:82228). Metropolitan areas are often used as proxies for local job markets. Robots introduced within a geographic area are more likely to have a direct effect on the local job market, in that they are more likely to displace or complement workers within a local job market compared with a more geographically dispersed or distant labor market. Thus, the unit of analysis for this study is the metropolitan area-year, and all variables are time varying by year.

I examine the effects of industrialized robots on different categories of occupations for 327 metropolitan areas in two years, 2010 and 2015, which are the years for which robot data are available. Metropolitan areas are defined by the U.S. Office of Management and Budget as consisting of “at least one urbanized area of 50,000 or more inhabitants” (U.S. Census Bureau 2018). The geographic boundaries of some metropolitan areas have been modified over time because of changes in the geographic distribution of the population. For example, there were 362 in 2010 and 383 in 2017. Because of missing data for some of the metropolitan areas that were redefined between these years, the regression models used in this study did not include data for all metropolitan areas during this period, only for those that were delineated similarly in 2010 and 2015.

Measures

The majority of the data used to create the dependent variables come from the Bureau of Labor Statistics (BLS).⁶ Each dependent variable is measured in 2011 and 2016. These are the years following those in which the industrialized robot variable is available: 2010 and 2015. The dependent variables are lagged one year to account for the temporal lag that likely exists between the use of industrial robots and job losses or gains.

I use five dependent variables in this study. The first is measured as the share of total employees, that is, the number of workers employed in all occupations, except farming and the military, as a percentage of the civilian population in the labor force over age 16. The BLS calculates this variable by consolidating data on detailed occupations. The labor force population variable derives from the professional version of Social Explorer (<https://www.socialexplorer.com>; see the variable called “civilian population in the labor force 16 years and over”), which publishes data from the census and the American Community Survey. To align with previous studies on the topic, I follow the convention in the labor economics literature by excluding farming and military occupations from analyses (e.g., Acemoglu and Autor 2011). Excluding these two employment sectors is not without theoretical merit. Still, I exclude farming occupations from my analysis because the unit of analysis is the metropolitan area; there is a substantial amount of missing data for farming occupations for urban metropolitan areas because agricultural activities are more likely to be pursued in rural locations. My rationale for excluding military occupations is that they are difficult to categorize by skill level because of the vast heterogeneity of skills that constitute different military occupations, which range from those that require cognitive tasks, such as analyst, medical, and leadership positions, to manual and routine tasks for those in product supply positions.

The remaining dependent variables are based on a typology Jaimovich and Siu (2012) developed that situates the variety of occupations into four broad categories (cf. Foote and Ryan 2015). The typology includes two dimensions that describe ideal-typical tasks that characterize the occupations: routine or nonroutine and cognitive or manual. Routine tasks include activities that can be “performed by following a well-defined set of procedures” (Jaimovich and Siu 2012:2). Nonroutine tasks are characterized by creativity and flexibility. Manual tasks require physical labor, while cognitive-based tasks require abstract thinking and/or mental exertion. Jaimovich and Siu mapped these tasks onto the skill-based occupational categories identified above in the discussion of the SBTC and job polarization views, but they include two middle-skill categories: middle-skill occupations characterized by routine and cognitive tasks and middle-skill occupations characterized by

⁵See the Excel files posted at Muro (2017).

⁶Employment data for each year are available at BLS (2018b).

	Non-Routine	Routine
Cognitive	High Skill (Example: doctor)	Middle Skill (Example: office support staff)
Manual	Low Skill (Example: retail worker)	Middle Skill (Example: manufacturing worker)

Figure 1. Types of skill-based occupations.

routine and manual tasks. Employees in high-skill occupations engage typically in nonroutine and cognitive tasks (e.g., managers, specialists in business and financial operations, and others professionals, such as scientists, doctors, and lawyers); employees in middle-skill occupations carry out both routine and cognitive tasks (e.g., employees in sales and office and administrative support occupations) and routine and manual tasks (e.g., employees in production, maintenance, and construction occupations); and employees in low-skill occupations perform nonroutine and manual tasks (e.g., cooks and waiters, retail workers, protective services, personal care, groundskeepers, janitors) (see Figure 1).

