Disparities in Robot Adoption among U.S. Manufacturers: A Critical Economic Development Challenge

Nancey Green Leigh[a]*, Heonyeong Lee[b], and Benjamin Kraft[c]

[a] *Professor, School of City and Regional Planning, College of Design, Georgia Institute of Technology, 245 4th Street NW, Suite 204, Atlanta, GA 30332-0155, United States of America (corresponding author). Email: ngleigh@design.gatech.edu;*

[b] *Ph.D. Student, School of City and Regional Planning, College of Design, Georgia Institute of Technology, 245 4th Street NW, Suite 204, Atlanta, GA 30332-0155, United States of America. Email: leehy@gatech.edu*

[c] *Research Planner, Research and Special Project Division, Montgomery County (Maryland) Planning Department, 2425 Reedie Drive, Wheaton, MD 20909, United States of America. Email: Benjamin.Kraft@montgomeryplanning.org*

Disparities in Robot Adoption among U.S. Manufacturers: A Critical Economic Development Challenge

The growing recognition of industrial robots as a source of innovation and competitiveness for manufacturing is motivating calls for a supportive industrial ecology and policy framework. However, the available data on robotics are limited and provide little evidence of the factors that stimulate robot adoption at the firm level. Based on survey results of 428 manufacturing establishments, this study examines 1) the current diffusion of robotics in manufacturing and 2) establishment- and regional-level characteristics associated with robot adoption. Our analysis results show that an establishment involved with mass-production and in an auto-related industry is likely to adopt robots, and robots are now penetrating small- and medium-sized establishments and a broader manufacturing sector. Furthermore, being in a roboticized region – a region with a large pool of existing robot users and robot-related skilled labour – positively affect establishment's decisions on robot adoption. This implies cumulative advantage (and disadvantage) regarding technology upgrading and a need for policies that can encourage wider adoption of robots.

Keywords: word; industrial robot; technology adoption; manufacturing; robot cluster; cumulative advantage

Introduction

While the recent advancement of robotics and automation technology offers opportunities for firms and regional economies to increase their productivity and flexibility, it also creates pressures to reform and reconfigure manufacturing processes and industrial ecology. Growing attention has been given to industrial robots because they are viewed to be key components of more rapid and flexible modes of production required for mass production as well as mass customization (Pedersen et al. 2016). Industrial robots also contribute to less energy-intensive production systems, thereby advancing industrial sustainability (Ahn 2016; Pham and Ahn 2018).

Over the last 30 years, the cost of industrial robots has fallen sharply. One source tracking industrial robot costs shows that the cost of an industrial robot fell from over $130,000 in 1995 to less than $30,000 towards the end of the 2010 to 2020 period (Korus 2019). Recently, pricedeclines are flattening while while robots have gained greater functionality and value. Advances in collaborative robot (cobot) development hold the promise of much higher levels of adoption across the manufacturing sector, as cobots can operate with humans in a highly interactive environment that has greater application flexibility and complex functional capability (Pham and Ahn 2018). In the 2009-2018 period following the Great Recession, the rate of installation of industrial robots grew 12 percent per year from 2011 to 2016 (International Federation of Robotics 2017).

As the costs of robotics and related technologies fall, there have been calls for policies to support manufacturers in upgrading their production systems (Atkinson 2019). Fear of losing manufacturing competitiveness has in part generated emerging support on both sides of the political aisle for industrial policy focused on increasing the deployment of 21st century manufacturing technology (Krein 2019). In U.S. metropolitan regions that have higher concentrations of workers with robotics skills, local manufacturing industries grew more rapidly from 2010 to 2016 than did regions with fewer of these workers, indicating roboticization is associated with sectoral and regional competitive advantages (Leigh, Kraft, and Lee 2020).

Still, the question of which regions and industries are gaining or losing in the technology race is an open one. In the European Union (EU), there is evidence that member nations—after an initial period of robotic divergence in the early days of industrial robotics—are now converging in their manufacturing sectors' use of robotics (Jungmittag 2020).

From an economic development perspective, greater understanding of the trends in manufacturing robot adoption at the subnational, industrial, and firm levels is needed. However, the data necessary to provide a full understanding currently does not exist. The research presented here illustrates what can be added to our understanding of the impacts of roboticization from non-traditional datasets and from an author-administered survey.

The International Federation of Robotics (IFR) currently offers the only globally harmonized dataset of robot sales and operational stocks, but these data are only available at the national level. The IFR dataset is comprehensive and useful for many purposes, but has several problems that are summarized in Leigh, Kraft, and Lee (2020) and Raj and Seamans (2018). The annual European Manufacturing Survey (EMS) does collect data on robot use at the firm level, but does not include firms with less than 20 employees (Raj and Seamans 2018), a key category for questions about manufacturing competitiveness. In the United States, two surveys conducted by the Census Bureau – Annual Survey of Manufacturers and Annual Business Survey – collected the first data on robots in 2018 and recently published survey results (Zolas et al. 2021).

The number of studies on the use and diffusion of robotics is growing, but the studies provide little evidence of the factors that stimulate robot adoption at the firm level. Rather than examining robot adoption, existing robotic studies focus almost exclusively on robotics' impacts on employment and productivity at meso or macroeconomic levels (Acemoglu and Restrepo 2020; Graetz and Michaels 2017, 2018). Studies of manufacturing technology adoption, summarized in the following section explore a broader suite of advanced manufacturing technologies (AMTs) that were developed and widely adopted at different times. For example, CNC machining was invented and widely adopted before modern industrial robotics, the latter of which can now perform some tasks commonly done by the former. While useful, these studies can only provide limited insight into firm decision-making specifically on robot adoption. Furthermore, existing studies focus primarily on establishments' characteristics, while literature from economic geography and social science has emphasized the importance of spatial contexts in firms' choice on the adoption of advanced technologies (Gertler 1995, 2003; Kelley and Helper 1999; Harrison, Kelley, and Gant 1996).

Because both geography and organizational characteristics are important factors in firms' decisions to make technological upgrades, we designed a survey to capture both types of data and their relationship to robot adoption at the firm level in the U.S. In this paper, we report and analyse the results of this survey. Information on survey methods and results can be found in an interactive-data-browsing tool (https://planning.gatech.edu/sites/default/files/pled/).

Broadly, our survey results reveal that approximately 27% of manufacturing establishments employed robots in their manufacturing processes, and 25% of these establishments had adopted robots within the previous five years (we label these new robot adopters). Furthermore, compared to early-robot adopters,new robot adopters tend to have fewer employees and to come from a wider array of industrial sectors.

In contrast to previous studies on technology adoption more narrowly focused on establishment characteristics, our research investigates the impacts of regional characteristics, including agglomeration and diversity. Our models, based on survey-collected data, indicate that the presence within a region of a large stock of existing robots, as well as jobs with related skills, can stimulate establishments' decisions on whether to adopt robots. Other establishment-level characteristics, such as industry sector, production volume, and adoption of types of advanced technology, also influence robot adoption. Our findings suggest that regional context plays an important role in stimulating robot adoptions in the manufacturing sector.

