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ABSTRACT

We use data from the Annual Survey of Manufactures to study the characteristics and geography of investments in robots across U.S. manufacturing establishments. We find that robotics adoption and robot intensity (the number of robots per employee) is much more strongly related to establishment size than age. We find that establishments that report having robotics have higher capital expenditures, including higher information technology (IT) capital expenditures. Also, establishments are more likely to have robotics if other establishments in the same Core-Based Statistical Area (CBSA) and industry also report having robotics. The distribution of robots is highly skewed across establishments' locations. Some locations, which we call Robot Hubs, have far more robots than one would expect even after accounting for industry and manufacturing employment. We characterize these Robot Hubs along several industry, demographic, and institutional dimensions. The presence of robot integrators and higher levels of union membership are positively correlated with being a Robot Hub.

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1. Introduction

New technologies are the key drivers of productivity growth (Romer 1990). Early evidence using national-level data from 17 countries between 1993 and 2007 suggests that robots, like prior generations of general-purpose technologies, are driving productivity growth (Graetz & Michaels 2018). Moreover, according to data on industrial robots compiled by the International Federation of Robotics (IFR), since 2010 the number of industrial robot shipments has nearly quadrupled, from about 100,000 to almost 400,000 per year, suggesting a growing impact of robots on the economy. Though robots are more common in manufacturing, other sectors are increasingly using robots. The overall impact of robots on the economy may be complex, which explains why scholars are still working to understand how robots affect firms, employment, and regional economies.

Broadly speaking, the literature has taken two approaches to studying these issues empirically. One approach uses the distribution of employment in each industry, across geographies, to allocate national industry-level counts of robot shipments compiled by the IFR. This approach was popularized by Acemoglu and Restrepo (2020) and has been used in numerous other studies, including those by Faber (2020) and Dauth et al. (2021). Critically, this approach assumes that the geographic distribution of robots for a given industry is the same as the distribution of employment for that industry.

A second approach uses administrative robot import data or survey data on robot use to identify firms that are adopting robots. Import data have been used to study the role of robots in firms in Canada (Dixon, Hong, and Wu 2021), France (Acemoglu, Lelarge, and Restrepo 2020; Bonfiglioli, Crino, Fadinger, and Gancia, 2021), Spain (Koch, Manulov, and Smolka 2021), and the Netherlands (Humlum 2021). Firm survey data are less common but have been used in the U.S. (Acemoglu et al. 2022), Germany (Benmelech and Zator 2021), and the Netherlands (Bessen, Goos, Salomons, and van den Berge 2019). One drawback of this approach is its focus on firms instead of establishments (since a firm might have establishments in multiple locations).

Given the drawbacks of both approaches, and their limitations in describing geographic variation in robot adoption, there have been calls for more systematic collection of data on robots and other new technologies at the establishment level (Mitchell and Brynjolfsson 2017; Raj and Seamans 2018). We address that need by describing new establishment-level data on robots collected by the U.S. Census Bureau's Annual Survey of Manufacturers (ASM) and documenting several findings from the data.

First, we characterize establishments with robots along several dimensions and find that establishments with robots have more employees, lower earnings per worker, a higher share of production workers, and more capital expenditures, including expenditures on computers and peripheral data processing equipment.

Second, we find that the physical distribution of robots is highly skewed across locations, even after accounting for differences in industry composition and manufacturing employment across locations. Some locations, which we call "*Robot Hubs*", have a very high concentration of establishments with robots after controlling for their industry mix. This finding suggests that there are limitations to using the aggregated IFR data to understand how robots affect local regions and firms. This finding also complements recent research by Green Leigh, Lee and Kraft (2022) on the geographic concentration of robot adoption.

Third, we characterize these Robot Hubs according to several industry, demographic, and institutional dimensions. We find that Robot Hubs are more likely to have higher union membership, have robot integrators (firms that specialize in helping manufacturers install robots), and have a higher share of production workers than other locations.

Our documentation of these patterns contributes to the literature in several ways. First, we call attention to the limitations of relying on data from IFR to measure the geographic distribution of robots and propose additional controls that could help address these limitations. Notably, the presence of integrators in a locality is highly correlated with establishment-level robot use in that area. Approaches that rely on the IFR data should therefore consider weighting the disaggregation in a way that accounts for integrators. Specifically, according to our results, an area with at least one integrator is 20-25 percentage points more likely to be a Robot Hub than an area with no integrators, everything else held constant. Second, given the geographic concentration of robot adoption, the local spillover effects from automation (positive or negative) will likely be experienced in relatively few areas.[2] Third, our findings on the presence of Robot

[2] The indirect effects of automation can be felt farther away in asmuch as robot-using firms operate in national markets and compete with firms outside their local area. Robot-adopting firms can gain market share and potentially displace less productive non-robot-using firms in geographically distant locations.

Hubs suggests that future research should dig deeper to understand the causes and consequences of agglomeration in technology adoption, similar to work in other settings, including automobiles (Klepper 2002), computing (Saxenian 1996), venture capital (Chen, Gompers, Kovner, and Lerner 2010), and patenting (Ellison, Glaeser, and Kerr 2010), to name a few. Finally, we document establishment-level characteristics of robot adopters and find suggestive evidence of complementarities. We hope these initial statistics spur additional research into how robots are affecting U.S. manufacturers, their workers, and communities.

The paper proceeds as follows. Section 2 describes the ASM robotics data. Section 3 describes characteristics of establishments with robotics. Section 4 presents evidence of the geographic variation of establishments using robots. Section 5 describes the characteristics of Robot Hubs. Section 6 concludes.

2. ASM Robotics Data

The Annual Survey of Manufacturers (ASM) is sent to a sample of approximately 50,000 establishments in the manufacturing sector every year.[3] The frame, constructed using the Census Bureau's Business Register and Economic Censuses (conducted every five years), is segmented into mail and non-mail components. The non-mail component, roughly two-thirds of all manufacturing establishments (approximately 187,000), contains plants that, due to their size, are not eligible to receive a mailed form. Data for these establishments are based on administrative records (e.g., employment) or are entirely imputed (e.g., using capital expenditures). The mail-eligible sample, roughly one-third of all manufacturing establishments (approximately 102,000), assigns all plants a stratified random probability of receiving a form; large plants are sampled with certainty, and the remainder are assigned probabilities proportionate to size and are sampled within industries and product classes. Of the mail-eligible sample, roughly half will be surveyed. Sample weights are applied to surveyed plants to recover the full mail-eligible sample. Our analyses focus on the subset of the mail-eligible sample with reported values, weighted with sample weights throughout. Our analysis shows that robot users are relatively large and disproportionately likely to fall into the eligible sample that we focus on. That said, in future years, it will be increasingly important to monitor the behavior of non-mail units, particularly if robots become more accessible to smaller establishments.

[3] See https://www.census.gov/programs-surveys/asm/technical-documentation/methodology.html for more information on ASM methodology.

In 2017, the U.S. Census Bureau, working together with external researchers, developed a series of questions on the adoption and use of robots. The questions underwent extensive cognitive testing, as described in Buffington, Miranda, and Seamans (2018). Starting with the 2018 wave, three questions about robots were included in the ASM. These questions asked manufacturers how many robots they were currently using, how many they had purchased, and how much they had spent on robotic equipment (see Appendix A for the definition of robot and the precise questions used). These questions were included in the 2018 through 2020 Annual Survey of Manufacturers.[4]

Similar types of questions about robots and other technologies have been included in two waves of the Census Bureau's Annual Business Survey (ABS).[5] Direct comparison between the ABS and ASM responses is challenging for several reasons. First, the ASM surveys manufacturing establishments, which may be associated with multi-unit firms, and the ABS surveys firms across all sectors, which may have multiple establishments. Second, the definition of robots provided to respondents on the survey forms are quite different---the ASM form provides significant detail about the type of equipment that should and should not be included, whereas the 2017 ABS does not. Finally, the ASM questions reference a single year whereas the ABS asks about a window of time. For comparison, we focus on the responses of single-unit manufacturing firms across the ASM and ABS. We find a significant share of firms that provide seemingly inconsistent responses across the surveys.[6]

According to summary statistics from the Census Bureau's experimental ASM tabulations on industrial robotic equipment, approximately 9.8% of plants surveyed in 2018 reported being exposed to robots.[7] Because robot-using plants tended to be larger, 22.5% of employment in

[4] See https://www.census.gov/library/publications/2022/econ/2019-asm-robotic-equipment.html for more information on the 2018 and 2019 ASM robot data.
[5] The ABS issued two waves of technology-focused modules that included questions about the use of robotics. The first, for ABS 2018 or "Year 1", focused on a broad set of advanced technologies including touch screens, machine vision, and robotics. The second, ABS 2019 or "Year 2", focused on the impacts of automation technologies such as specialized software and robotics, on workers.
[6] See Appendix B for additional details on ASM-ABS comparisons.
[7] The Census Bureau's ASM experimental products on industrial robotic equipment use a broad definition of exposure to robots that aggregates information on active robots, robots purchased, and capital expenditures on robotic equipment. See the experimental product methodology documentation for additional details.

manufacturing was in plants that had robots.[8] In 2019, approximately 11.1% of plants reported having one or more robots, representing 25.7% of manufacturing employment.

Robotics use varies significantly across manufacturing industries. For example, in 2018, the share of employment in plants with robots was 39.3% in the transportation equipment manufacturing industry (NAICS 336) but only 3.8% in the leather and allied products manufacturing industry (NAICS 316); the electrical equipment, appliance, and component manufacturing industry (NAICS 335) fell in between at 27.3%.

For the analyses we perform in this paper, we use the three robotics questions to identify plants that use robots or workers who are exposed to robots. We identify a plant as a robot user if it reports having active robots, having purchased robots, or having made capital expenditures on robots. Plants that report no active or purchased robots, and no capital expenditures on robots, are classified as not using robots.

Workers are considered to be exposed to robots if they work in a plant classified as using robots. This definition is the same as that used by the experimental ASM tabulations on industrial robotic equipment published by the U.S. Census Bureau. However, whereas the experimental products relied on imputed values for robot exposure, our analyses use only reported values. This is because, despite producing quality tabular estimates, establishment-level imputations of robot use are relatively noisy (Goldschlag et al. 2022). We augment our ASM responses with information on firm age and firm size drawn from the Longitudinal Business Database (LBD) (Miranda and Jarmin 2002; Chow et al. 2021).

Other research has highlighted the skewed adoption of technologies across firms of different size and age. For example, Acemoglu et al. (2022), reporting results from the 2019 Annual Business Survey, show that the share of firms reporting robot use increases with firm size, though appears to have a U-shaped relationship with firm age within 6-digit NAICS industries---that is, very young and very old firms are more likely to have robots than middle-aged firms.[9] This U-shaped relationship roughly holds across the firm age distribution. Moreover, the strong relationship between firm size and robot use appears to hold for other technologies as well, including AI,

[8] See https://www.census.gov/library/publications/2022/econ/2019-asm-robotic-equipment.html.