The rest of the dependent variables reflect the occupational groupings distinguished by these types of tasks. Each variable is created by consolidating data on much more detailed occupational data from the BLS. The second dependent variable used in the analysis, then, is the share of high-skill occupations (nonroutine cognitive), measured as employees in high-skill occupations as a proportion of the civilian population in the labor force over age 16. To create this variable, I aggregated employment data from the following occupations: management; business and financial operations; computer and mathematical; architecture and engineering; life, physical, and social science; social services; legal; education, training, and library; arts, design, entertainment, sports, and media; and health care practitioners. The third dependent variable is the share of middle-skill routine cognitive occupations, which is measured as employees in the middle-skill occupations that can be typified by routine and cognitive tasks as a proportion of the civilian population in the labor force over age 16. To construct this variable, I aggregated employee data from the following occupations: sales, office and administrative support and health care support. The fourth dependent variable, the share of middle-skill routine manual occupations, is measured as employees in the middle-skill occupations that can be distinguished by routine and manual tasks as a proportion of the civilian population in the labor force over age 16. This variable includes data that I aggregated from the following occupations: construction, maintenance and repair, production, and transportation. These occupations are considered “blue

collar.” The fifth dependent variable is measured as the share of low-skill occupations (routine and manual), or service sector occupations, as a proportion of the civilian population in the labor force over age 16. For this variable, I aggregated data from the following occupations: food preparation and serving related, personal care and service, protective services, and building and grounds cleaning.

The Brookings Institution makes available the key independent variable used in this study, industrial robots, for the years 2010 and 2015.⁷ These data were collected by the International Federation of Robotics (IFR), a consortium of robotics industry associations and other research institutes (IFR 2019). The IFR (2017) defines an industrial robot as an “automatically controlled, reprogrammable” machine for use in “industrial automation applications” (p. 32). Applications of industrial robots may consist of assembling and moving products, welding, painting, and packaging. While typical settings in which industrial robots may be used include manufacturing in a wide range of industries related to food, metal, plastic, electronics, and automotive and transportation, other settings include agriculture, mining, electricity, gas, water supply, construction, education, and research and development. One limitation of these data is that they constitute only a portion of all robots or artificial intelligence used in workplaces. Nevertheless, even if these robots do not substitute directly for workers in a particular setting, they may also complement employee labor or generate jobs for high-skill employees who program, develop, use, or maintain the robots.

I also include a number of control variables in the regression models for the years 2010 and 2015, the same years in which the robot incidence data are available and one year prior to the year in which the dependent variables are measured. First, I account for temporal effects by including a year variable. Second, household income is the median household income in a given metropolitan area and is measured in thousands of dollars (in 2010 inflation-adjusted dollars). This variable accounts for economic differences across metropolitan areas (data source: Social Explorer).

The other variables included in the regression model constitute the same control variables that were included in the study by Acemoglu and Restrepo (2017), with a few exceptions. The first set of variables are demographic and come from Social Explorer. Population is the number of people within each core-based statistical area (the variable is logged to normalize its distribution). The share of the working-age population is measured as total employees as a proportion of the civilian population in the labor force age 16 and older. College degree is the proportion of the population age 25 and older with at least a bachelor’s (four-year) degree, as well as those with master’s, professional, or doctoral degrees. This variable is calculated by dividing the number of people in the

⁷See Muro (2017). To find the data, scroll to the end of the page.

population with at least a bachelor's degree by the total population age 25 and older. High school degree is the proportion of the population age 16 and older with at least a high school degree. This variable is calculated by dividing the number of people in the population with at least a high school degree by the population age 16 and over. Black is the share of the population that is Black as a proportion of the population (the square root of the variable is used to normalize its distribution). Hispanic is the share of the population that is Hispanic as a proportion of the population (the square root of the variable is used to normalize its distribution). Asian is the share of the population that is Asian as a proportion of the population (the square root of the variable is used to normalize its distribution).