Technology Adoption and Diffusion in Manufacturing Sector

Current Status of Industrial Robot Diffusion in the U.S.

The manufacturing sector has, by far, the highest robotics adoption rate in the global and U.S. economies. However, there is substantial variation in adoption rates across countries and sectors within manufacturing. As a key indicator of diffusion, the International Federation of Robots (IFR) ranks nations by their number of robots per 10,000 manufacturing employees. The U.S. ranks seventh with 189 robots per 10,000 manufacturing employees, a number dwarfed by Korea which leads the world with 631 robots per 10,000 employees. While Singapore and Denmark rank 2nd and 3rd, they are not necessarily comparable to the U.S. because of their significantly different industrial compositions. Neither nation has auto manufacturing, and Singapore's manufacturing is almost entirely dedicated to computer chip making. However, countries with industrial compositions more comparable to the U.S., such as Germany, Japan, and Sweden, also have significantly higher robot densities.

Across the world, as previously noted, robot adoption rates are strongly correlated with the presence of auto manufacturing, where the U.S. has a high incidence of robot use, second only to Korea (See Table 1). Of note is that the U.S. is unique among manufacturing peers for its relatively low robot use in non-auto manufacturing sectors. Although it has been increasing since 2011 (7.0%), the U.S. still ranks eighth globally with 101 robots per 10,000 employees.

Another indicator, 2016 robot sales, also shows that robot use in U.S. manufacturing is disproportionally concentrated in the auto industry, accounting for

51.9 percent of total robot sales, compared to 34.0 percent of global robot sales. However, in all countries the number of robots outside the industry is growing at a faster rate than within the auto industry, implying that robotic technologies are penetrating a wider range of manufacturing subsectors.

[Table 1]

Previous Studies of Technology Adoption

Since Griliches (1957) finding that the adoption of hybrid corn technology spreads at a fairly predictable rate as farmers become aware of the efficiency gains it affords them, there has been a rich body of literature about technology adoption by business firms. A sub-body of literature in this tradition examines the adoption of advanced manufacturing technologies (AMT), which differ from innovations like hybrid corn significantly in terms of complexity, variety, and initial expense. In the case of AMTs, the promise of efficiency is a necessary but not sufficient criteria for adoption (Helper 1995).

Studies on the adoption of AMT in the manufacturing sector shows that the most consistent predictor of a manufacturing plant′s decision to adopt AMT is size. Larger firms are more able to internalize costs associated with introducing new technology, and to realize their efficiencies through economies of scale . A recent study found that small and medium metalworking firms tend to prefer complementary rather than substitutive technology to minimize disruption to a firm's existing workflow (Waldman-Brown 2020). In the one study where size was not a significant factor in influencing the likelihood of robot adoption, the authors cautioned that their establishment sample contained disproportionately large establishments (Doms, Dunne, and Troske 1997).

There are other important factors related to size that influence the decision to adopt technology. Prior use of other types of AMT and the closely related concept of "sunk costs" of technology onboarding—costs associated with learning, training, and reconfiguring or adding new capital to accommodate the new technology—are repeatedly shown to be factors (Astebro 2004). This implies that intra-firm adoption (the adoption of additional technology by firms or establishments that already have other technology) is another important driver (Mandfield 1989; Gómez and Vargas 2009).

These findings suggest larger firms are likely to have pre-existing technological advantages, and the gap between small, non-technology adopting plants, and large, technologically advanced plants, will continue to grow as prior investments in technology beget more investments. This advantage extends to human resources, where, despite evidence for workers′ increasing skill levels as a result of technology at the individual plant scale (Fernandez 2001) and the economy-wide scale (Autor, Levy, and Murnane 2003), a highly skilled workforce appears to be a prerequisite for acquiring advanced technology across a large sample of U.S. plants (Doms, Dunne, and Troske 1997). However, Dunne and Troske (2005) find that this effect may hold for design and engineering technologies, but not production technologies—the category into which robotics falls.

Gómez and Vargas (2009, 2012), find that financial constraints (measured by debt-to-asset ratio) reduce the probability that a plant will adopt robots but do not affect the probability of adopting other technologies. During the period reflected by their dataset (1994-2002), robots would have been very expensive, especially relative to other technologies like CAD and CNC. Despite significant reductions in robot prices since that time period, robots remain among the most expensive pieces of automation equipment. This has long been recognized as a barrier to adoption, and certainly one of the drivers of the development of less expensive, small payload co-robots (also known as collaborative robots). It remains to be seen whether the availability of co-robots will significantly reduce the price-barrier to robot adoption.

Lastly, Gómez and Vargas (2012) find that foreign ownership increases a plant′s likelihood of incorporating robots. This is an important variable in light of data related to global robot diffusion (Table 1), suggesting that in addition to the simple fact of the location of production, corporate supply chains and internal cultures related to technology may influence the likelihood of adopting robots. In other words, a Japanese-owned manufacturing establishment in the U.S. may be more likely to adopt robots than a U.S.-owned establishment, because the parent firm overall has more experience with robots. This dynamic has been shown with other advanced manufacturing technologies (Gertler 1995; Park and Leigh 2017).

While plant size is an important determinant of robot adoption, it is a vague construct around which to frame research: there is no mechanism by which to simply enlarge plants, and even if this was possible, we would not expect the mere addition of employees to solve technological adoption problems. In fact, plant size is highly correlated with various establishments' characteristics, so misspecification of such characteristics may lead to overestimating plant size impacts. A more thorough approach can be found in Helper (1995), which measures plant size (as annual sales amounts), but also assesses market power and customer commitment as determinants in the decision to adopt technology. Helper found that when sales, market power (plant's share of market for its specific product), and customer commitment (length of contract to produce the product) are entered into the same model, all are positive predictors of an establishment's decision to add technology, with the latter two variables imparting larger marginal effects on the probability.

Spatial Context of Robot Diffusion

Geography is a generally overlooked but important factor in technology adoption. There is evidence that small and medium-size manufacturing establishments can overcome size disadvantages in technological adoption when located in areas with diverse industry mixes (often called "urbanization economies") (Kelley and Helper 1999; Harrison, Kelley, and Gant 1996). Urban diversity fosters knowledge transfers and attracts new and innovative activities (Glaeser et al. 1992; Henderson 1997; Henderson, Kuncoro, and Turner 1995). Geographical proximity allows frequent face-to-face interactions and trust building among individuals across firms. Intense and diverse interactions provide a firm with a channel to learn about various aspects of emerging technologies, from word-of-mouth, direct observation of early adopters, or other informal mechanisms (Harrison, Kelley, and Gant 1996).

The proximity to technological product suppliers and service providers is another factor that may stimulate the adoption of advanced technologies. For a manufacturer, the ability to quickly respond in the event of breakdowns is one of the crucial decision criteria in adopting new technologies (Gertler 1995). The proximate location of suppliers ensures timely and reliable technical assistance. Thus, a firm within a dense supplier network is more likely to adopt advanced technologies. Proximity also supports more intense technical services that require face-to-face interactions, such as site visits and employee training. In turn, this increases user confidence in adopting new technologies (Gertler 1995).