[9] The Annual Business Survey covers all non-farm sectors of the economy, including manufacturing. Both Acemoglu et al. (2022) and the analyses that follow use the same concept of firm size, which includes all of the firm's establishments both in manufacturing and other sectors.

dedicated equipment, specialized software, and cloud computing. Thus, our prior is that robot adoption also varies with *establishment* size and age distribution. While the correlation with size might be partly endogenous, the relationship with age is likely subject to complex technology adoption decisions by the firm as well as the level of robot penetration in the industry and prevalence within local geographies.

Table 1 provides robot use rates by establishment size and establishment age. Panel A presents the unadjusted use rates, and Panel B presents use rates de-meaned by industry (3-digit NAICS). We present industry de-meaned rates because production processes, average plant size, and robot use decisions may differ significantly by industry. The results in the two panels depict similar patterns: robot adoption appears to differ primarily by establishment size, with no obvious patterns by age. Larger establishments are much more likely to report having a robot than smaller establishments, even after controlling for industry composition.

To aid the comparison of differences between establishment and firm-level, Table 2 shows the percentage of establishments that use robots by firm age and firm size. We find similar patterns of rising use in firm size in the ASM data, with weak evidence that young high-growth manufacturing firms are more likely to adopt than established ones. For example, among the 250 to 999 size class, we find use rates to be higher among the 0-5 age bin than any of the other age bins.[10]

3. Patterns Among Establishments with Robots

Next, we investigate which establishments report using robots. To do this, we estimate a series of establishment-level OLS regressions on an indicator for whether the establishment uses robots. We include the following establishment-level variables: total capital expenditure (*Total CapEx*), IT capital expenditure (*IT CapEx*), other capital equipment expenditure (*Other CapEx*), production worker share (*Prod Worker Share*), pay per worker measured in the first quarter of the calendar year (*Pay/Worker*), and labor share (*Labor Share*). We bin establishments into quartiles for each capital expenditure variable. The first quartile is excluded from the regression, allowing us to

[10] The 42 year-old firm and establishment age bins correspond to the “Left Censored” group in the LBD, which are those firms that are first observed in 1976 and for which the LBD is unable to assign a definite age.

measure the relative propensity to use robots across the distribution of capital expenditures.Summary statistics and correlations for these variables are presented in Table 3.

We present the results two ways. First, in Table 4A, we walk in the variables described above. Column 1 includes only *Total CapEx* quartiles. The coefficients are positive and statistically significant, suggesting that establishments with higher capital expenditures are more likely to have robots. Moreover, we see that establishments with the most *Total CapEx* (Quartile 4) are the most likely to use robots. The difference in robot use between Quartile 1 and 4 is over four times larger than the gap between Quartile 1 and 2. Column 2 adds in *IT CapEx* quartiles. For *IT CapEx*, effects appear concentrated at the very top of the expenditure distribution with only the Quartile 4 estimate being positive and statistically significant. Column 3 adds in *Other CapEx*, which also has a positive and statistically significant coefficient. Meanwhile, the coefficient on *Total CapEx* in columns 2 and 3 remains positive and significant, though the magnitude drops. This suggests that the difference in capital expenditures between establishments with robots and those without is related to investments in other, possibly complementary, equipment. Across the first three columns, for each type of capital expenditures, we find coefficient estimates rising monotonically from establishments with the least to expenditures to those with the most. As shown in columns 4 and 5, we find that the coefficients on the CapEx variables are largely unchanged when we add *Prod Worker Share* and then *Pay/Worker* and *Labor Share*.

The coefficient on *Prod Worker Share* is positive and significant, suggesting that establishments with higher production worker share are more likely to use robotics -- one standard deviation above the mean is associated with a 1% higher likelihood of using robots. The coefficient on *Pay/worker* is negative and significant, suggesting that establishments with higher pay per worker are *less* likely to have a robot. We find no correlation between *Labor Share* and robot use in Table 4A.

Next, in Table 4B we replicate Table 4A but add firm size (indicators for 20-249, 250-999, 1000+ employees) and firm age (indicators for 6-15, 16-41, and 42+ years) fixed effects, 3-digit NAICS industry fixed effects, and state fixed effects.[11] These additional dummy variables help to control for a number of differences across establishments, including features related to their parent firm (size and age), industry, and geography. The magnitude of the coefficients reported in columns 1

[11] Firms first observed in the LBD in 1976 do not have a well defined firm age and are often labeled "Left Censored". Since our analyses focus on 2018, these firms have a firm age of at least 42 years.

through 5 drops relative to their counterparts in Table 4A, but the direction and significance remain unchanged, with the exception of *Labor Share*, where we now find a weak, negative relationship with robot use. We include an additional column that includes all the coefficients and fixed effects in column 5 along with establishment size (indicators for 20-99, 100-249, and 250+ employees) and age (indicators for 6-15, 16-41, and 42+ years) fixed effects. The magnitudes, direction, and significance are mostly unchanged with the exception of investments in IT, which are no longer related to robot use once we include establishment size and age controls.

Taken together, our results suggest that robot-using plants are relatively capital intensive (particularly in other types of capital), hire disproportionally more production workers, and pay lower average wages than their non-robot-using counterparts. At face value, these results suggest that robots are mostly complements to production workers, not substitutes for them.

To further explore the role of establishment and firm characteristics, we next estimate a series of regressions of the presence-of-robots indicator on firm and establishment size and age indicators. These results are presented in Table 5. Column 1 of Table 5 includes only the indicators for firm age and firm size. There is a notable pattern: none of the coefficients on firm age indicators are significant, whereas all the indicators on firm size are positive and significant relative to the smallest size category. Moreover, the coefficients appear to increase monotonically with firm size. This may in part reflect a mechanical relationship. Large firms may have more opportunities to use robots to the extent that they have more activities, workers, and production lines. Column 2 includes only indicators for establishment age and establishment size. Similar to the firm effects regression, none of the coefficients on establishment age indicators are significant while all the establishment size estimates are positive and significant. Moreover, the coefficients appear to increase monotonically with establishment size. Next, in column 3, we include all the indicators for firm age, firm size, establishment age, and establishment size. The coefficients for the establishment size groups are very similar to those in column 2, while the firm size effects have either lost significance or flipped signs, becoming negative rather than positive as in column 1. At the establishment level, establishment size seems to be a much stronger predictor of robot use than establishment age, firm size, or firm age.

In order to both assess the explanatory power of geography and show how firm and establishment effects change when we control for differences across geographies, column 4 adds in Core-Based Statistical Area (CBSA) fixed effects. The results are qualitatively similar to those presented in column 3, but the amount of variation explained (R^2) rises by over 47% from 0.080 to 0.118. The takeaway appears to be that, when trying to understand which establishments use robots, (1) size is more important than age, (2) establishment size is more important than firm size, and (3) geography appears to play an important role.

To further explore how geographic factors affect the decision to use robots, we next include indicators for "robot exposure." To do this, we compute each establishment's local geographic exposure to robots as captured by the robot use rate among all other establishments in the establishment's CBSA and 3-digit industry. Establishments in an industry-geography cell where many other establishments use robots will have a high robot exposure measure. We group establishments into quartiles based on their local exposure. Establishments will not have a local exposure measure, and will be excluded from the analysis, if (1) they are not located in a CBSA or (2) they are the only establishment within their CBSA and 3-digit industry.

Column 5 of Table 5 replicates column 3 but adds indicators for robot exposure quartiles (excluding quartile 1). The results on the firm and establishment age and size indicators are qualitatively similar to those presented in column 3. Of note, the coefficient for the largest robot exposure quartile is positive, significant, and more than twice as large in magnitude as the coefficient on the other two quartiles. Remember that the robot exposure measure is constructed at the industry and CBSA level. This suggests that even after accounting for industry and CBSA, robot adoption is not uniform, and instead varies with other geographic factors (in this case, the number of *other* local establishments that have also adopted robots).

As noted above, the strong positive relationship with firm size, in the absence of establishment size controls, could be mechanically related to large firms having more production lines at risk of automation. Table 6 explores the relationship between robot intensity (the number of robots per worker, inclusive of both production and non-production workers) and firm and establishment size and age. This analysis addresses the possible scale effects in the extensive margin of robot use and also sheds light on the presence, if any, of a minimum efficient scale in the use of robots. Column 1 of Table 6 includes only the indicators for firm age and firm size; Column 2 includes only the indicators for establishment age and establishment size; next, in column 3, we include all the indicators for firm age, firm size, establishment age, and establishment size; the final column includes controls for robot exposure.

The firm and establishment size and age patterns described in Table 5, which reflected extensive margin relationships, also appear on the intensive margin in Table 6. Coefficients increase monotonically with firm size (column 1) and establishment size (column 2), but firm size estimates become insignificant when controlling for establishment size (column 3). At the establishment level, establishment size is again a much stronger predictor of robot intensity than establishment age, firm size, or firm age. We find robot exposure is strongly related to the plant's robot intensity. The similarity in results between Tables 5 and 6 provide strong evidence that establishment size matters for the adoption of robots and size effects do not simply reflect mechanical extensive margin effects.

To illustrate the relationships between size, age, and geographic exposure, we present a series of histograms showing robot use rates broken out by these factors. Figure 1 presents a histogram of robot use rates by establishment age bins and robot exposure quartile. Robot use tends to increase with establishment age, although the pattern is not entirely monotonic. Notably, use also tends to increase with robot exposure, as we saw in Table 5 column 5. In Figure 1, the use rates for establishments in the fourth quartile of robot exposure lie above the use rates for all the establishments in the other quartiles. Regardless of its age, an establishment is much more likely to use robots if many other establishments in its industry and geography also use robots. Furthermore, younger establishments appear to be affected disproportionately by robot exposure.

Figure 2 presents a similar histogram, but breaks out the establishments by size instead of age. Here we see a much steeper gradient of use across establishment size bins, consistent with the regression results presented in Table 5. Robot exposure matters less in that there is no consistent difference in robot use rates (after accounting for size) across the first three quartiles of robot exposure. However, it is apparent that robot use is higher for establishments in the fourth quartile of robot exposure that are also large (100-249 and 250+ employees). The establishments that are both large and young –either high-growth establishments or establishments that were large from the outset – are most likely to be affected by robot exposure.

Figures 3 and 4 focus on the role of firm age and firm size. The patterns differ slightly from the establishment age and size results, but the importance of robot exposure remains noticeable. There appear to be clear differences in robot use across geographies, which we turn to next.