The next set of Acemoglu and Restrepo's (2017) control variables capture the industrial structure of metropolitan areas. The data for these variables, except for the last one, come from the county business patterns data sets that are published by the U.S. Census Bureau (n.d.). The share of employees in manufacturing is measured as the count of employees in manufacturing industries divided by total employees. Manufacturing industries are identified by North American Industry Classification System (NAICS) codes that begin with the numbers 31, 32, and 33. The share of employees in durable manufacturing is measured as the count of employees in durable manufacturing industries divided by total employees. *Durable goods* refers to consumer goods that do not wear out quickly and do not need to be purchased frequently, such as a washing machine (an example of a nondurable good would be laundry detergent). Durable manufacturing industries are identified by NAICS codes that begin with the numbers 321 (wood product manufacturing), 327 (nonmetallic mineral product manufacturing), 331 (primary metal manufacturing), 332 (fabricated metal product manufacturing), 333 (machinery manufacturing), 334 (computer and electronic product manufacturing), 335 (electrical equipment, appliance and component manufacturing), 336 (transportation equipment manufacturing), 337 (furniture and related product manufacturing), and 339 (miscellaneous manufacturing). The share of employees in construction is measured as the count of employees in construction industries divided by total employees. Construction industries are identified by NAICS codes that begin with the number 23.

The share of female employees in manufacturing is the number of women employed in manufacturing industries divided by the total number employed in manufacturing. These variables were generated from the ind1990 variable (codes 100–392 identify employees who work in manufacturing) in the American Community Survey microdata made publicly available by Integrated Public Use Microdata Series USA (Ruggles et al. 2019). One drawback of the Integrated Public Use Microdata Series micro-level data is that geographic coverage is limited because of concerns about protecting the confidentiality of respondents in areas with

smaller populations. Micro data from locales with smaller populations are excluded to avoid the possibility that respondents could be identified on the basis of demographic and other information included for each respondent. As a result, when I include the variable for female employees in manufacturing, the number of metropolitan areas available for the analysis is reduced. To deal with these missing data I used multiple imputation, using the `mi impute` command in Stata 15 (StataCorp, College Station, TX). The imputed values are based on the other independent and dependent variables in the regression analysis. This boosted the number of observations for the female employees in manufacturing variable by 200 (from 454 to 654). The final estimates pool results from 20 multiple imputation data sets. The results from the imputed models that include the variable female in employees in manufacturing do not differ substantially from those models that do include the variable, so I report the results for the latter.

Acemoglu and Restrepo's (2017) remaining control variables are intended to measure other labor market dynamics, and the data come from a variety of sources. The share of routine jobs is a measure of routine jobs as a proportion of total employment. I identify routine jobs from the following types of occupations on the basis of Jaimovich and Siu (2012): office and administrative support, sales, production, transportation and material moving, installation, maintenance and repair, and construction and extraction. The data sources for this variable are the BLS data sets used to create the dependent variables. It should be noted that this operationalization of routine tasks as well as the typology used to categorize occupations by skill level have limitations. These limitations will be discussed in the conclusion of the paper.

Offshoring of goods is measured as offshored goods as a proportion of total employees. Offshored goods refers to the "imports of intermediate material inputs into the production of final goods" (Wright 2014:68). This variable was created on the basis of data made available by Wright.⁸ Wright's data are separated by industry, so the data were aggregated following Acemoglu and Restrepo's (2017) analysis. Wright's data on imports by U.S. firms were obtained from the Census Bureau's Linked/Longitudinal Firm Trade Transaction Database (see also Feenstra and Jenson 2009), but for more information about how the measure was calculated, see Wright (2014). Unfortunately, the variable was created by Wright only for the years 1993 through 2007. Therefore, I used multiple imputation to impute data for 2010 and 2015, the years under investigation in my study, on the basis of country-level data that I collected for the same independent variables used in my regression models from 1993 through 2007, the years for which Wright's offshoring variable is available. I imputed using the same procedures discussed above for the variable female in employees in manufacturing.

⁸The data used by Wright (2014) are available online.