The impacts of “localization economies” (those that are highly specialized in a single industry) on the adoption of advanced technology is more subtle. As a product enters a mature stage, locations that offer more cost-efficient production become more attractive over higher cost urban environments that facilitate research and experimentation of innovation (Duranton and Puga 2001; Vernon 1966). As a result, while innovative activities occur mostly in diversified cities, production largely occurs in more specialized cities. Previous studies found a negative correlation between narrow specialization and the adoption of new production process (Harrison, Kelley, and Gant 1996; Feldman and Audretsch 1999). However, it is unclear to what extent industry can be considered homogenous. While previous studies generally used 2-digit NAICS codes, such as manufacturing, this is too broad for studying robot adoption given the significant spatial heterogeneity found in the concentration of the robot industry (Leigh and Kraft 2017).

Methodology

Survey of Advanced Technology and Robotics in U.S. Manufacturers

The empirical study presented in this paper identifies characteristics of establishments that adopt robots in their manufacturing processes. This study is primarily motivated by three concerns: First, there is a deficit of appropriate data on robotics that is a major barrier to understanding firms’ strategic decisions on robot adoption (Leigh, Kraft, and Lee 2020). Second, previous studies on technology adoption in manufacturing establishments were not specifically focused on robotics, but rather, based on broad definitions of advanced technologies. However, the central role that robots now have in advanced production systems (Brossog, Bornschlegl, and Franke 2015) warrants a specific analysis of their impacts. Third, previous studies largely omit a geographical perspective, even though it is widely acknowledged that geographical "proximities" play a crucial role in production process innovations through localized knowledge spillovers (Gertler 1995, 2003; Audretsch and Feldman 2004; Bathelt, Malmberg, and Maskell 2004).

To gain insight into the use of robotics and automation technology in U.S. manufacturing, we conducted a national survey titled the "Survey of Advanced Technology and Robotics in U.S. Manufacturing." The survey was administered through the national survey research organization, NORC, at the University of Chicago. The sample frame from which the survey sample was selected is largely considered a nationally representative frame of U.S. manufacturing establishments. We employed a business database from Mergent Intellect which includes virtually all manufacturing establishments in the U.S. to develop the sample frame. A probability-based stratified sample of manufacturing establishments that had at least ten employees was selected from the sample frame. Because the number of responses from the initial survey was insufficient after several rounds of prompting, the sample frame was augmented with members of various state Manufacturing Extension Partnership programs for whom contact information was publicly available (as noted below, survey weights were post-stratified to account for varied response tendencies by strata, one of which was Census Division).

The distribution of completed surveys was dispersed across the 81 strata constructed using three industry groups (automotive and other transport, computer and electronics, and all other manufacturing), three company sizes (small, medium, or large number of employees), and the nine Census Divisions to ensure a representative sample of manufacturing establishments.

The survey questionnaire asked about 1) basic establishment characteristics, 2) robots and other advanced technologies used in manufacturing processes, 3) development, installation, and maintenance of robots and 4) related worker skill and educational requirements. A total of 42 survey questions were developed using inputs from cognitive interviews and pre-test results. For the paper-and-pencil version of the questionnaire, see supplemental data.

A total of 8,100 survey invitation letters were sent to eligible respondents via mail and/or email from September to November 2018. The survey was conducted through either a web questionnaire or a paper-and-pencil version. The latter was available upon request by the respondents. To encourage survey participation, the recruitment mode included email reminders and phone prompts with offers of incentives (electronic gift cards).

In the end, 428 valid responses from U.S. manufacturing establishments were collected across the desired categories of manufacturing industry group, company size, and Census division. The response rate was 5.3%, and survey weights were post-stratified to match benchmark distribution of the strata with some collapsing of post-strata required.

Our survey response rate was lower than the 9.6% of a previous U.S. manufacturing survey conducted with a similar sample frame size (Mabert, Soni, and Venkataramanan 2000). However, that survey's respondents were drawn from the membership list of a professional industry association and had a vested interest in participating, in contrast to our respondent list which was drawn from a business database that incorporates multiple secondary data sources. This is one of several reasons that may explain the lower response rate. Additional factors include: 1) comprehensive nature of the survey, 2) greater number of questionnaires undelivered for address errors, and 3) general trend of declining survey response rates combined with lower survey response rates generated by web-based survey administration.

The authors tested potential non-response bias by comparing response rates across plant sizes and industry types. The response rate tends to be the highest from plants with 500 or more employees (6.1%) and computer-related manufacturing plants (6.3%). We further conducted chi-squared tests to examine differences in the distribution between actual and expected responses across plant sizes and industry types. The test results reveal that industry types are not significantly related to the response tendency ($P(\chi^2 \geq 4.37) = 0.112$), while plant size has some association with it ($P(\chi^2 \geq 4.65) = 0.098$). To account for potential bias due to differential nonresponse or noncontact by strata, the sample design weights for survey completes were adjusted using post-stratification to benchmarks constructed from the sample frame. Thus, the final survey weights account for both the complex sample design of the survey as well as potential bias caused by nonresponse error.

The distribution of completed surveys by industry group and establishment size is shown in Table 2. The geographical distribution of surveyed manufacturers is provided in Figure 1.

[Table 2]

[Figure 1]

Analytic Model

We model the probability of robot adoption for a manufacturing establishment i in a metropolitan area j as a function of establishments' and MSAs' characteristics (X_i, X_j). Our dependent variable is a dummy variable coded as "1" if an establishment reported that it uses robots in its manufacturing processes and “0” if not. The definition of robots includes traditional industrial robots, collaborative robots, and autonomous guided vehicles. To help survey respondents understand the exact term, we provided a booklet of definitions and examples of robots. To model binary outcomes, this study chooses logit as a link function over probit mainly because it offers an additional method of interpretation using odd ratios. Our base model specification employed a logistic regression with the following form:

$$log \frac{P(E=1)_{ij}}{1-P(E=1)_{ij}} = \beta_0 + \beta_1 X_i + \beta_2 X_j + \varepsilon_{ij}$$

Independent variables at the establishment level include employment size, as well as dummy variables indicating industrial types, the presence of unions in the state, recent patterns of offshoring and reshoring activities, exporting activities, production volume, and adoptions of other advanced technologies. These variables are directly captured from survey results. For example, the offshoring variable is coded as “1” if an establishment responded “Yes” to the survey question asking whether any portion of establishment’s production work been relocated to a non-U.S. location since 2010, and “0” if the answer was “no.”.

To control for metropolitan-level effects, we include six variables in the model. Employment density, the total employment of the MSA divided by its size, controls for an urban agglomeration effect. We take the natural log to this variable to avoid potential problems associated with heteroscedasticity. We also enter average schooling years into the model to control the varying level of human capital across MSAs. Urban specialization and diversity are captured by Location Quotient and Shannon Evenness Index, respectively. These variables are created from 2018 U.S. Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW) data and processed at the two-digit North American Industry Classification System (NAICS) code level.