4. Geographic Variation of Robot Use

To explore the geographic variation in the count of robots, we compute the share of active robots across CBSAs. In contrast to the robot use analyses, which combined information on the count of robots, robot purchases, and capital expenditures on robotic equipment, here we focus on the count of active robots across geographies. Specifically, we classify CBSAs into ten equal sized bins based upon the count of active robots reported by establishments in each CBSA. We then compute the share of all active robots accounted for by CBSAs in each bin, which are shown in Figure 5. In Figure 5 we see significant concentration of industrial robotic equipment across geographic areas. In half of the CBSAs, almost no establishments report having a robot (deciles 1-5). In contrast, the top 10% of CBSAs, by count of active robots, have over 77% of all robots. As discussed earlier, use of robotic equipment varies dramatically across industries. As such, the geographic concentration of robots shown in Figure 5 may simply reflect the concentration of industries most likely to use robots. To control for industry composition effects, and given our sample size, we shift our analysis to the broader state geography and control for geography.

Figure 6 shows the distribution of industry de-meaned robot use rates for state-industry pairs. Here we again use our broader definition of robot usage that relies on the count of active robots, count of purchased robots, and capital expenditures on robotic equipment. For each state-industry cell, we compute the robot use rate in that cell and subtract from it the national use rate in the associated industry. For a given industry, a state with a robot use rate higher than the industry average is assigned a positive de-meaned use rate; a state with lower robot use rates is assigned a negative de-meaned value. De-meaning the data in this way allows us to focus on the differences in robot use within industries, across geographies. The figure shows two versions of the histogram – one weighted by state-industry and one where each state-industry is weighted by its number of establishments.

The figure shows that even within industry, robot use rates vary significantly by state. Many state-industry pairs fall below the national industry use rates and are assigned a negative de-meaned use rate. Almost 27% of state 3-digit NAICS combinations have use rates more than 5 percentage points lower than their associated national 3-digit NAICS average. Moreover, the Figure 6 exhibits a long right tail, where a relatively small number of state-industry pairs have higher use rates than the average by industry. We find that over 12% of state-industry pairs have use rates more than 10 percentage points higher. This dispersion of within-industry use rates does not simply reflect variation in relatively small, noisy cells. On an employment weighted basis, 15% of state-industry pairs have use rates more than 5 percentage points lower than the national rate, and 16% have use rates 5 percentage points higher than the national rate.

Figure 7 demonstrates this within industry variation across geography for an industry that has significant robot usage--Auto Manufacturing industry (NAICS 336). We group states into four equally sized bins based upon the robot use rate of auto manufacturing establishments in the state, limiting the analysis to those states that have auto manufacturing establishments. The bottom quarter of states, by use rate, have an average use rate of less than 1%. In contrast, the 25% of states with the highest use rates have an average use rate of 39%. This suggests that even in an industry where plants are more likely to use robots, the use of robots is dramatically higher in some geographies than in others.

5. Robot Hubs

We want to understand what local characteristics are associated with robot activity. To better focus our analysis on geographies that exhibit higher-than-expected use rates, we create a binary indicator that flags CBSAs with higher use rates than one would expect given their industry mix.[12] We identify these geographies in several steps. First, we de-mean CBSA industry-level (3-digit NAICS) use rates by subtracting from each the national industry-level use rates (similar to Figure 6). This provides a measure of how intensively an industry within a given CBSA uses robots relative to other geographies with activity in that industry. Second, we aggregate to the CBSA level by computing the average of the de-meaned use rates, weighting by the number of reported establishments in the CBSA-industry cell. Finally, we identify the geographies in the top 25% of the average, de-meaned use rate distribution that also have at least 20 reported establishments. We call these geographies "Robot Hubs." Geographies that are flagged as Robot Hubs have, across their manufacturing industries, higher robot use rates than the typical use rates in those industries.

[12] It is important to abstract away from industry mix for this type of analysis because a geography might have a high overall use rate because it has a significant amount of activity in a high-use industry, such as Auto Manufacturing (NAICS 336), even if the manufacturing establishments in that geography adopted at a lower rate than the typical auto manufacturing plant.

To explore the characteristics of Robot Hubs, we run a series of OLS regressions, at the CBSA level, on an indicator for whether the CBSA is a Robot Hub. We include several CBSA-level variables motivated by insights found in the literature. Some of the most salient co-variates of the adoption of automation technologies such as robotics includes complementary investments (Brynjolfsson, Jin and McElheran 2021), the cost and skill of labor (Acemoglu et al., 2022), and historical agglomeration effects. With these relationships in mind, we use data on the location of integrators from the Robotics Industry Association to construct an indicator for the presence of one or more robot integrators in the CBSA (*Has Integrator*). We integrate data on the percentage of employees with union membership (*Union Membership*) (Hirsch and Macpherson 2003). We create an indicator for whether the CBSA was historically a top manufacturer, defined as being a CBSA in the top 40 of manufacturing employment 30 years earlier, using data from the Business Dynamics Statistics (*Top Manuf 30 Yrs Prior*). Using data from the American Community Survey, we compute the share of population with a high school degree or less (*Share with High Sch Deg*) and the share of population with a bachelor's degree (*Share with Bachelor's Deg*). Using data from the Occupational Employment and Wage Statistics, we compute the share of employees working in a STEM-related occupation (*Share of STEM Workers*) and the share of production workers (*Share of Prod Workers*). Summary statistics and correlations for these variables are presented in Table 7.

In Table 8 we present results from a series of OLS regressions correlating different local characteristics and our Robot Hub indicator. Note that we restrict our sample to the 250 CBSAs for which we have data on each of the variables presented in Table 7 to allow for easier comparison across the columns. Column 1 includes an indicator for the presence of one or more integrators in the CBSA. This indicator, *Has Integrator*, is positive and statistically significant. The coefficient of approximately 0.24 means that CBSAs with one or more integrators are approximately 24% more likely to be a Robot Hub. In columns 2 through 5 additional variables are added sequentially into the same regression. The coefficient on *Has Integrator* remains positive and statistically significant, ranging in value from approximately 0.2 to 0.25. Column 2 adds in *Union Membership*, column 3 adds in the indicator *Top Manuf 30 Yrs Prior,* column 4 adds in *Share with High Sch Deg* and *Share with Bachelor's Deg*, and column 5 adds in *Share of STEM Workers* and *Share of Prod Workers*. In column 5, which includes all the CBSA-level variables, *Has Integrator, Union Membership*, and *Share of Prod Workers* are all positive and statistically significant. None of the other variables are significant. The most important correlates of the higher-than-expected use of robots in a given geography is the presence of robot integrators, union membership, and the share of production workers.

Finally, we compare the relationship between the CBSA characteristics we find to be informative in Table 8 with other measures found in the literature. Acemoglu and Restrepo (2020) find that geographies that were more exposed to robots, as measured by robot penetration in similar industries in European countries, saw declines in their employment-to-population ratio and log hourly wages. In Table 9, we estimate regressions similar to those in Table 8, but including the change in employment-to-population ratio and log hourly wage measures.[13] Here we focus on direct exposure to robots as measured by the ASM data rather than instrumenting using penetration in other countries as done by Acemoglu and Restrepo (2020). We find no statistically significant relationship with the change in employment-to-population ratio (column 1) but a statistically significant negative correlation with changes in log hourly wages (column 3). When included along side our measures from Table 8, we find that the presence of integrators and union membership remain strongly positively associated with Robot Hubs. We also find that the relationship with changes in log hourly wages (column 4) weakens in significance.

6. Conclusions

In this paper we present results on the distribution of robots in U.S. manufacturing by establishment characteristics and geography using new establishment-level data collected by the U.S. Census Bureau's Annual Survey of Manufacturers for reference year 2018. This is the first establishment-level analysis of the use of robots in U.S. manufacturing, leveraging data on approximately 35,000 establishments.

We find that establishments with robots tend to be larger, have higher earnings per worker, have a larger share of production workers, and spend more on capital expenditures, including IT, than establishments without robots. These patterns are suggestive of complementarities between

[13] The change in employment-to-population ratio and change in log hourly wage measures in Acemoglu and Restrepo (2020) are observed at the commuting zone-level, a higher level of geographic aggregation than the CBSA codes we use. To incorporate these measures into our data we concord the commuting zone employment-to-population measures to CBSA codes, then take the mean across the duplicate many-to-many matches, weighted by the 1990 population counts used in Acemgolu and Restrepo (2020). We do the same for the change in log hourly wage measure, aggregating across commuting zone-demographic group combinations, again weighting by the size of those groups.

robot adoption and IT, a pattern seen with other types of technologies (Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson, Jin and McElheran 2021). Moreover, they suggest that robot-using plants tend to be those that hire a disproportionately higher share of production workers than non-robot-using plants of similar size and age.

We also find that the distribution of robots is highly skewed across locations, even after accounting for the different mix of industry and manufacturing employment across locations. Some locations, which we call Robot Hubs, have far more robots than one would expect after accounting for industry mix. Robot Hubs tend to be in areas that have at least one robot integrator, higher union membership, and a higher share of production workers than other locations. These patterns may be useful to researchers who are relying on aggregate data to infer the presence of robots, such as the data from the International Federation of Robots used in papers by Acemoglu and Restrepo (2020), Faber (2020), and Dauth et al. (2021). Our findings may also be useful to scholars studying patterns of adoption of other types of technologies, such as those documented in Aghion et al. (2021), Bessen et al. (2020) and others.

Given the cross-sectional nature of the data—the data are currently available for 2018, but additional years will soon be available—the correlations we observe are not necessarily causal. Nevertheless, the patterns in the data provide useful information about the distribution of robots across establishments and geographies. In particular, they raise questions about *why* the distribution of robots appears to be so geographically skewed, as well as the role Robot Hubs play in the regional performance and outcomes of firms and workers, providing a useful starting point for future research.

The patterns we find in the data raise multiple questions for future research. For example, does the minimum efficient scale for robot adoption vary with establishment characteristics? Also, why is union membership positively correlated with Robot Hubs? Is this because establishments in areas with more union membership have a greater incentive to adopt robots to substitute for labor? Or is it because of complementarities, perhaps arising from collaboration in training and adaptation of the workforce to new technologies?

There are also a number of interesting follow-on questions for future research. One set of questions concerns the link between robot adoption and international trade. Such questions include: Do robot adopters experience an increase in export activity? Have Robot Hubs seen an increase in reshoring? How have Robot Hubs been affected by supply chain disruptions? Another set of questions concerns the link between robot adoption and other investments: Do adopters spend more on R&D, software, or other intangible investments? Do they spend more on purchased technical services, which should include payment to integrators? And, how much value is captured by the integrators themselves, and what accounts for them not being more geographically widespread? Our hope is that the patterns in the data that we document in our paper spark further research in this area that are of use to scholars, practitioners and policymakers.