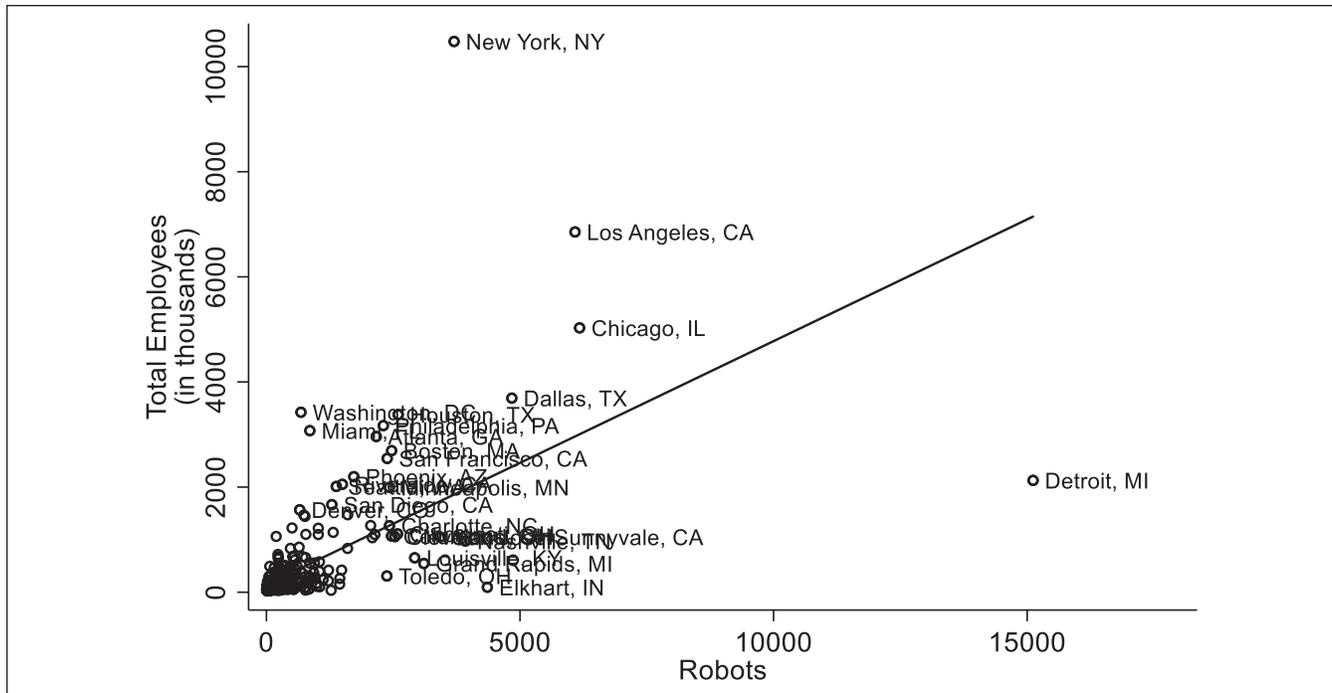


Figure 2. Plot of robot incidence and total employees for metropolitan areas.

The results from the imputed models do not differ substantially from those models that do include the variable, so again, I report the results for the models that include the variable.

I depart from Acemoglu and Restrepo (2017) in that I do not include control variables for geographic regions (i.e., census division dummy variables), because I use a fixed-effects regression model specification that accounts for unobserved heterogeneity, rendering useless time-invariant covariates. I also depart from Acemoglu and Restrepo by dropping variables for exposure to imports from China and Mexico from the analysis. I drop these variables because of concerns related to multicollinearity. The variables exposure to imports from China and Mexico are strongly negatively correlated with population at -0.972 and -0.973 , respectively.

Analytic Strategy

I use a fixed-effects regression model (maximum likelihood estimation) to estimate whether the variable industrial robots is associated with the prevalence of different types of skill-based occupations. Fixed-effect models adjust the standard errors to account for metropolitan-level unobserved heterogeneity for the years included in the analysis, which effectively eliminates the sources of metropolitan-specific, time-invariant omitted variable bias. The results of Hausman tests performed for each statistical model indicate that a fixed-effect model is a more appropriate specification than a random-effects model.

The first two models report the results for the estimated coefficients that predict the total people employed as a proportion of the labor force population. Model 1 is the bivariate model, while model 2 includes the remaining covariates. Models 3 through 10 include the coefficients for the bivariate and multivariate models for the remaining dependent variables: the proportion of high-skill, middle-skill routine cognitive, middle-skill routine manual, and low-skill occupations. All analyses are performed in Stata 15.