The other two variables, Modified Robot Exposure (MRE) and Robot Skill Demand Index (RSDI), are the key explanatory variables. The MRE variable is derived from a ratio of robots to human workers in each industry and MSA manufacturing employment at the 3-digit level. As a result, this represents the estimated number of robots used in an MSA-manufacturing sector. The RSDI variable is the percentage of manufacturing jobs in a regional labour market that are associated with robot-related skills. We use job-posting data from Burning Glass Technology to calculate RSDI. For more detailed discussion regarding MRE and RSDI, see Leigh, Kraft, and Lee (2020).

We use the MRE and RSDI variables primarily because they are derived directly from robot-related industry and labour demand. Thus, we can capture the characteristics of robot-related industrial ecology rather than general characteristics of a regional manufacturing sector. Furthermore, with the MRI and RSDI variables it is possible to investigate the mechanism by which specialization in robotics stimulates robot adoption. From the establishment perspective, a higher regional MRE indicates there are more robot users in close proximity. As a result, learning from peers is more likely to occur. Similarly, a higher RSDI indicates there are more employees and expertise that can contribute to knowledge spillovers. Thus, both variables provide information about the robustness of the regional robotics-industrial ecosystem.

Results

Robot diffusion in U.S. manufacturing

Out of 428 completed surveys, 116 establishments reported adopting robots, generating a weighted incidence robot use of 27.1%. The survey results show that there is significant variation in robot adoption rates across establishments of different size and industry sector (Table 3). Large automotive and related establishments were most likely – and small establishments outside of the auto sector least likely – to adopt advanced technologies, including robots. This finding is consistent with that of a recent study showing the use of robots is disproportionately distributed across U.S. firms (Zolas et al. 2021). According to this study, the distribution of robots is the most highly skewed in favour of larger firms among nine AMTs surveyed.

Firms that recently relocated some portion of production outside the U.S. (offshoring) or into the U.S from a foreign location (reshoring) were significantly associated with robot adoption rates. That is, robot adoption rates were higher for establishments that engaged in offshoring and reshoring, by 22.6 and 52.0 percent respectively, relative to those who did not make transnational changes in production location. Notably, reshoring establishments were more likely than either offshoring establishments or establishments with no foreign production relocations to adopt robots. While we cannot determine whether this association is causal in either direction—that is, whether using robots causes firms to reshore manufacturing capacity, or reshoring causes robot adoption—this evidence does support associations between technology and reshoring that others have made (Ancarani et al. 2015; Fratocchi 2017).

[Table 3]

Establishment characteristics associated with robot adoption

We examined characteristics associated with robot adoption using logistic regression. These include establishment-level variables for industry, production volume, and advanced technology as well as metropolitan-level characteristics (See Table 4).

[Table 4]

Logistic regression results for the establishment level variables are shown in Table 5. The key variables of interest, industry and establishment size, are found to be predictors of robot adoption in the model: larger firm size substantially increases the likelihood of adoption, while not being in the automotive industry substantially decreases it (Baseline model). Converting coefficients to probabilities, the findings can be interpreted as follows: there is a 57% probability that a unionized, 40-employee automotive manufacturer with moderately high-volume production, and without offshoring or relocation activity, uses robots. An automotive plant with 300 employees has a 72% probability of using robots. In contrast, a 40-employee plant in a non-automotive industry with the same characteristics as above has a 31% probability.

In the next two models, we progressively enter additional variables to examine how establishment size affects robot adoption. These variables are production volume and adoption of other advanced technologies, both of which are highly correlated with establishment employment size. The production volume control model clearly shows that establishments with higher production volumes are more likely to adopt robots. The establishment size variable maintains statistical significance. However, after controlling for other advanced technology variables, it loses its statistical significance, indicating technological experience and production volume are more predictive than the size of establishments in decisions to adopt robots.

Establishments with low production volumes (i.e., “small batch”) were relatively unlikely to adopt robots. Reasons for this slow uptake cannot be discerned from the survey questions. However, qualitative research the authors are conducting suggests possible explanations. One is that small-batch firms may lack the capital to invest in robots. Additionally, the current state of robot development may not be capable of performing the types of operations that small manufacturers need. Despite significant advances in robotics, many processes for manufacturing non-durable goods, such as food, beverages, and apparel, still do not lend themselves to the technology. Alternatively, manufacturers that consider themselves artisanal may market their production process itself. Using robots may dilute their claim to handmade products.

Finally, robot suppliers may not prioritize marketing robots to small manufacturers that need only one or two robots. They may opt instead to pursue bigger and more profitable orders from larger manufacturers. Further research on small and medium-sized manufacturers is needed to understand why they lag in advanced technology adoption.

[Table 5]

Robot Adoption by Metropolitan Characteristics

We now move to logistic regression results with MSA-level variables (Table 6). In Table 6, we present average marginal effects in addition to coefficient estimates to facilitate interpretations. Average marginal effects represent an average change in probability when one unit increase in the corresponding independent variable. Unlike regression coefficient or odd ratios, this measure directly captures independent variables' effects on probabilities allowing comparability across groups and interpretation of substantive effects (Mood 2010). The model also includes geographic dummies that represent nine Census divisions for control.

Compared to the results presented in Table 5, we found that several establishment-level variables lose their statistical significance after controlling MSA-level effects. In particular, industry dummies (Auto and Other durable) that have shown statistical significance in Table 5 lose their statistical significance in Table 6. This indicates that sectoral and geographic influences on technology adoption are highly interrelated. They are difficult to disentangle because sub-sectoral concentrations are strongly geographically based. On the other hand, product volume and advanced technology dummies show consistent statistical significance. These findings, again, suggest that researchers should focus more on related technology experience and production methods than the mere size of establishments in studying decisions to adopt robots.

We found that employment density and urban agglomeration variables, as well as the education level of local labour markets, were not statistically significant. A potential explanation for this lack of statistical significance is the highly uneven geographical concentration of robot users and suppliers. While there is increasing penetration of robotics technology in the broader manufacturing sector, its use in mass production systems is still predominantly confined to the auto industry. Robot suppliers and integrators tend to co-locate with these traditional robot-adopting industries and thus are concentrated in the same metropolitan areas (Leigh and Kraft 2017). Variables that represent urban diversity cannot capture such patterns of geographical clustering, and, thus, fail to reflect the benefits of proximity between potential robot users and various robot-related industries.

The robot exposure (MRE) and robot skill demand (RSDI) variables, which represent the concentration of potential robotics users and robot-related skills, show positive statistical correlations. To elaborate, both MRE and RSDI have substantive affects on establishments' decisions to adopt robots. If the increase in MRE and RSDI was one unit, the average probability to adopt robots increases by 0.7 and 1.2 percent, respectively. For one standard deviation increase in MRE and RSDI, the probabilities of adopting robots increase approximately by 6.4 and 7.9 percent on average. These results suggest that regional industry composition that offers greater opportunities to learn from early adopters, as well as access to robot-related skilled work, positively influences establishment robot adoption.