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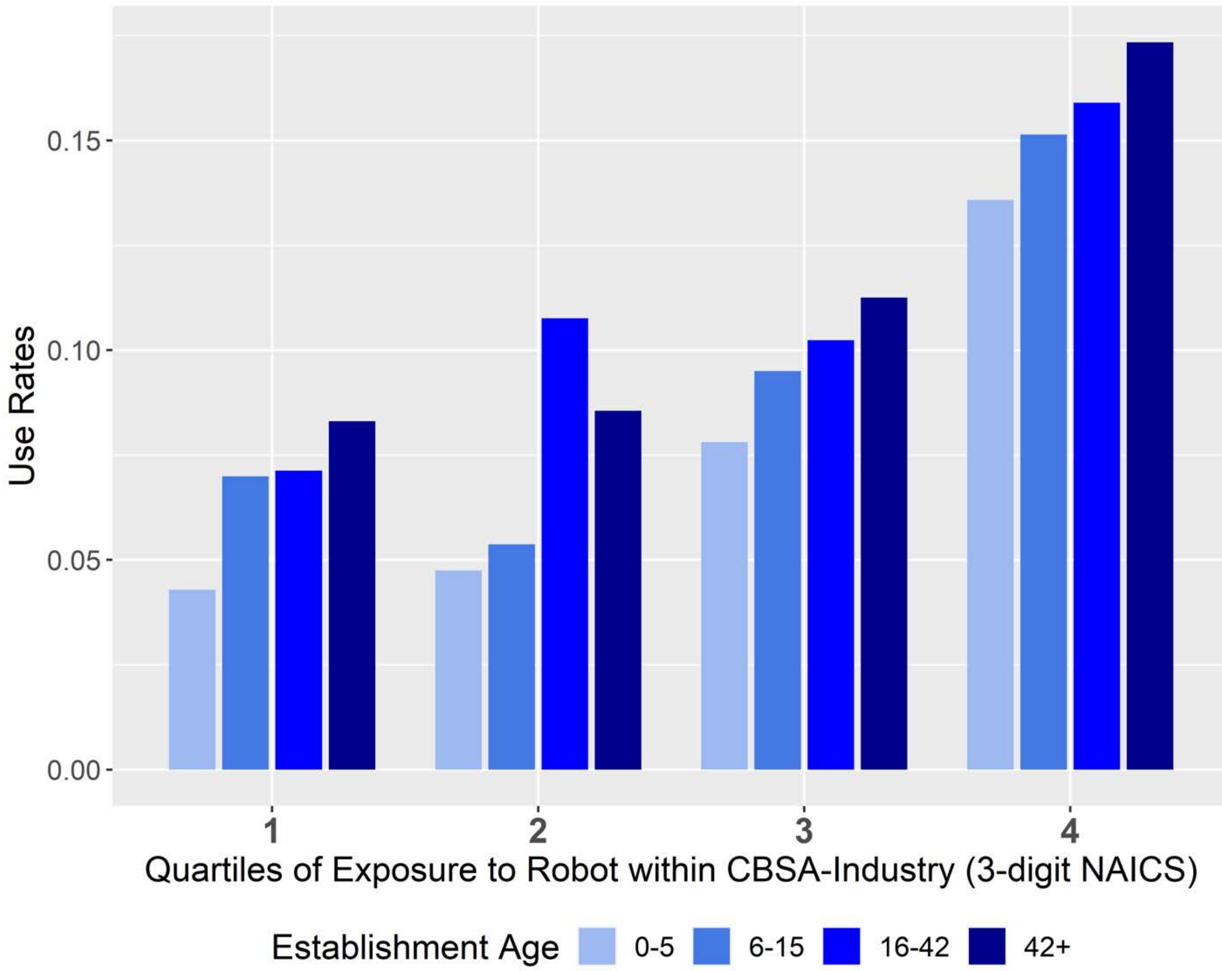
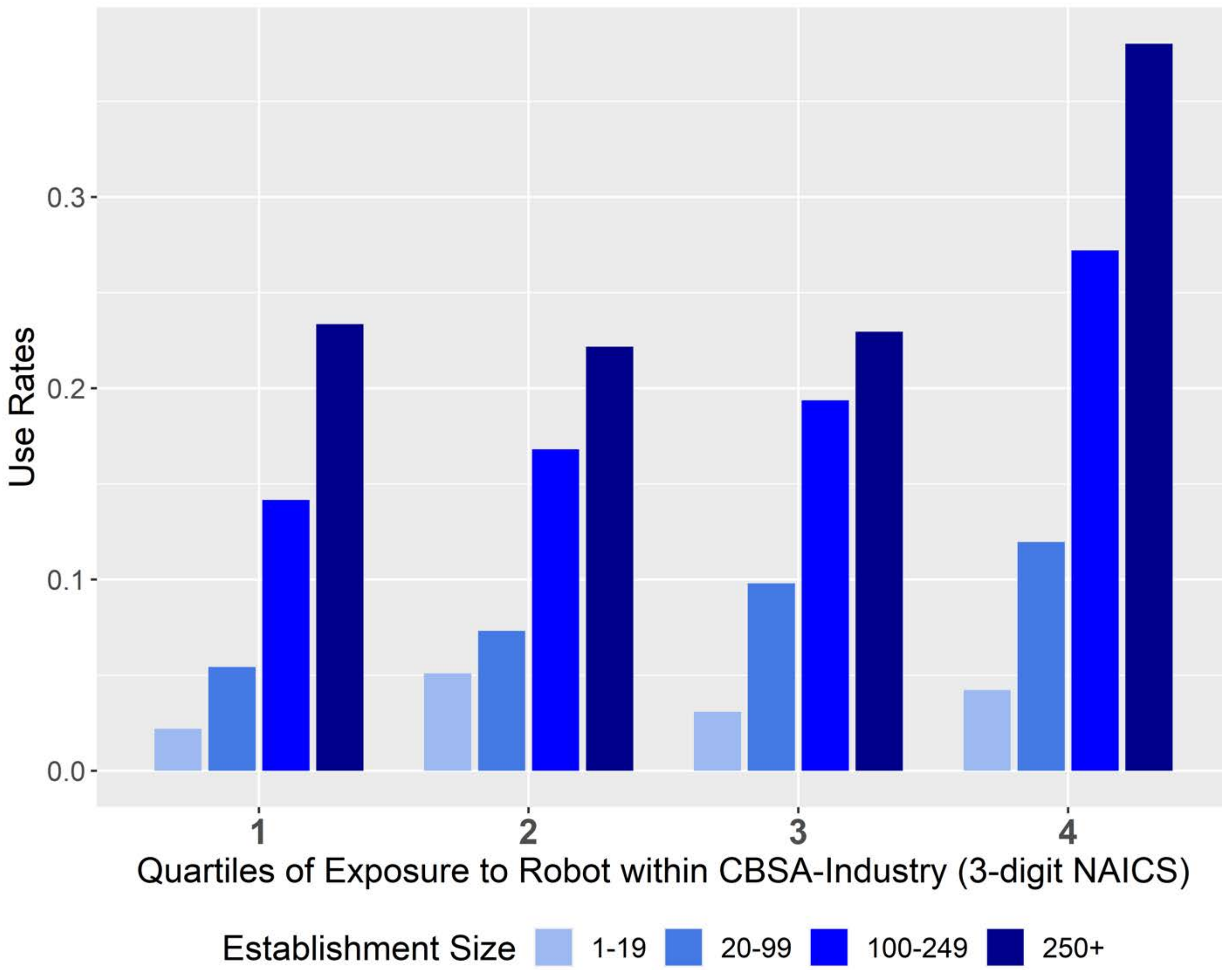
Figures and Tables

Figure 1: Histogram of Robot Use Rates by Robot Exposure and Establishment Age



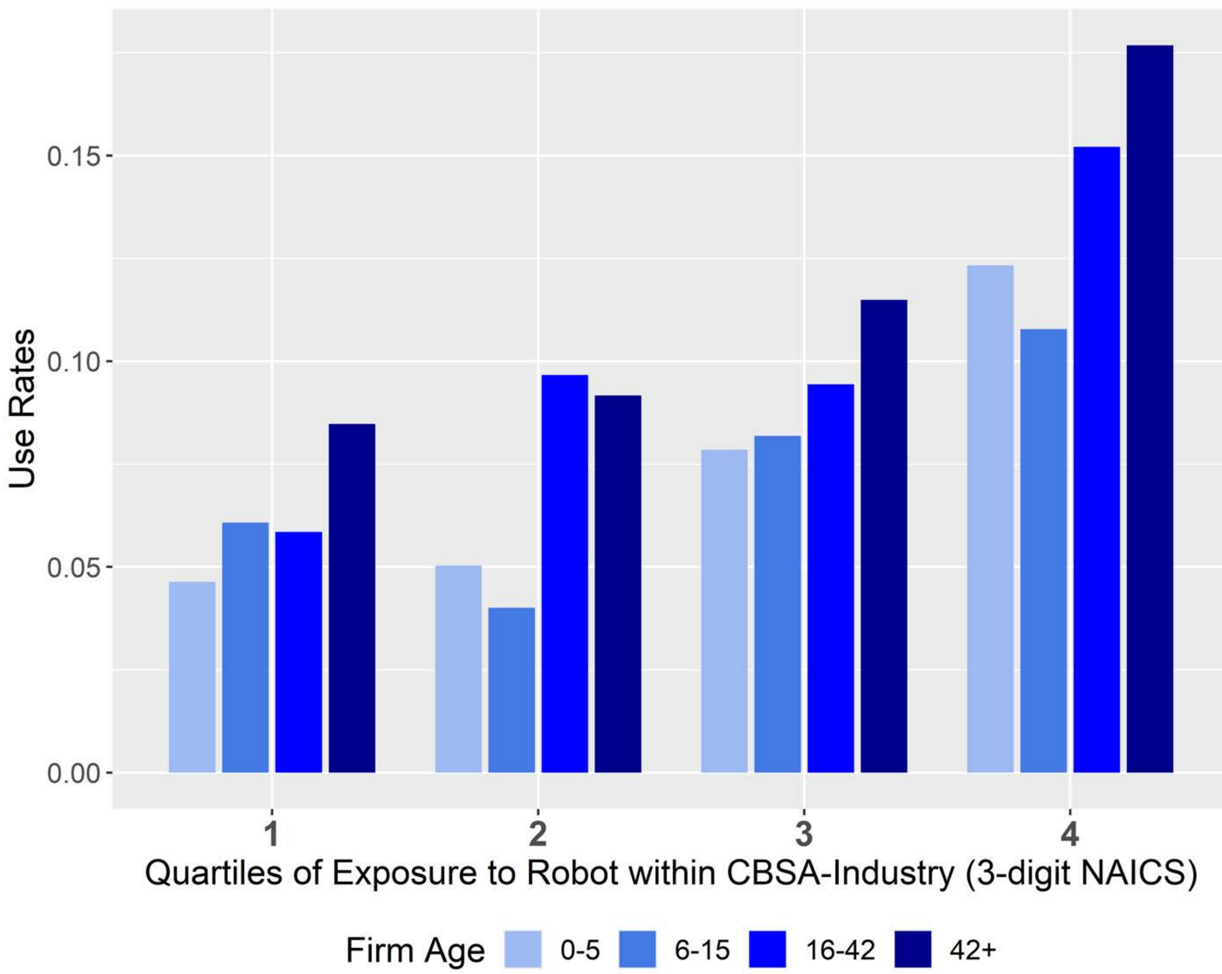
Note: Figure shows establishment-level use rates (0 to 1) by CBSA-industry-level exposure and establishment age. Establishment age is derived from the LBD and based upon the first year the establishment had positive employment in the pay period that includes March 12. CBSA-industry-level exposure is computed as the use rate among all other establishments within the focal establishment's CBSA-industry cell. The use rate measure is then classified into four equal-sized quartile bins (quartiles). Establishments are weighted using ASM sample weights.