Results

The metropolitan areas in the top 10 for robot incidence in 2015 are Detroit, Michigan; Chicago, Illinois; Los Angeles, California; Dallas, Texas; Elkhart, Indiana; Louisville, Kentucky; Grand Rapids, Michigan; San Jose, California; New York, New York; and Nashville, Tennessee. A report by the Brookings Institution analyzes the IFR's robot data and shows that the use of robots is most prominent in mid-western and southern states, states with large amounts of manufacturing activity (Muro 2017). Figure 2 shows the relationship between robot incidence and total employment for metropolitan areas in 2015. Overall, Figure 2 indicates that a strong, positive relationship exists between robots and employment. Additionally, besides highlighting outliers above and below the mean, this graph indicates that a number of research and technology hubs have higher than average robot-to-employee ratios. Those visible to the eye are Dallas, Washington, D.C. (including Arlington and

Table 1. Descriptive Statistics for Independent Variables.

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Robot incidence	343.70	850.58	1.00															
2. Year	2012.83	2.48	.29	1.00														
3. Median household income (in thousands)	49.70	9.45	.30	.33	1.00													
4. Population (in thousands)	622.76	1356.50	.67	.07	.40	1.00												
5. Share of working-age population	.79	.04	-.05	.07	-.01	-.13	1.00											
6. Share of college degree	.26	.05	.25	.13	.59	.34	.21	1.00										
7. Share of high school degree	.25	.05	-.05	-.04	-.36	-.27	.15	-.66	1.00									
8. Share of Blacks	.11	.11	.24	.01	-.16	.25	-.03	-.04	.09	1.00								
9. Share of Hispanics	.13	.16	-.08	.07	.12	.23	-.37	-.12	-.40	-.25	1.00							
10. Share of Asians	.03	.03	.27	.13	.59	.46	.01	.51	-.53	-.03	.25	1.00						
11. Share of employees in manufacturing	.12	.07	.31	-.02	-.21	-.26	-.08	-.34	.36	-.02	-.20	-.18	1.00					
12. Share of employees in durable manufacturing	.05	.04	.49	.14	-.02	.01	-.02	-.15	.28	-.04	-.20	-.09	.70	1.00				
13. Share of employees in construction	.05	.02	-.22	-.03	.12	.04	-.11	.01	-.13	-.05	.14	-.04	-.27	-.23	1.00			
14. Share of female employees in manufacturing	.12	.14	-.21	-.01	-.13	-.41	.05	-.13	.17	-.10	-.23	-.22	.17	.01	-.04	1.00		
15. Share of routine jobs	.48	.17	.01	.05	.01	-.04	-.06	-.11	.02	.06	.13	.01	.12	.08	.01	.04	1.00	
16. Exposure to offshoring	.01	.01	-.37	-.06	-.22	-.40	.02	-.22	.05	-.11	.10	-.13	.03	-.07	-.02	-.53	.01	1.00

Alexandria, Virginia), San Diego, San Francisco, Phoenix, and Minneapolis. Those that are below the mean are unsurprising and include manufacturing centers such as Toledo, Ohio; Elkhart, Indiana; and Grand Rapids, Michigan. To ensure that outliers do not bias the results of the regression models below, I follow Acemoglu and Restrepo (2017) by excluding from the regression models metropolitan areas above the 99th percentile for robot incidence. These results do not differ significantly from the ones I report below.

Descriptive statistics for the independent variables included in the regression models are found in Table 1. The strongest correlations are between robot incidence and population (0.67), college degree and high school degree (–0.66), and employees in manufacturing and employees in durable manufacturing (0.70). To address potential problems attributable to collinearity, I estimated coefficients for models with and without these variables. The effects for robots did not differ substantially in models estimated without these variables from those that include them; therefore, I report the latter.