Among MSA-level variables, manufacturing LQ that represents the concentration of the manufacturing industry in a region shows a negative statistical relationship. Results suggest that for one standard deviation increase in manufacturing LQ is associated with an 8.0 percent point decrease in the probability to adopt robots in an establishment on average. This finding is consistent with previous studies that suggest a negative relationship between narrow specialization and the adoption of a new production process (Harrison, Kelley, and Gant 1996; Feldman and Audretsch 1999).

[Table 6]

Characteristics of emerging robot-adopting manufacturers

In our final analysis of the manufacturing survey results, we compared establishments that adopted robots more than 10 years ago (early adopters) to those that adopted within the last 10 years (late adopters). We examined three variables: employment (108 respondents among a total of 116 respondents provided this figure for their establishment), reshoring, and belonging to an auto-related sector.

We found that late robot adopters differed from early adopters with respect to employment size and the industrial sector. The average employment size of the early robot adopters was 162, while that of the late robot adopters was 48. Of the early robot adopters, 26.4% were in an auto-related industry compared to just 6.9% of late adopters. That is, the results provide further evidence of the early adoption of robots by large producers in auto-related industries, relatively late adoption by small and medium-sized manufacturers in non-auto-related industries.

We found weak statistical significance for the reshoring variable that examines the potential relationship between growth in reshoring and the robot adoption rate. However, the reshoring variable only captures the relocation of production processes back to the U.S since 2010, and further investigation is needed.

[Table 7]

Discussion

The research presented in this paper fills some of the knowledge gap on establishments' adoption of robots, which is critical for understanding how this advanced technology will affect U.S. manufacturing establishments as well as the labour markets and regional economies in which they are situated. The results of our "Survey of Advanced Technology and Robotics in U.S. Manufacturers," based on responses from 428 U.S. manufacturing establishments, identify 1) the current extent of robot diffusion, 2) establishment- and regional-level characteristics associated with robot adoption, and 3) differences in characteristics between early- and late-robot adopters of robots. Providing establishment-level data on robot adoption as well as that on establishments' decisions to adopt robots provides unique opportunities to consider the implications for regional economic evolution.

Our findings indicate that the adoption of robots parallels the results of previous studies of the adoption of manufacturing technology. Large firms are more likely to use robots and are also more likely to have adopted them early (Zolas et al. 2021). This is especially true in the automotive industry, which is the industry where industrial robots were introduced. Also, robots beget more robots. Firms and regions where robots were first adopted now have the most robots. This pattern of adoption suggests the importance of peer-learning, knowledge spillovers, and availability of skilled workers in establishments' decisions on robot adoption.

These findings have several implications. First, cumulative advantage plays a role at both the establishment and regional levels. In the absence of policy interventions, places with more robots and robot skills (identified by the RSDI variable in the models) are likely to become more roboticized, while regions without a strong robotic base are in danger of falling behind. Similarly, and in line with prior research on AMT adoption, the presence of technologies such as sensors and machine vision in regions and establishments also increase the likelihood of robot adoption, as these technologies require similar operational skills and are often used complementarily (Frank, Dalenogare, and Ayala 2019).

The cumulative advantage that stems from regions with higher AMT adoption, contrary to traditional perspectives, may warrant policy support. Some of the most "robotic" regions in the U.S. are home to large, old-line industries such as automotive manufacturing that have struggled in recent decades due to industrial restructuring (Leigh and Kraft 2017). Rather than trying to level the robotic "playing field" across regions, an appropriate policy goal could be the enhancement of these regions' existing robotic advantage to help them to become more globally competitive. This strategy would be in line with a long tradition of regional resilience literature which seeks to use existing institutional knowledge, networks, culture, history, and technology to help declining regions evolve (see Christopherson, Michie, and Tyler (2010) and Boschma (2015)). However, regions with historical manufacturing bases that lag in robot adoption (e.g., non-auto industry in rural or exurban regions) also warrant policy attention.

In both types of regions, however, targeting small and medium manufacturing establishments (SMEs) is warranted. Unlike large manufacturers, SMEs have difficulty accessing specialist resources, such as the latest knowledge of technology, finance, and managerial practices. To access such resources, SMEs rely more heavily on a local innovation ecosystem that generates knowledge flows and collaborative networks (Bougrain and Haudeville 2002; Combes et al. 2012). Policy interventions that promote social relations and local knowledge transfer could create a supportive environment for SMEs' robot adoption and, thus, enhance productivity and secure employment in SMEs (Ballestar et al. 2020).

Although our survey shows some signs that smaller manufacturers have recently begun to adopt robots at a faster pace, a significant lag still exists. As a starting point, Waldman-Brown (2020) suggests that SMEs consider technological upgrading when doing so will meet at least one of the following three criteria: 1) proven technologies with proven payoff periods; 2) the ability to make non-disruptive, incremental changes to production processes rather than a complete retooling; and 3) immediate competitive necessity such as a large order that cannot be filled by incumbent workers. SMEs generally do not undertake comprehensive, planned retooling operations the way large plants do, so policies should be designed to reflect the incremental nature of small-scale robot adoption.

The question of disparities in robot use between industrial sectors is also important. Although we found that geographic influences on technology adoption are highly interrelated and difficult to disentangle due to spatial concentration of subsectors, there is a distinct sectoral divide in roboticization. Part of this divide is due to the different materials and processes used in production. For example, pharmaceutical manufacturing uses advanced manufacturing technologies, but has little need for robots because it rarely uses discreet, solid objects until the packaging phase of production. Thus, policy should focus on sectors where robotics can add value. Some of these industries may have low-margins (e.g.,wood products and furniture manufacturing) that may be hesitant to make large investments and have not been marketed to by robotics suppliers and systems designers.

How further roboticization would impact workers is a separate question beyond the scope of this article. But these results should cause us to look carefully at findings from existing studies that cover timeframes before roughly 2010 (e.g. Acemoglu and Restrepo (2020)) because as our study shows, only large plants primarily in the auto industry were roboticized at the time. These plants have a large influence on regional industrial ecosystems, but it is also conceivable that worker displacement from a recently roboticized automotive assembly plant in the earlier days of industrial robotics may not have affected the workforce of the plant's smaller suppliers who likely would not have adopted robots yet. It should also be kept in mind that there has been a severe shortage of manufacturing workers for many years and adding robots to establishments to handle high-volume routine tasks can free up workers for higher-skilled tasks that cannot be performed by robots or entail maintenance and programming of the robots. Our research of the industry has found anecdotal evidence of these trends, but a formal study is needed.

Conclusion

Industrial robots are not a new technology, but they have had a relatively slow uptake until the last decade. Due to recent technological advancements, they have become cheaper and more versatile which has led to a surge in robot sales. Our survey results show that robots are now penetrating small- and medium-sized establishments and a broader manufacturing sector. However, the auto industry and mass-production manufacturers are still the dominant users of industrial robots. As such, their uneven spatial distribution, and their suppliers' tendency to co-locate with them (Leigh and Kraft 2017), results in a spatially clustered pattern of the robot industry.