Figure 2: Histogram of Robot Use Rates by Robot Exposure and Establishment Size



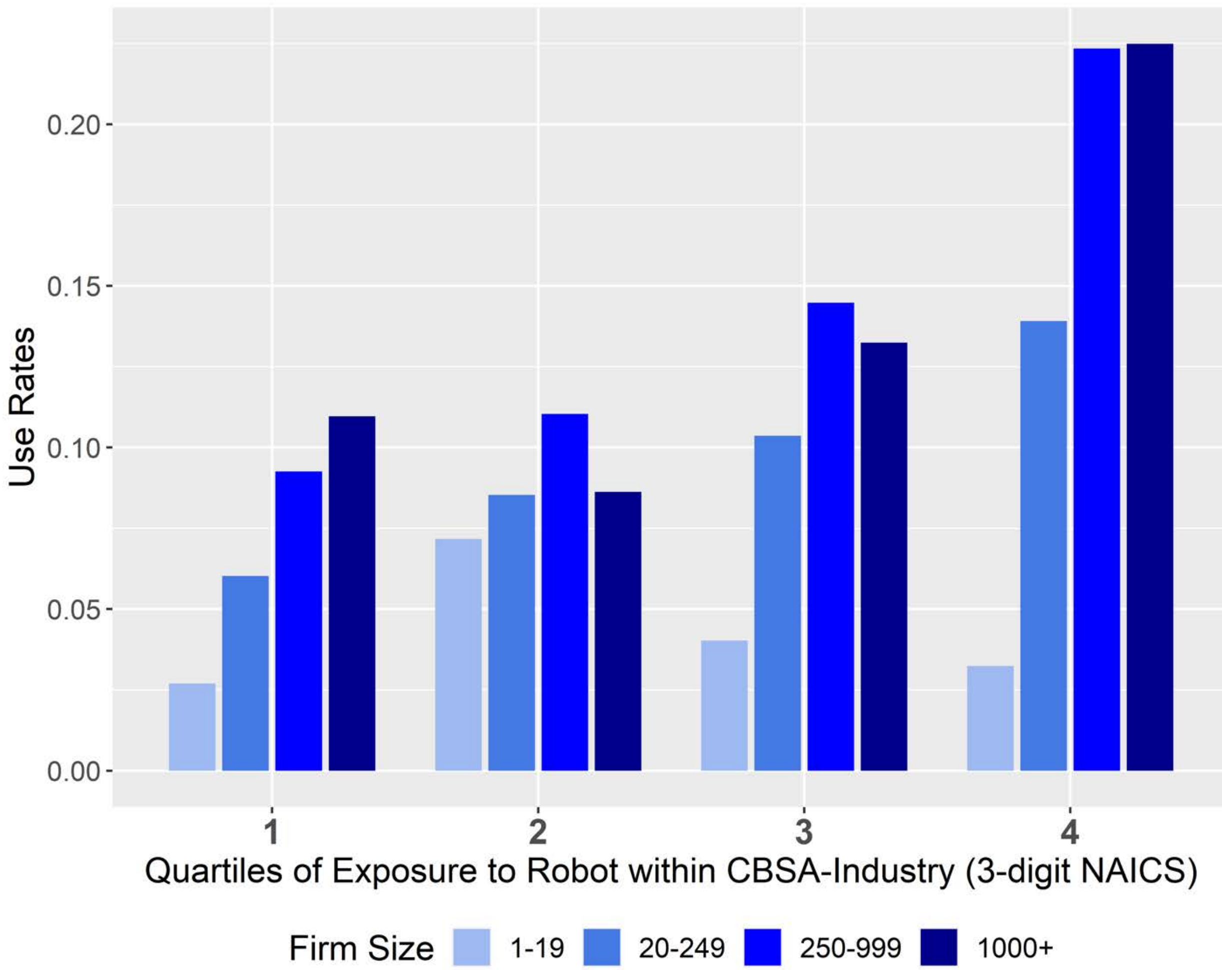
Note: Figure shows establishment level use rates (0 to 1) by CBSA-Industry-level exposure and establishment size. Establishment size is total employment in the pay period that includes March 12. CBSA-Industry-level exposure is computed as the use rate among all other establishments within the focal establishment's CBSA-industry cell. The use rate measure is then classified into four equal-sized quartile bins (quartiles). Establishments are weighted using ASM sample weights.

Figure 3: Histogram of Robot Use Rates by Robot Exposure and Firm Age



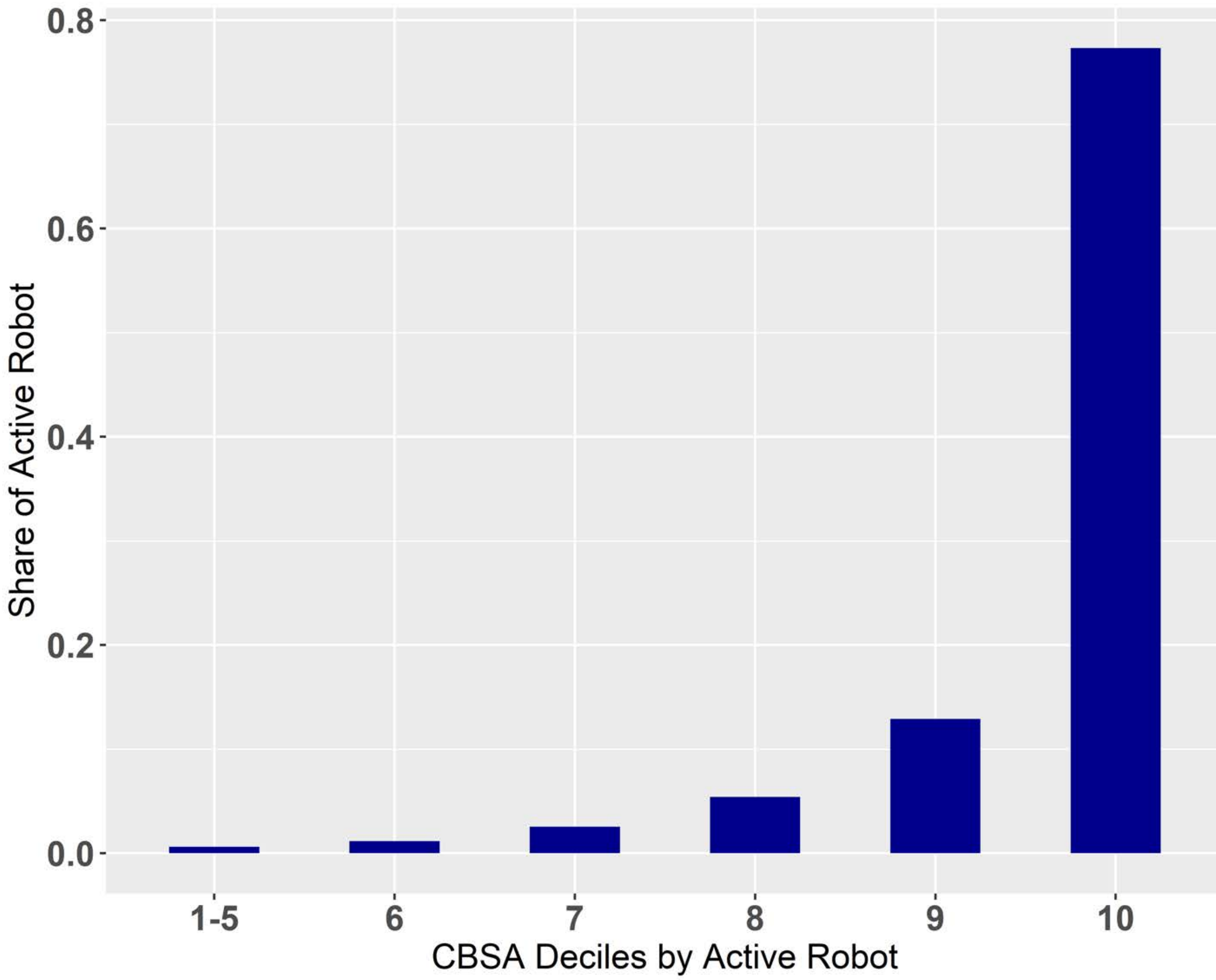
Note: Figure shows establishment-level use rates (0 to 1) by CBSA-industry-level exposure and firm age. Firm age is derived from the LBD and is based upon the age of the old establishment in the year the firm is first observed. CBSA-industry-level exposure is computed as the use rate among all other establishments within the focal establishment's CBSA-industry cell. The use rate measure is then classified into four equal-sized quartile bins (quartiles). Establishments are weighted using ASM sample weights.