Table 2 shows the estimated coefficients for the fixed-effects models predicting total employment as a share of the population age 16 and older and occupations by skill type as a share of the labor force. Robot incidence has a positive and significant effect on high-skill (model 4) and middle-skill (routine manual) occupations (model 8), controlling for the other independent variables. These results suggest that the presence of robots complements the tasks

these employees perform and proliferates the number of these types of jobs that are available. These results also suggest that robots are more likely to proliferate occupations that create robots (high-skill occupations) or occupations that work with or work in the same firms as industrial robots (middle skill routine manual). Robot incidence has no significant effect on the other dependent variables, though the effect for total employment is significant at $p = .059$. Overall, the results from the models provide some support for the complementary view. But clearly the results do not support the displacement view.

Parameter estimates for several control variables have statistically significant effects. The year variable has a positive and significant effect on low-skill occupations (model 10), when the other variables are included in the model. This effect provides partial support for the claim made by proponents of the job polarization view that low-skill occupations are on the rise (though middle-skill occupations are not in decline in the models reported here). Household income produces mixed results depending on the type of occupation. Household income produces a positive effect on total employees (model 2) and a negative effect on low-skill occupations (model 10). These results are intuitive and indicate that higher incomes indicate a greater share of overall employment. But in metropolitan areas with higher incomes, low-skill jobs may be more difficult to find. Population has a negative and significant effect in each model except for one (model 8). These results indicate that the larger the pool of potential employees in a

Table 2. Estimated Coefficients for Fixed-Effects Models Predicting the Share of Different Types of Occupations.

Independent Variable	Share of High Skill				Share of Middle Skill				Share of Low Skill	
	Share of Total Employees		(Nonroutine Cognitive)		(Routine Cognitive)		(Routine Manual)		(Manual Nonroutine)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Robot incidence (logged)	.016*** (.002)	.012 (.006)	.018*** (.001)	.011* (.006)	.001 (.001)	.003 (.005)	.016*** (.002)	.016* (.007)	1.449*** (.080)	.143 (.316)
Controls										
Year		-.001 (.001)		.002 (.001)		.001 (.001)		-.001 (.001)		.321*** (.060)
Median household income (in thousands)		.022*** (.004)		-.003 (.003)		-.002 (.003)		-.002 (.004)		-.584*** (.184)
Population (logged)		-.083*** (.018)		-.071*** (.016)		-.077*** (.014)		-.005 (.020)		-2.250* (.888)
Share of working-age population		-.093*** (.032)		-.052 (.029)		-.040 (.025)		.016 (.036)		-1.390 (1.612)
Share of college degree		.006 (.078)		.086 (.069)		.020 (.060)		-.085 (.087)		.100 (3.909)
Share of high school degree		-.110 (.078)		.040 (.070)		-.033 (.060)		-.106 (.087)		4.644 (3.919)
Share of Blacks (square root)		.037 (.073)		.071 (.065)		.166** (.056)		.052 (.081)		5.544 (3.636)
Share of Hispanics (square root)		-.063 (.109)		-.111 (.096)		-.095 (.083)		.159 (.120)		-6.316 (5.423)
Share of Asians (square root)		.120 (.091)		.128 (.081)		.024 (.070)		.084 (.101)		6.859 (4.542)
Share of employees in manufacturing		.161 (.083)		-.043 (.073)		.019 (.063)		.222* (.091)		-4.624 (4.096)
Share of employees in durable manufacturing		-.003 (.065)		-.051 (.058)		.004 (.050)		.153* (.073)		-.357 (3.265)
Share of employees in construction		.107 (.157)		.493*** (.138)		.014 (.120)		.342* (.173)		7.017 (7.799)
Share of female employees in manufacturing		-.047 (.026)		-.007 (.023)		-.040* (.019)		-.012 (.026)		-1.845 (1.180)
Share of routine jobs		-.035* (.014)		.008 (.013)		-.015 (.011)		.001 (.016)		-.156 (.720)
Exposure to offshoring		-3.261* (1.469)		.669 (1.279)		-1.473 (.986)		-.008 (1.393)		-52.900 (60.886)
Constant	.370*** (.008)	4.409 (2.397)	.163*** (.006)	-2.960 (2.117)	.245*** (.006)	.492 (1.822)	.121*** (.008)	1.763 (2.635)	8.062*** (.375)	-601.175*** (118.570)
Metropolitan areas	327	327	327	327	327	327	327	327	327	327
Observations	654	654	654	654	654	654	654	654	654	654

* $p < .05$, ** $p < .01$, and *** $p < .001$ (two-tailed tests).

given metropolitan area, the fewer jobs that will be available for almost each type of occupation.