Our analysis shows that being in robot clusters positively affects establishments' decisions to adopt robots. In particular, we found that an establishment is more likely to adopt robots when it is located in a region with a large number of existing robot users and robot-related skilled labour. This finding implies that the disparity in robot adoption rates across regions could widen over time and manufacturers located in less-roboticized regions may become less competitive without appropriate policy interventions. Consideration of current technological, economic, and institutional contexts to robot adoption is required for effective policy making. For a better understanding of effective policy and strategies, research is needed that specifically identifies technology adoption barriers (e.g., difficulty obtaining financing to purchase robots/robotic systems, difficulty in finding robotics-skilled workers, or nsufficient technical assistance).

Many manufacturers, especially small- and medium-sized ones, lack the knowledge to be able to evaluate whether using robots would be cost effective and enhance their competitiveness. Closing this knowledge gap could help small- and medium-sized manufacturers and their host economies to survive and grow. Doing so may help to increase the United State' manufacturing competitiveness. Presently, the U.S. ranks only seventh in the world in industrial robot adoption. Further, the Covid-19 driven economic crisis of 2020 has created extraordinary challenges for U.S. manufacturing. An explicit industrial policy that specifically includes expanding robot adoption may be a promising step for recovering from the worst economic downturn since the Great Depression.

Table 1. Number of robots per 10,000 employees in auto and non-auto industry by country

Auto industry			Non-auto industry		
Countries by rank	# of robots per 10,000 Emp.	CAGR (2011-2016)	Countries by rank	# of robots per 10,000 Emp.	CAGR (2011-2016)
South Korea	2,145	8.6%	South Korea	475	12.8%
United States	1,261	2.7%	Japan	214	1.4%
Japan	1,240	-4.8%	Germany	181	4.8%
France	1,150	-5.4%	Sweden	164	5.2%
Germany	1,131	-0.1%	Italy	153	4.1%
Spain	1,051	-2.1%	Taiwan	147	11.8%
Austria	846	7.5%	Austria	106	7.2%
Taiwan	844	11.8%	United States	101	7.0%
Italy	800	-6.8%	Spain	87	6.0%
Sweden	704	9.1%	France	81	6.9%

Note: Created by authors using IFR data

Table 2. Number of surveyed manufacturers by industry and establishment size

	Industrial sectors (Cases)			
Plant size	Auto-related	Computer-related	Others	All manufacturers
Small	18	30	129	177
Medium	29	58	120	207
Large	8	6	30	44
Total	55	94	279	428

Note: Auto-related industry is classified with NAICS 3361-3363 and computer-related is NAICS 334-335. For all industrial categories, small is 10-49 employees, medium is 50-499 employees, and large is 500+ employees.

Table 3. Robot adoption rates by selected plant characteristics

Characteristic	Number of Cases	Number of robots adopted	Percent robot adoption	F-statistics
Plant sizes				7.15***
Small	177	34	19.2%	
Medium	207	62	30.0%	
Large	44	20	45.5%	
Industry				6.81***
Auto-related	55	25	45.5%	
Computer-related	94	17	18.1%	
Others	279	74	26.5%	

Offshoring				4.07**
Yes	38	23	60.5%	
No	274	93	33.9%	
Reshoring				7.99***
Yes	21	18	85.7%	
No	291	98	33.7%	
Exporter				0.22
Yes	68	20	29.4%	
No	360	96	26.7%	
Geography				2.91**
East North Central	80	29	36.3%	
East South Central	26	7	26.9%	
Middle Atlantic	53	16	30.2%	
Mountain	23	5	21.7%	
New England	31	8	25.8%	
Pacific	91	19	20.9%	
South Atlantic	51	12	23.5%	
West North Central	49	12	24.5%	
West South Central	24	8	33.3%	
Total	428	116	27.1%	

Table 4. Summary statistics

	# of Obs.	Mean	Std. Dev.	Min	Max
Plant Characteristics					
Robot dummy	397	0.262	0.440	0.000	1.000
Log transformed employment	397	4.237	1.511	0.000	9.190
Industry Dummies					
Auto	397	0.123	0.329	0.000	1.000
Computer	397	0.262	0.440	0.000	1.000
Other durable manufacturing	397	0.219	0.414	0.000	1.000
Other non-durable (reference)	397	0.395	0.490	0.000	1.000
Union dummy	397	0.063	0.243	0.000	1.000
Offshoring dummy	397	0.149	0.356	0.000	1.000
Reshoring dummy	397	0.091	0.288	0.000	1.000
Exporter dummy	397	0.171	0.377	0.000	1.000
Production volume dummies					
Small batch	351	0.174	0.379	0.000	1.000
Somewhat small batch	351	0.225	0.418	0.000	1.000
Medium (reference)	351	0.311	0.463	0.000	1.000
Somewhat high volume	351	0.154	0.361	0.000	1.000
High volume	351	0.137	0.344	0.000	1.000
Advanced technology dummies					
Rapid prototyping	351	0.256	0.437	0.000	1.000
Additive manufacturing (3-D printing)	351	0.288	0.453	0.000	1.000
CAD/CAM	351	0.752	0.432	0.000	1.000

Sensors and machine vision	351	0.536	0.499	0.000	1.000
Advanced materials	351	0.219	0.414	0.000	1.000
CNC machines	351	0.593	0.492	0.000	1.000
MSA Characteristics					
Log transformed employment density	114	3.725	0.971	0.948	5.894
Average schooling years	114	13.584	0.525	11.984	15.177
Manufacturing LQ	114	1.212	0.627	0.206	3.364
Industrial diversity	114	0.881	0.036	0.746	0.939
MRE (Modified Robot Exposure)	114	26.808	9.164	10.422	59.643
RSDI (Robot Skill Demand Index)	114	27.939	6.547	13.043	54.745

Table 5. Logistics regression results of robot adoption

	Baseline model		Production volume controls		Advanced technologies controls	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	-3.690***	0.536	-3.668***	0.615	-4.575***	0.742
Log (employment)	0.393***	0.092	0.324***	0.105	0.178	0.118
Industry Dummies						
Auto	1.644***	0.426	2.146***	0.476	1.583***	0.538
Computer	0.165	0.422	0.665	0.463	0.286	0.504
Others durable	1.164***	0.362	1.386***	0.386	1.017**	0.432
Union dummy	0.340	0.467	-0.018	0.488	0.321	0.526
Offshoring dummy	0.194	0.361	0.099	0.383	-0.018	0.423
Reshoring dummy	1.020**	0.422	0.818*	0.433	0.304	0.473
Exporter dummy	-0.138	0.325	0.029	0.352	0.112	0.394
Production volume dummies						
Small batch			-1.060**	0.493	-1.076**	0.541
Somewhat small batch			0.133	0.361	0.406	0.399
Somewhat high volume			0.939**	0.384	1.236***	0.427
High volume			0.941**	0.409	1.066**	0.459
Advanced technology dummies						
Rapid prototyping					0.571*	0.343
Additive manufacturing					0.633*	0.365
CAD/CAM					0.472	0.449
Sensors and machine vision					0.952***	0.326
Advanced materials					0.162	0.354
CNC machines					0.582	0.357
Observations		411		365		365
Log likelihood		-208.396		-183.380		-162.996
Pseudo R-squared		0.1728		0.2647		0.2722

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% significance levels.