Figure 4: Histogram of Robot Use Rates by Robot Exposure and Firm Size



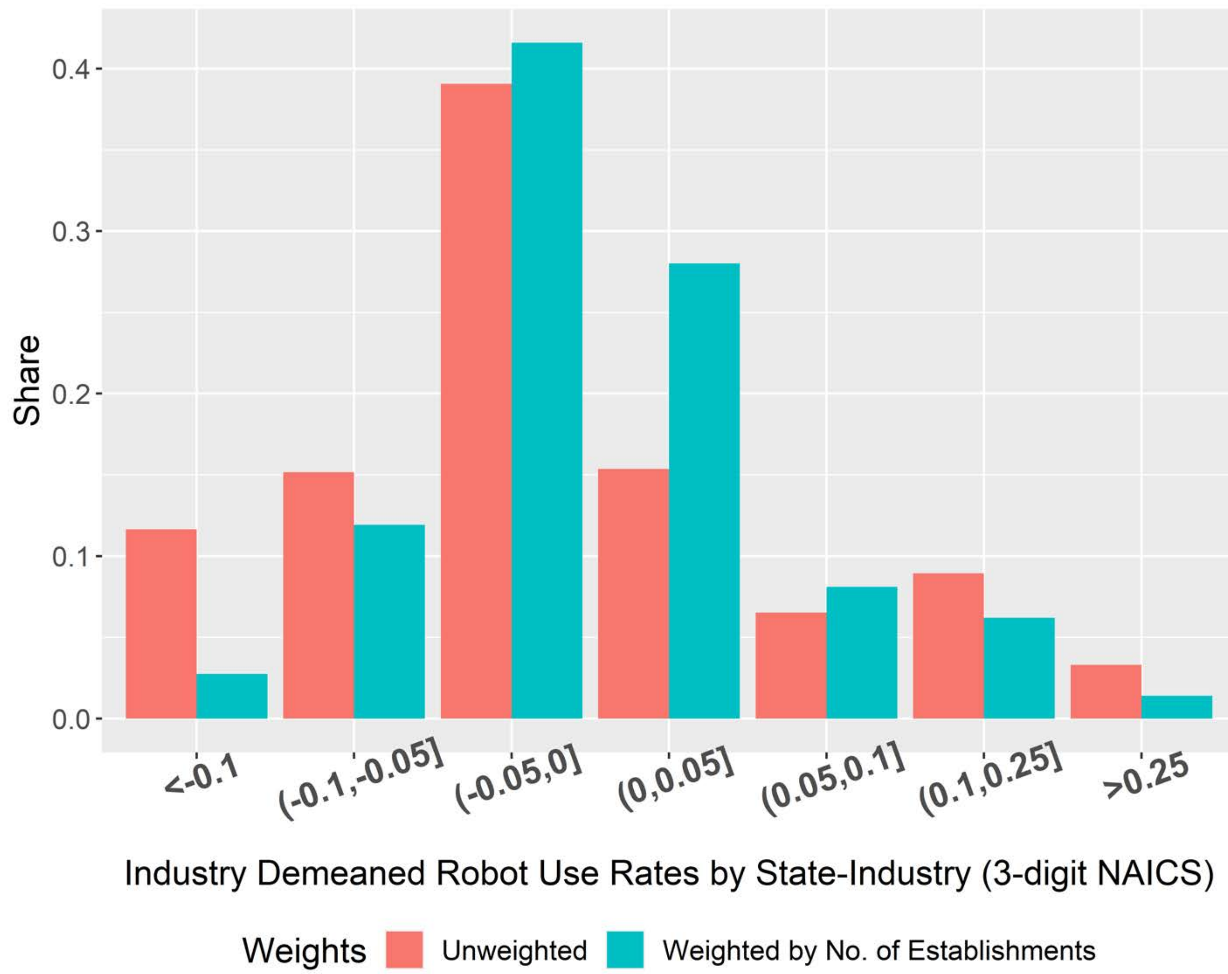
Note: Figure shows establishment-level use rates (0 to 1) by CBSA-industry-level exposure and firm size. Firm size is derived from the LBD and is based upon the total employment across the firm's establishments. CBSA-industry-level exposure is computed as the use rate among all other establishments within the focal establishment's CBSA-industry cell. The use rate measure is then classified into four equal-sized quartile bins (quartiles). Establishments are weighted using ASM sample weights.

Figure 5: Histogram of Active Robots by CBSAs



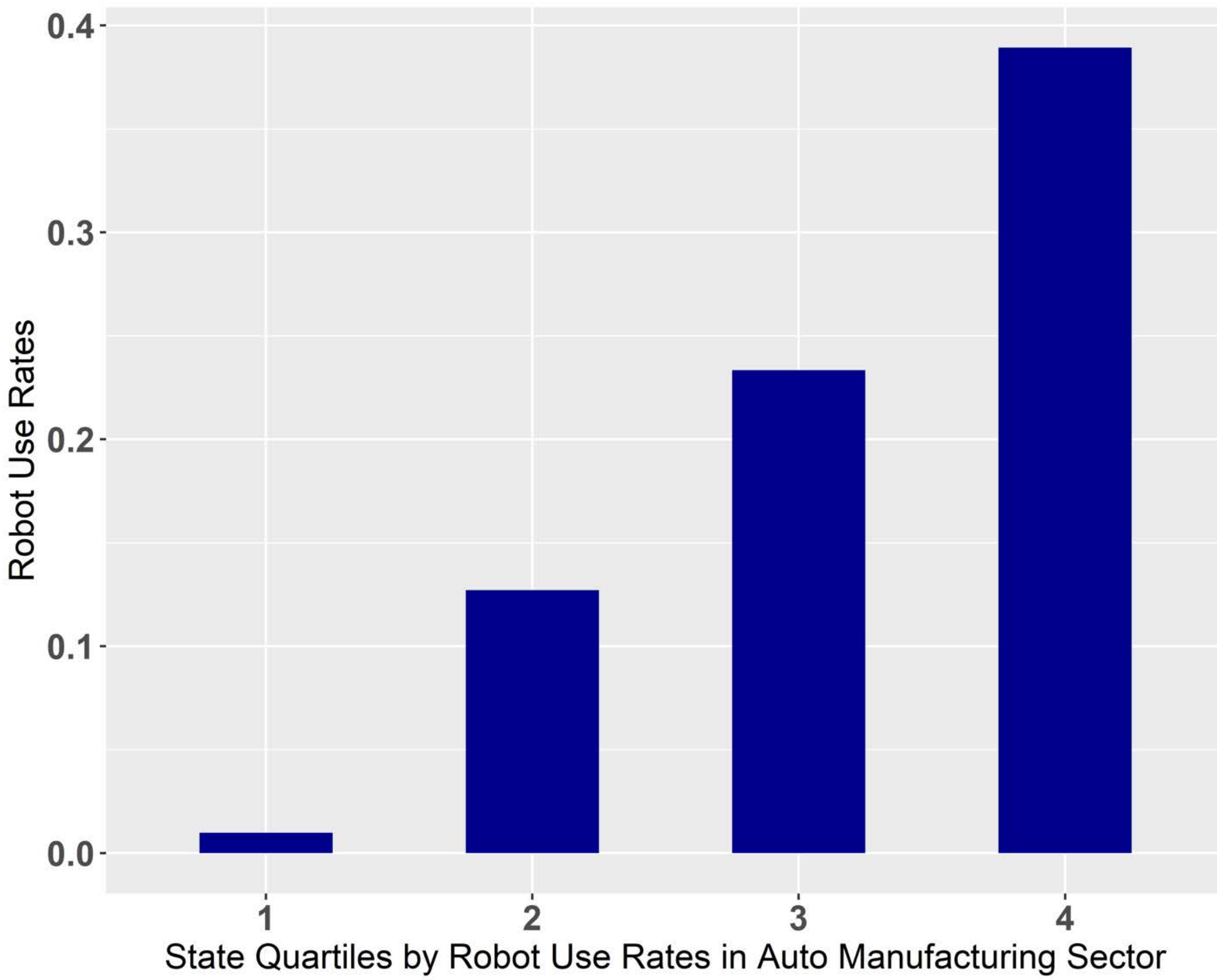
Note: Figure shows the share of all active robots measured using responses to the question “What was the number of industrial robots IN OPERATION at this plant?” The total count of all active robots is computed for each CBSA and then CBSAs are classified into 10 equal-sized bins (deciles) based on the number of active robots in the CBSAs. The share of all active robots is the computed for CBSAs within each bin. Establishments are weighted using ASM sample weights.

Figure 6. Distribution of Industry De-meaned State-Industry Robot Use Shares



Note: Figure shows the share of state-industry pairs within de-meaned use rate bins, unweighted, and weighted by the count of establishments in the state-industry cell. De-meaned use rate bins are computed by subtracting the national industry use rate associated with a given state-industry pair. Positive de-meaned values reflect state-industry cells where the use rate in that state-industry is higher than the national use rate for that industry. Establishments are weighted using ASM sample weights.

Figure 7. Auto Manufacturing Robot Use Rates



Note: Figure shows the robot use rate within groupings of states in the Automobile Manufacturing industry (NAICS 336). States with automobile manufacturing employment are grouped into four equal-sized bins (quartiles) based on the use rate of automobile manufacturing establishments in the state. Establishments are weighted using ASM sample weights.

Table 1: Robot Use Rates (Panel A) and Industry De-Meaned Use Rates (Panel B) by Establishment Age and Size

Panel A	Establishment Age			
Estab Size	0-5	6-15	16-41	42+
1-19	3.02%	2.89%	3.83%	2.33%
20-99	8.49%	8.97%	8.25%	8.23%
100-249	18.84%	19.65%	19.55%	19.66%
250+	25.70%	29.08%	29.09%	29.44%

Panel B	Establishment Age			
Estab Size	0-5	6-15	16-41	42+
1-19	-10.13%	-9.95%	-9.08%	-11.37%
20-99	-5.81%	-4.76%	-5.90%	-6.11%
100-249	3.86%	4.85%	4.76%	4.84%
250+	10.41%	13.26%	13.84%	14.40%

Notes: Panel A presents robot use rates by establishment age and establishment size bins. Panel B presents robot use rates de-meaned by industry. To construct the de-meaned use rates, we first compute the use rate by establishment age, establishment size, and 3-digit NAICS, then subtract from each cell the national use rate by 3-digit NAICS. Last, we take the mean of each of these cells, weighting by the total number of establishments in each cell. Subtracting the national 3-digit NAICS use rate means some cells will have negative values. Establishments are weighted using ASM sample weights.

Table 2: Robot Use Rates by Firm Age and Size

	Firm Age			
Firm Size	0-5	6-15	16-41	42+
1-19	4.49%	3.90%	4.50%	1.88%
20-249	8.55%	8.38%	9.67%	9.78%
250-999	22.73%	14.76%	15.58%	13.33%
1000+	-	-	13.54%	14.95%

Notes: This table presents robot use rates by firm age and firm size bins. Some firm size and firm age bins are excluded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights.

Table 3: Summary Statistics and Pairwise Correlations for Establishment Characteristics

	Mean	Std Dev	N	Total CapEx	IT CapEx	Other CapEx	Prod Worker Share	Pay/Worker (1st QTR)	Labor Share
Total CapEx	2,906	26,510	35,000	1					
IT CapEx	84.65	842	35,000	0.2045	1				
Other CapEx	2,134	20,660	35,000	0.9514	0.1503	1			
Prod Worker Share	0.74	0.21	35,000	-0.005744	-0.04342	-0.003119	1		
Pay/Worker (1st QTR)	13.79	7.38	35,000	0.1064	0.08826	0.1019	-0.221	1	
Labor Share	0.22	0.15	35,000	-0.06784	-0.03413	-0.06471	-0.07126	-0.07971	1

Notes: This table presents summary statistics (mean, standard deviation, number of observations) and pairwise correlations for the variables we use in establishment level regressions. The data come from the 2018 Annual Survey of Manufactures (ASM). Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights.