The results for working-age population, share of routine jobs, and exposure to offshoring are significant predictors in model 2. Several occupational variables have positive and significant effects in model 8, predicting the share of

middle-skill occupations characterized by routine and manual tasks. These variables include the share of employees in manufacturing, durable manufacturing, and construction occupations. These results are straightforward. These occupations are categorized as middle-skill occupations with routine and manual tasks, so there is a positive and

significant relationship for these independent variables measured in 2015 with these types of occupations as measured in 2016, the year from which the dependent variables come. Other variables that have significant effects include the share of employees in construction (model 4), the share of Blacks (model 6), and the share of female employees in manufacturing (model 6).

Discussion and Conclusion

The research question I ask in this study, whether robots are stealing our jobs, is intentionally provocative. It reflects widespread anxiety that robots may be rendering humans obsolete in the workplace, the displacement view. In reality, the debate is overstated. Robots have differential effects depending on the type of occupation. Yet the results of the regression models presented here show that robots are not stealing jobs from any of the types of occupations I examine. I find no evidence to indicate that robots are displacing workers, at least not in the metropolitan areas or years included in this study. Results from the regression models provide some support for the complementary view, the view that workplaces integrate both employees and robots in ways that generate more value for human labor. Specifically, I find that robot incidence positively affects high-skill occupations. Employees in high-skill occupations are the ones that are most likely to create, develop, and program robots. I also find that robot incidence positively affects middle-skill workers who are more likely to engage in routine and manual tasks. These are the middle-skill jobs that robots ostensibly are displacing, but in fact represent the types of occupations that are most likely to work alongside industrial robots. Although my study lends partial support to Autor and Salomons's (2018) finding of a positive relationship between robots and jobs more generally, I also extend their work by examining the effects of robots on different types of jobs.

Why is the relationship between robot use and employment positive in the years examined in this study, compared with earlier years studied by Acemoglu and Restrepo (2017)? Although the question is difficult to answer definitively without additional longitudinal analysis that compares the relationship between robots and jobs for the past and most recent periods, the findings from my analysis are suggestive. During the years 1990 through 2007, the period Acemoglu and Restrepo examined, manufacturing jobs declined in the United States. However, beginning in 2010, manufacturing jobs have experienced a steady uptick, in the first consistent yearly increase over an eight-year span since the 1960s.⁹ One explanation for the different findings between my study and

that of Acemoglu and Restrepo may be that employees in manufacturing occupations who lost their jobs because of automation in the past represented a certain amount of excess or slack in the labor market. It could be that a lower limit or threshold was reached, and the remaining positions in manufacturing jobs were more difficult to automate (and may be automated in the future) or continued to remain essential to organizational operations. Future research should examine a longer time scale with control variables for different time periods.

An optimistic explanation is that the displacement of workers in the past may have reversed because of newfound complementarities between robots and humans in manufacturing jobs. Perhaps the manufacturing occupations that were easy to automate in the past have been automated, and the remaining occupations are conducive to a certain level of symbiosis between humans and robots. Daugherty and Wilson (2018) provided compelling anecdotal evidence for this argument. They claimed that we are witnessing a new business and technology climate in which humans and robots are more likely to work together effectively, each playing a key role in performing a number of workplace tasks. They stated that humans are necessary to develop, train, and manage various robotic and artificial intelligence applications. To use Daugherty and Wilson's words, humans "are *enabling* those [robotic] systems to function" (p. 8).