Table 6. Impacts of MSA-level variables on robot adoption

	Coefficient	Std. Err.	Avg. Marginal Effects	Std. Err.
Plant characteristics				
Constant	2.233	10.170		
Log (employment)	0.180	0.155	0.023	0.019
Industry Dummies				
Auto	0.929	0.698	0.120	0.092
Computer	0.288	0.593	0.035	0.071
Others durable	0.686	0.518	0.086	0.063
Union dummy	0.444	0.653	0.056	0.082
Offshoring dummy	0.053	0.524	0.007	0.066
Reshoring dummy	0.175	0.628	0.022	0.079
Exporter dummy	0.446	0.500	0.056	0.062
Production volume dummies				
Small batch	-1.157	0.709	-0.110*	0.059
Somewhat small batch	0.519	0.497	0.067	0.063
Somewhat high volume	1.835***	0.550	0.271***	0.079
High volume	1.352**	0.585	0.192**	0.087
Advanced technology dummies				
Rapid prototyping	0.533	0.428	0.067	0.053
Additive manufacturing	0.613	0.462	0.077	0.057
CAD/CAM	0.686	0.586	0.086	0.073
Sensors and machine vision	1.560***	0.428	0.196***	0.049
Advanced materials	0.396	0.434	0.050	0.054
CNC machines	0.251	0.444	0.032	0.056
MSA characteristics				
Log (employment density)	-0.060	0.265	-0.008	0.033
Average schooling years	-0.239	0.426	-0.030	0.053
Manufacturing LQ	-1.012*	0.567	-0.127*	0.070
Industrial diversity (SEI)	-8.597	9.755	-1.080	1.222
MRE	0.059**	0.025	0.007**	0.003
RSDI	0.097**	0.048	0.012**	0.006
Observations	292			
Log-likelihood	-114.577			
Pseudo R-squared	0.3461			

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% significance levels.

The log likelihood-ratio test result of the nested model is statistically significant at the 1% level.

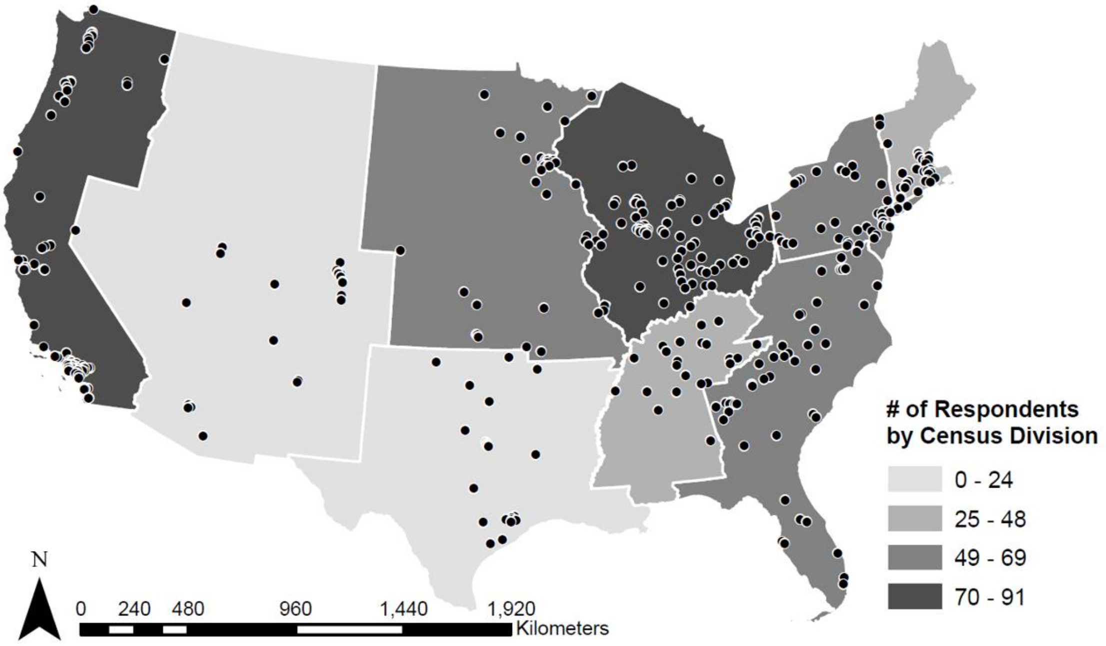
Table 7. Comparison of early- and late-robot adopters

Groups	Observation	Mean	DF	T-statistics
Log transformed employment			108	-3.792***
Early adopter	82	5.088		
Late adopter	26	3.861		
Reshoring dummy			116	1.482*

Early adopter	87	0.126		
Late adopter	29	0.241		
Auto-related industry dummy			116	-2.245**
Early adopter	87	0.264		
Late adopter	29	0.069		

Note: Statistical significance of presented t-statistics is based on one-tail tests. ***, **, * denote statistical significance at 1%, 5%, and 10% significance levels.

Figure 1. Geographical distribution of surveyed manufacturers



Note: Among 428 surveyed manufacturers, Figure represents the location of 400 surveyed manufacturers for which their exact location is known.

References

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and jobs: Evidence from US labor markets." *Journal of political economy* 128 (6):2188-244.

Ahn, Dong-Gyu. 2016. "Direct metal additive manufacturing processes and their sustainable applications for green technology: A review." *International Journal of Precision Engineering and Manufacturing-Green Technology* 3 (4):381-95.

Ancarani, Alessandro, Carmela Di Mauro, Luciano Fratocchi, Guido Orzes, and Marco Sartor. 2015. "Prior to reshoring: A duration analysis of foreign manufacturing ventures." *International Journal of Production Economics* 169:141-55.

Astebro, Thomas. 2004. "Sunk costs and the depth and probability of technology adoption." *The Journal of Industrial Economics* 52 (3):381-99.

Atkinson, Robert D. 2019. "Robotics and the Future of Production and Work." In.: Information Technology and Innovation Foundation.

Audretsch, David B, and Maryann P Feldman. 2004. "Knowledge spillovers and the geography of innovation." In *Handbook of regional and urban economics*, 2713-39. Elsevier.

Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The skill content of recent technological change: An empirical exploration." *The quarterly journal of economics* 118 (4):1279-333.

Ballestar, María Teresa, Ángel Díaz-Chao, Jorge Sainz, and Joan Torrent-Sellens. 2020. "Knowledge, robots and productivity in SMEs: Explaining the second digital wave." *Journal of Business Research* 108:119-31.

Bathelt, Harald, Anders Malmberg, and Peter Maskell. 2004. "Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation." *Progress in human geography* 28 (1):31-56.

Boschma, Ron. 2015. "Towards an evolutionary perspective on regional resilience." *Regional Studies* 49 (5):733-51.

Bougrain, Frédéric, and Bernard Haudeville. 2002. "Innovation, collaboration and SMEs internal research capacities." *Research policy* 31 (5):735-47.