Table 4A. OLS Regressions of Robot Presence on Establishment Characteristics

	Dependent Variable: Robot Use Indicator				
Variables	(1)	(2)	(3)	(4)	(5)
Total CapEx					
Quartile 2	0.04684***	0.04187***	0.02592***	0.02472***	0.02515***
	[0.004879]	[0.004982]	[0.005731]	[0.00574]	[0.005749]
Quartile 3	0.1119***	0.1032***	0.05261***	0.05135***	0.0518***
	[0.005482]	[0.005725]	[0.008516]	[0.00852]	[0.008565]
Quartile 4	0.2025***	0.19***	0.06249***	0.06145***	0.06248***
	[0.006047]	[0.00676]	[0.01125]	[0.01123]	[0.01128]
IT CapEx					
Quartile 2		0.0001584	0.0002543	0.00001589	0.00008735
		[0.005047]	[0.005021]	[0.00501]	[0.005014]
Quartile 3		0.007761	0.008434	0.009247*	0.009231*
		[0.005501]	[0.005493]	[0.005493]	[0.005484]
Quartile 4		0.02726***	0.02609***	0.0301***	0.03057***
		[0.006769]	[0.006728]	[0.006748]	[0.006774]
Other CapEx					
Quartile 2			0.01362**	0.015***	0.01485***
			[0.00557]	[0.005594]	[0.005591]
Quartile 3			0.05215***	0.05293***	0.05361***
			[0.008162]	[0.008168]	[0.008154]
Quartile 4			0.1511***	0.1509***	0.1523***
			[0.01141]	[0.01138]	[0.01143]
Prod Worker Share				0.04917***	0.04353***
				[0.008415]	[0.008449]
Pay/Worker (1st QTR)					-0.0007523***
					[0.0002559]
Labor Share					-0.003019
					[0.01364]
Firm Age FE	N	N	N	N	N
Firm Size FE	N	N	N	N	N
State FE	N	N	N	N	N
Industry (3-digit NAICS) FE	N	N	N	N	N
Establishment Age FE	N	N	N	N	N
Establishment Size FE	N	N	N	N	N
Observations	35,000	35,000	35,000	35,000	35,000
R-squared	0.05566	0.0566	0.06505	0.0661	0.06636

Notes: This table presents results from establishment-level OLS regressions on an indicator for whether the establishment has a robot. Independent variables are “walked in” from columns 1 to 5. Establishments are binned into quartiles based upon each type of capital expenditure with the first quartile indicator for each type excluded from the regression. No firm or establishment age or size dummies are included. No state or industry dummies are included. The data come from the 2018 Annual Survey of Manufactures (ASM). Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Significance is indicated with *** p<0.01, ** p<0.05, * p<0.1

Table 4B. OLS Regressions of Robot Presence on Establishment and Firm Characteristics

	Dependent Variable: Robot Use Indicator					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Total CapEx						
Quartile 2	0.03799***	0.03431***	0.02382***	0.02311***	0.02304***	0.01876***
	[0.004791]	[0.004844]	[0.00567]	[0.005666]	[0.005691]	[0.005715]
Quartile 3	0.09387***	0.08779***	0.05133***	0.05082***	0.05059***	0.03852***
	[0.005385]	[0.005576]	[0.008336]	[0.008337]	[0.008372]	[0.008446]
Quartile 4	0.1764***	0.1676***	0.06498***	0.065***	0.06517***	0.0387***
	[0.00636]	[0.007]	[0.01092]	[0.0109]	[0.01095]	[0.01087]
IT CapEx						
Quartile 2		-0.0006304	-0.000508	-0.0007493	-0.0006228	-0.0001015
		[0.004979]	[0.004967]	[0.004958]	[0.004957]	[0.004933]
Quartile 3		0.007597	0.007512	0.00791	0.008116	0.007845
		[0.005414]	[0.005428]	[0.005424]	[0.005424]	[0.005393]
Quartile 4		0.01827***	0.0172**	0.01995***	0.02057***	0.007946
		[0.006797]	[0.006778]	[0.006764]	[0.006768]	[0.0068]
Other CapEx						
Quartile 2			0.009157	0.0103*	0.01026*	0.01092*
			[0.005657]	[0.00567]	[0.005666]	[0.005655]
Quartile 3			0.03788***	0.03847***	0.03896***	0.03231***
			[0.008235]	[0.008237]	[0.008228]	[0.008203]
Quartile 4			0.1273***	0.1271***	0.1282***	0.1019***
			[0.01141]	[0.01139]	[0.01139]	[0.01149]
Prod Worker Share				0.04707***	0.03986***	0.0404***
				[0.009561]	[0.009281]	[0.009238]
Pay/Worker (1st QTR)					-0.001035****	-0.000843***
					[0.00029]	[0.0002864]
Labor Share					-0.02605*	-0.04207***
					[0.01519]	[0.01523]
Firm Age FE	Y	Y	Y	Y	Y	Y
Firm Size FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Industry (3-digit NAICS) FE	Y	Y	Y	Y	Y	Y
Establishment Age FE	N	N	N	N	N	Y
Establishment Size FE	N	N	N	N	N	Y
Observations	35,000	35,000	35,000	35,000	35,000	35,000
R-squared	0.08891	0.08935	0.09519	0.09607	0.09663	0.1082

Notes: This table presents results from establishment-level OLS regressions on an indicator for whether the establishment uses robots. Establishments are binned into quartiles based upon each type of capital expenditure with the first quartile indicator for each type excluded from the regression. Dummy variables for firm and establishment age and size are included where indicated. Dummy variables for state and industry dummies are included where indicated. Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Significance is indicated with *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. OLS Regressions of Robot Presence on Firm and Establishment Age and Size Class Dummies

Variables		Dependent Variable: Robot Use Indicator (1)	(2)	(3)	(4)	(5)
Firm Age						
	6-15	-0.004096		-0.01913*	-0.01854*	-0.01817*
		[0.008238]		[0.01006]	[0.01003]	[0.01003]
	16-41	0.005671		-0.006715	-0.006685	-0.006676
		[0.006459]		[0.007885]	[0.008093]	[0.007877]
	42+	0.002832		0.0008745	0.002146	0.001154
		[0.007134]		[0.009373]	[0.009533]	[0.009371]
Firm Size						
	20-249	0.04749***		-0.001821	-0.00435	-0.001624
		[0.006144]		[0.006498]	[0.006578]	[0.006455]
999	250-	0.08994***		-0.01569*	-0.02025**	-0.0163*
		[0.008731]		[0.009511]	[0.009482]	[0.009473]
	1000+	0.09405***		-0.01854**	-0.02095**	-0.01897**
		[0.008011]		[0.009468]	[0.009406]	[0.009444]
Establishment Age						
	6-15		0.005832	0.01397*	0.01159	0.01321
			[0.006928]	[0.008544]	[0.008154]	[0.008509]
	16-41		0.004743	0.005816	0.004975	0.005768
			[0.004922]	[0.006022]	[0.006201]	[0.006007]
	42+		-0.001647	-0.005986	-0.008653	-0.006305
			[0.005638]	[0.007644]	[0.007801]	[0.00762]
Establishment Size						
	20-99		0.04387***	0.04576***	0.04587***	0.04532***
			[0.004908]	[0.005148]	[0.005144]	[0.00513]
249	100-		0.1499***	0.1556***	0.1542***	0.1546***
			[0.006797]	[0.007115]	[0.007204]	[0.00711]
	250+		0.2291***	0.2404***	0.2369***	0.2398***
			[0.008706]	[0.009546]	[0.009631]	[0.009527]
Robot Exposure						
2						0.01748**
						[0.007184]
3						0.001587
						[0.005884]
4						0.03528***
						[0.00592]
3-digit NAICS FE		Y	Y	Y	Y	Y
CBSA FE		N	N	N	Y	N
Observations		29,500	29,500	29,500	29,500	29,500
R-squared		0.04372	0.07969	0.08014	0.1184	0.08227

Notes: This table presents results from establishment-level OLS regressions on an indicator for whether the establishment has a robot. All the regressions include dummy variables for 3-digit NAICS code. Column 1 includes firm age and size dummy variables. Column 2 includes only establishment age and size dummy variables. Column 3 includes both firm and establishment age and size dummy variables. Column 4 replicates column 3 and adds in CBSA dummy variables. Column 5 replicates column 3 and adds in dummy variables for quartiles of exposure to other robot-adopting establishments. The excluded age categories are the youngest (age 0 to 5) and the excluded size categories are the smallest (employment of 1 to 19). Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Significance is indicated with *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. OLS Regressions of Active Robots Intensity on Firm and Establishment Age and Size Class Dummies

		Dependent Variable: Active Robots / Emp			
Variables		(1)	(2)	(3)	(4)
Firm Age					
	6-15	0.01999		-0.124	-0.1137
		[0.1362]		[0.1581]	[0.1585]
	16-41	0.1293		-0.06666	-0.06124
		[0.1001]		[0.1249]	[0.125]
	42+	0.1173		0.0391	0.0479
		[0.1057]		[0.1356]	[0.1359]
Firm Size					
	20-249	0.9839***		-0.03802	-0.04239
		[0.1625]		[0.1569]	[0.1569]
	250-999	1.431***		-0.1824	-0.1963
		[0.1715]		[0.1739]	[0.174]
	1000+	1.427***		-0.26	-0.2701
		[0.1704]		[0.1752]	[0.1753]
Establishment Age					
	6-15		0.06018	0.1073	0.09934
			[0.09836]	[0.1122]	[0.1124]
	16-41		0.09278	0.1065	0.1047
			[0.07377]	[0.08751]	[0.08737]
	42+		0.04038	-0.01361	-0.02284
			[0.07875]	[0.09781]	[0.09766]
Establishment Size					
	20-99		1.034***	1.067***	1.065***
			[0.1306]	[0.1118]	[0.112]
	100-249		2.019***	2.099***	2.094***
			[0.1317]	[0.1142]	[0.1144]
	250+		2.46***	2.609***	2.612***
			[0.136]	[0.1244]	[0.1244]
Robot Exposure					
	2				0.1664
					[0.1101]
	3				0.02438
					[0.07807]
	4				0.333***
					[0.06402]
Industry (3-digit NAICS) FE		Y	Y	Y	Y
Observations		29,500	29,500	29,500	29,500
R-squared		0.04372	0.07969	0.08014	0.08227

Notes: This table presents results from establishment-level OLS regressions on the number of robots per worker at the establishment. All the regressions include dummy variables for 3-digit NAICS code. Column 1 includes firm age and size dummy variables. Column 2 includes only establishment age and size dummy variables. Column 3 includes both firm and establishment age and size dummy variables. Column 4 replicates column 3 and adds in dummy variables for quartiles of exposure to other robot-adopting establishments. The excluded age categories are the youngest (age 0 to 5) and the excluded size categories are the smallest (employment of 1 to 19). Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Significance is indicated with *** p<0.01, ** p<0.05, * p<0.1

Table 7. Summary Statistics for CBSA Characteristics

	Mean	Std Dev	N	Has Integrator	Union Membership	Top Manuf 30 Yr Prior	Share of High Sch Deg	Share of Bachelor's Deg	Share of STEM Workers	Share of Prod Workers
Has Integrator	0.1934	0.3958	250	1						
Union Membership (%)	5.579	4.678	250	0.1004	1					
Top Manuf 30 Yrs Prior	0.1481	0.356	250	0.4703	0.06714	1				
Share with High Sch Deg	27.79	5.773	250	-0.07442	0.0141	-0.1512	1			
Share with Bachelor's Deg	18.65	4.46	250	0.2258	-0.00353	0.2819	-0.691	1		
Share of STEM Workers	4.742	2.823	250	0.3148	0.04764	0.3983	-0.4877	0.6565	1	
Share of Prod Workers	6.141	3.979	250	0.0861	-0.0347	-0.00203	0.3316	-0.2081	-0.1224	1

Notes: This table presents summary statistics (mean, standard deviation, number of observations) and pairwise correlations for the variables we use in CBSA level regressions. The data sources are listed in the text. Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Shares are in percentage points.