More conceptual and empirical work remains, however, to understand better the impacts of robots on jobs. For instance, the typology I borrowed from extant scholarship to categorize occupations is problematic. The skill required to complete tasks in certain occupations is in the eye of the beholder. Who is to say that a midlevel manager (i.e., a high-skill occupation) is more skilled or capable or should be valued more highly than an insightful and talented automobile mechanic (a middle-skill occupation) or hair stylist (a low-skill occupation). The labels scholars have used to categorize skilled occupations are essentially a proxy for the education required to obtain the occupation with very little measurement of the skill used by employees in these occupations (Morris and Western 1999). Second, as Autor (2015) argued, many studies that examined occupations and automation and categorized occupations by skill level assumed that entire occupations can be categorized along one or two dimensions. Yet almost every occupation consists of a collection of heterogeneous tasks, some of which may be routine and others not. Most jobs contain both routine and nonroutine tasks, whether the occupation is labeled high skill, middle skill, or low skill. As a result, the potential for an entire occupation to be replaced by a robot or automation is typically overestimated. Many jobs with tasks that have been automated end up adapting, though some certainly do not, and take on new roles or responsibilities. For instance, Michael Watson, a supply chain consultant, predicts that in the trucking industry, which is expected by many to be affected adversely by

⁹For data on the number of manufacturing jobs in the United States over time, see the BLS's (2018a) "Data Tools" function. After navigating to the Web site, select "Manufacturing" and then click "Retrieve data." Next, identify the appropriate years of interest and select "Go."

autonomous vehicles, employees will still be in high demand. He states that self-driving trucks are likely to decrease the costs of transportation and increase the number of warehouses for goods as a way to improve local services. Thus, more local employees will be needed to do things like interact with customers, stock shelves and ensure that products are displayed correctly, and gather information on competitors' product displays (Price 2017).

Another limitation of this study involves the measure of industrial robots I used. Because of issues related to data (un)availability, it does not include service or other types of robots that may affect jobs. Service robots typically engage in tasks such as cleaning or attending to human needs. Examples include robots that carry luggage at airports or care for the needs of the elderly. Japan has been a leader on this front (cf. Foster 2018). Another critique of the robot measure I use is that it does not measure automation more generally. Commonly cited examples of the deleterious effects of automation on jobs that incite anxiety today include the decline in grocery store retail cashiers, who have been replaced by self-checkout scanners, and indications that the transportation industry seems poised to be disrupted by autonomous vehicles.

Accordingly, future scholarship needs to be more dynamic to examine the complex relationship between technology and employment. We need to develop new and more relevant measures of automation and more precise ways to examine the tasks employees undertake. We also need frameworks that account for the types of occupations that will emerge in the future as a result of implementing new technologies in the workplace. Occupational categories have evolved in the past and will continue to in the future. From 2010 to 2018, a relatively short period, 12 percent of occupations changed substantively (beyond definitional clarifications). Most of these changes resulted from splitting existing occupations into more detailed occupational categories on the basis of changes in the job market. Some of these new categories resulted from changing industry norms such as fund-raising managers. But other occupations are related directly to technological advances, and their existence is technology dependent, such as database architects and financial risk specialists.¹⁰ It also would be unsurprising if new occupations do not emerge in the future with job descriptions that include the maintenance, training, or management of robots and robot-human relationships (cf. Wilson, Daugherty, and Morini-Bianzino 2017). Nevertheless, these types of occupations likely would be accessible only to high-skill workers, further exacerbating the hollowing out of middle-skill occupations.

Although automation has historically had devastating effects on particular sectors of the job market such as

farming in the twentieth century (Dimitri, Effland, and Conklin 2005), proclamations of displacement among all sectors of the labor market are misplaced. In debates about the impact of robots on jobs, the appropriate question to ask is, Under what circumstances does displacement, complementarity, or neither occur? The answer may also depend on time period. Trucking, for instance, has been a strong job creator historically for individuals with low levels of education (Rotman 2017). Although some expect employment prospects to remain strong in the trucking industry, as mentioned above (Price 2017), autonomous vehicles are already being used by trucking companies to haul goods, which could end up having profoundly negative consequences on truck drivers and their households. Nevertheless, the primary conclusion of this study is that robots are not stealing jobs, at least not in the aggregate and not during the period examined here. With some luck and ingenuity, we could be entering a new era of technological advancement in which artificial intelligence allows robots to collaborate with humans in new ways in the workplace. Such collaborative relationships could offer a promising pathway into the future, even for employees in middle- and low-skill occupations.

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¹⁰For more information about the way the BLS changed occupational categories from 2010 to 2018, see BLS (2017).

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