Brossog, Matthias, Martin Bornschlegl, and Jörg Franke. 2015. "Reducing the energy consumption of industrial robots in manufacturing systems." *The International Journal of Advanced Manufacturing Technology* 78 (5-8):1315-28.

Christopherson, Susan, Jonathan Michie, and Peter Tyler. 2010. "Regional resilience: theoretical and empirical perspectives." In.: Oxford University Press.

Combes, Pierre-Philippe, Gilles Duranton, Laurent Gobillon, Diego Puga, and Sébastien Roux. 2012. "The productivity advantages of large cities: Distinguishing agglomeration from firm selection." *Econometrica* 80 (6):2543-94.

Doms, Mark, Timothy Dunne, and Kenneth R Troske. 1997. "Workers, wages, and technology." *The quarterly journal of economics* 112 (1):253-90.

Dunne, Timothy, and Kenneth Troske. 2005. "Technology adoption and the skill mix of US manufacturing plants." *Scottish Journal of Political Economy* 52 (3):387-405.

Duranton, Gilles, and Diego Puga. 2001. "Nursery cities: Urban diversity, process innovation, and the life cycle of products." *American economic review* 91 (5):1454-77.

Feldman, Maryann P, and David B Audretsch. 1999. "Innovation in cities:: Science-based diversity, specialization and localized competition." *European economic review* 43 (2):409-29.

Fernandez, Roberto M. 2001. "Skill-biased technological change and wage inequality: Evidence from a plant retooling." *American journal of sociology* 107 (2):273-320.

Frank, Alejandro Germán, Lucas Santos Dalenogare, and Néstor Fabián Ayala. 2019. "Industry 4.0 technologies: Implementation patterns in manufacturing companies." *International Journal of Production Economics* 210:15-26.

Fratocchi, Luciano. 2017. "Is 3D Printing an Enabling Technology for Manufacturing Reshoring?" In *Reshoring of Manufacturing*, 99-124. Springer.

Gertler, Meric S. 1995. "“Being there”: proximity, organization, and culture in the development and adoption of advanced manufacturing technologies." *Economic geography* 71 (1):1-26.

———. 2003. "Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there)." *Journal of economic Geography* 3 (1):75-99.

Glaeser, Edward L, Hedi D Kallal, Jose A Scheinkman, and Andrei Shleifer. 1992. "Growth in cities." *Journal of political economy* 100 (6):1126-52.

Gómez, Jaime, and Pilar Vargas. 2009. "The effect of financial constraints, absorptive capacity and complementarities on the adoption of multiple process technologies." *Research policy* 38 (1):106-19.

———. 2012. "Intangible resources and technology adoption in manufacturing firms." *Research policy* 41 (9):1607-19.

Graetz, Georg, and Guy Michaels. 2017. "Is modern technology responsible for jobless recoveries?" *American economic review* 107 (5):168-73.

———. 2018. "Robots at work." *Review of Economics and Statistics* 100 (5):753-68.

Griliches, Zvi. 1957. "Hybrid corn: An exploration in the economics of technological change." *Econometrica, Journal of the Econometric Society*:501-22.

Harrison, Bennett, Maryellen R Kelley, and Jon Gant. 1996. "Specialization versus diversity in local economies: The implications for innovative private-sector behavior." *Cityscape*:61-93.

Helper, Susan. 1995. "Supplier relations and adoption of new technology: results of survey research in the US auto industry." In.: National Bureau of Economic Research.

Henderson, Vernon. 1997. "Externalities and industrial development." *Journal of Urban Economics* 42 (3):449-70.

Henderson, Vernon, Ari Kuncoro, and Matt Turner. 1995. "Industrial development in cities." *Journal of political economy* 103 (5):1067-90.

International Federation of Robotics. "World Robotics Report 2017." IFR Press, Accessed September 26. https://ifr.org/ifr-press-releases/news/world-robotics-report-2016.

Jungmittag, Andre. 2020. "Robotisation of the manufacturing industries in the EU: Convergence or divergence?" *The Journal of Technology Transfer*:1-22.

Kelley, Maryellen R, and Susan Helper. 1999. "Firm size and capabilities, regional agglomeration, and the adoption of new technology." *Economics of Innovation and New technology* 8 (1-2):79-103.

Korus, Sam. 2019. "Industrial Robot Cost Declines Should Trigger Tipping Points in Demand." ARK Investment, Accessed Oct. 6, 2021. https://ark-invest.com/analyst-research/industrial-robot-cost-declines/.

Krein, Julius. 2019. "What Alexandria Ocasio-Cortez and Marco Rubio Agree On." In *The New York Times*.

Leigh, Nancey Green, Benjamin Kraft, and Heonyeong Lee. 2020. "Robots, skill demand and manufacturing in US regional labour markets." *Cambridge Journal of Regions, Economy and Society* 13 (1):77-97.

Leigh, Nancey Green, and Benjamin R Kraft. 2017. "Emerging robotic regions in the United States: insights for regional economic evolution." *Regional Studies*:1-13.

Mabert, Vincent A, Ashok Soni, and MA Venkataramanan. 2000. "Enterprise resource planning survey of US manufacturing firms." *Production and Inventory Management Journal* 41 (2):52.

Mandfield, Edwin. 1989. "The diffusion of industrial robots in Japan and the United States." *Research policy* 18 (4):183-92.

Mood, Carina. 2010. "Logistic regression: Why we cannot do what we think we can do, and what we can do about it." *European sociological review* 26 (1):67-82.

Park, Jeong-Il, and Nancey Green Leigh. 2017. "Foreign direct investment's role in strengthening metro manufacturing: a case study of the US state of Georgia." *Journal of Urban Affairs* 39 (5):597-617.

Pedersen, Mikkel Rath, Lazaros Nalpantidis, Rasmus Skovgaard Andersen, Casper Schou, Simon Bøgh, Volker Krüger, and Ole Madsen. 2016. "Robot skills for manufacturing: From concept to industrial deployment." *Robotics and Computer-Integrated Manufacturing* 37:282-91.

Pham, Anh-Duc, and Hyeong-Joon Ahn. 2018. "High precision reducers for industrial robots driving 4th industrial revolution: state of arts, analysis, design, performance evaluation and perspective." *International Journal of Precision Engineering and Manufacturing-Green Technology* 5 (4):519-33.

Raj, Manav, and Robert Seamans. 2018. "AI, labor, productivity, and the need for firm-level data." *Economics of artificial intelligence*.

Vernon, Raymond. 1966. "International investment and international trade in the product cycle." *The quarterly journal of economics*:190-207.

Waldman-Brown, Anna. 2020. "Redeployment or robocalypse? Workers and automation in Ohio manufacturing SMEs." *Cambridge Journal of Regions, Economy and Society* 13 (1):99-115.

Zolas, Nikolas, Zachary Kroff, Erik Brynjolfsson, Kristina McElheran, David N Beede, Cathy Buffington, Nathan Goldschlag, Lucia Foster, and Emin Dinlersoz. 2021. "Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey." In.: National Bureau of Economic Research.