Table 8. OLS Regressions of Robot Hub on CBSA Characteristics

	Dependent Variable: Robot Hub Indicator				
Variables	(1)	(2)	(3)	(4)	(5)
Has Integrator	0.2419***	0.2235***	0.2465***	0.2256***	0.1955**
	[0.07756]	[0.07837]	[0.08597]	[0.08743]	[0.08624]
Union Membership (%)		0.01543***	0.01552***	0.01562***	0.01637***
		[0.005357]	[0.005349]	[0.005339]	[0.005126]
Top Manuf 30 Yrs Prior			-0.05441	-0.07037	-0.08223
			[0.08841]	[0.08999]	[0.09049]
Share with High Sch Deg				0.01209**	0.007648
				[0.006082]	[0.006134]
Share with Bachelor's Deg				0.01598**	0.01324
				[0.008051]	[0.00881]
Share of STEM Workers					0.008282
					[0.01199]
Share of Prod Workers					0.02049**
					[0.009091]
Observations	250	250	250	250	250
R-squared	0.05146	0.08043	0.08207	0.09854	0.133

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

Notes: This table presents results from CBSA-level OLS regressions on an indicator for whether the CBSA is a Robot Hub. Independent variables are "walked in" from columns 1 to 5. Sources of the data are listed in the paper. Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Significance is indicated with *** p<0.01, ** p<0.05, * p<0.1

Table 9. Robot Hubs, CBSA Characteristics, and Changes in Employment and Wages

	Dependent Variable: Robot Hub Indicator			
Variables	(1)	(2)	(3)	(4)
Change in Employment/Population 1990-2007 (A&R 2020)	-0.02046	-0.009728		
	[0.01454]	[0.01599]		
Change in Log Hourly Wages 1990-2007 (A&R 2020)			-0.02096***	-0.009272
			[0.006651]	[0.007103]
Has Integrator		0.1928**		0.1786**
		[0.08597]		[0.08702]
Union Membership (%)		0.01787***		0.01653***
		[0.005187]		[0.00529]
Top Manuf 30 Yrs Prior		-0.09654		-0.08751
		[0.09338]		[0.0918]
Share with High Sch Deg		0.008843		0.006895
		[0.006199]		[0.006145]
Share with Bachelor's Deg		0.01559*		0.01501*
		[0.008898]		[0.008954]
Share of STEM Workers		0.005878		0.006115
		[0.01214]		[0.0118]
Share of Prod Workers		0.01827*		0.01715*
		[0.009567]		[0.009151]
Observations	250	250	250	250
R-squared	0.008701	0.1372	0.04003	0.1417

Notes: This table presents results from CBSA-level OLS regressions on an indicator for whether the CBSA is a Robot Hub. Sources of the data are listed in the paper. Change in employment-to-population ratio and change in log hourly wages are derived from Acemoglu and Restrepo (2020). Observation counts have been rounded to avoid the disclosure of sensitive information. Establishments are weighted using ASM sample weights. Significance is indicated with *** p<0.01, ** p<0.05, * p<0.1

Appendix A – ASM Robotics Survey Form

Figure A1. Industrial Robots and Robotic Equipment Module in the 2018 ASM Questionnaire

OMB No.: 0607-0449

Approval Expires: 04/30/2022

2018 Annual Survey of Manufactures (ASM)

MA-10000 - Annual Survey of Manufactures

Item 28: Special Inquiries - Industrial Robots and Robotic Equipment

.

EIN:
Store / Plant:
CFN:

ITEM 28: SPECIAL INQUIRIES - INDUSTRIAL ROBOTS AND ROBOTIC EQUIPMENT

INDUSTRIAL ROBOTIC EQUIPMENT

- Industrial robotic equipment (or industrial robots) are automatically controlled, reprogrammable, and multipurpose machines used in the industrial automated operations.
- Industrial robots may be mobile, incorporated into stand-alone stations, or integrated into a production line.
- An industrial robot may be part of a robotic cell (or work cell) or incorporated into another piece of equipment.
- Industrial robots are commonly used in operations such as welding, material handling, machine tending, dispensing, cleanroom, and pick and place.

REPORTING INDUSTRIAL ROBOTIC EQUIPMENT

- Estimates are acceptable.
- In (A), report capital expenditures in 2018 for new and used industrial robotic equipment for this establishment. Include other one-time costs, including software and installation.
- In (B) and (C), report the number of industrial robots in operation at this establishment and purchased for this establishment in 2018.
- For robots purchased as part of a work cell or other integrated robotic equipment, it may not be possible to report the expenditures on only the robots. In this case, report the expenditures on the integrated robotic equipment.

Examples of operations industrial robotic equipment can perform may include:

- Palletizing
- Pick and place
- Machine tending
- Machine handling
- Dispensing
- Welding
- Packing/repacking

Exclude:

- Automated guided vehicles (AGVs)
- Driverless forklifts
- Automated storage and retrieval systems
- CNC machining equipment

A. What were the capital expenditures in 2018 for new and used industrial robotic equipment, including software, installation, and other one-time costs?

Check if None ☐ | 2018 | $ ____ ,000.00

B. What was the number of industrial robots IN OPERATION at this plant in 2018?
If you are unable to provide the number of industrial robots IN OPERATION in 2018, please explain:

☐ | 2018 Number

C. What was the number of industrial robots PURCHASED for this plant in 2018?
If you are unable to provide the number of industrial robots PURCHASED in 2018, please explain: ☐

Appendix B – ASM and ABS Robotics Survey Response Comparison

In this section, we provide cross-tabulations that compare 2018 ASM with 2017 ABS (Year 1) and 2018 ABS (Year 2) robot use results. Since ASM surveys establishments and ABS surveys firms, a direct comparison between ASM and ABS is challenging because non-using establishments in ASM could be owned by a multi-unit robot user in ABS where the using establishments are not sampled by the ASM. To remedy this, we restrict the cross-tabulation sample to single-unit manufacturing firms. Due to this sample restriction, firm and establishment are synonymous in the following analyses. To broaden the analysis, we aggregate ABS intensity percentage ranges (Less than 5%, 5%-25%, and More than 25%) into adoption and “No use” and “Testing” into non-using. The ASM robot adoption is defined as in Section 2.

The cross-tabulation results are presented in Tables B1-B4. In Table B1, we find that a majority (86.3%) of ASM-ABS Year 1 matched single-unit firms report the same robot adoption pattern: 76% both No-No and 10.3% Yes-Yes. 9.9% of firms report Yes in ABS but No in ASM, and 3.8% firms report the opposite. Table B2 reports an employment-weighted version of Table B1. The rate of Yes-Yes matches are much higher. This reflects the fact that most robot users have a larger number of employees than non-robot users. We compare ASM Year 1 with ABS Year 2 in Table B3-B4, and the results are similar to the Year 1 comparisons.

Despite our efforts to make the samples comparable, we still find more than 10% (roughly 20% if weighted by employment) of firms report their robot adoption differently in ASM and ABS. There are several reasons we might expect ASM and ABS responses to differ, even when focusing on single unit manufacturing firms. First, ASM and ABS provide different definitions of robot adoption. Even between ABS Year 1 and ABS Year 2 the definitions offered on the form vary significantly. Second, differences in the time window of measurement between ASM and ABS may cause differences in response patterns. ASM surveys establishment robot use in 2018 while ABS surveys firms’ robot use in a three-year window (2015-2017 in ABS Year 1 and 2016-2018 in ABS Year 2). Thus, de-adoption of robots in 2018 would yield a No in ASM but a Yes in ABS, and first adoption in 2018 would yield a Yes in ASM but a No in ABS Year 1. Furthermore, firm restructuring may also result in the off-diagonal differences. For example, a multi-unit firm that spins off its only robot-using establishment before 2018 would report a Yes in ABS but a No in ASM. In addition to these conceptual issues, respondent recall errors (in the case of the windowed responses of ABS) and classical measurement error may explain some fraction of the disagreements between ASM and ABS.

Table B1. ASM Year 1 vs ABS Year 1 Robot-Use Cross-Tabulation, Establishment Weighted

	ABS Yr 1 Robot Use		
ASM Yr 1 Robot Use	No	Yes	Total
No	76.0%	9.9%	85.9%
Yes	3.8%	10.3%	14.1%
Total	79.8%	20.2%	100.0%

Notes: Table shows the percent of establishments (single unit firms) that respond as robot users (yes) or non-users (no) in the ASM and the ABS Year 1. No sample weights are used.

Table B2. ASM Year 1 vs ABS Year 1 Robot-Use Cross-Tabulation, Employment Weighted

	ABS Yr 1 Robot Use		
ASM Yr 1 Robot Use	No	Yes	Total
No	62.3%	14.2%	76.50%
Yes	4.3%	19.2%	23.50%
Total	79.8%	20.2%	100.0%

Notes: Table shows the percent of establishments (single unit firms) that respond as robot users (yes) or non-users (no) in the ASM and the ABS Year 1. Establishments are weighted by employment. No sample weights are used.

Table B3. ASM Year 1 vs ABS Year 2 Robot-Use Cross-Tabulation, Establishment Weighted

	ABS Yr 2 Robot Use		
ASM Yr 1 Robot Use	No	Yes	Total
No	73.2%	11.8%	85.00%
Yes	2.3%	12.7%	15.00%
Total	79.8%	20.2%	100.0%

Notes: Table shows the percent of establishments (single unit firms) that respond as robot users (yes) or non-users (no) in the ASM and the ABS Year 2. No sample weights are used.

Table B4. ASM Year 1 vs ABS Year 2 Robot-Use Cross-Tabulation, Employment Weighted

	ABS Yr 2 Robot Use		
ASM Yr 1 Robot Use	No	Yes	Total
No	56.2%	18.2%	74.40%
Yes	2.5%	23.1%	25.60%
Total	79.8%	20.2%	100.0%

Notes: Table shows the percent of establishments (single unit firms) that respond as robot users (yes) or non-users (no) in the ASM and the ABS Year 2. Establishments are weighted by employment. No sample weights are used.