Robot Hubs: The Skewed Distribution of Robots in U.S. Manufacturing

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New technologies drive productivity growth (Romer 1990). Preliminary evidence using national-level data from 17 countries between 1993 and 2007 suggests that robots, like prior generations of general-purpose technologies, are also driving productivity growth (Graetz & Michaels 2018). Moreover, according to data compiled by the International Federation of Robotics (IFR), since 2010 the number of robot shipments has nearly quadrupled from about 100,000 to almost 400,000 per year, so the impact of robots on the economy is likely even greater. However, while robotics may be contributing to GDP growth at a national level, scholars are still working to understand how robots affect employment and other outcomes at other levels of analysis, leading to calls for establishment-level measures of robots and other new technologies (Brynjolfsson & Mitchell 2017; Raj and Seamans 2019).

To address this need, the U.S. Census Bureau, working with external researchers, developed a series of questions on the adoption and use of robots. These questions have subsequently been included in the Annual Survey of Manufactures and other Census surveys (Buffington, Miranda & Seamans 2018; Zolas et al. 2020; Acemoglu et al. 2022). In this paper we present results on the distribution of robots in U.S. manufacturing, using the new establishment-level microdata collected by the U.S. Census Bureau. We use the data to present several facts about the location and use of robots.

We find that the distribution of robots is highly skewed across locations, even accounting for the different mix of industry and manufacturing employment. Some locations - which we call “Robot Hubs” - have many more robots than one would expect after accounting for industry and manufacturing employment. We characterize these Robot Hubs along several industry, demographic, and institutional dimensions, and find that the presence of robot integrators and union membership are distinguishing features of Robot Hubs.

I. Data

The U.S. Census Bureau's Annual Survey of Manufacturers (ASM) is sent to a sample of about 50,000 establishments in the manufacturing sector.[1] Starting with the 2018 survey year, three questions about the use of robots were included in the ASM. These questions asked establishments how many robots they had in use, how many robots they had purchased, and how much they spent on robotic equipment.[2]

We combine the answers to the three robotics questions into a broad indicator of the presence of robotics at the establishment. This indicator captures whether an establishment has active robots, has purchased robots, or has made capital expenditures on robotic equipment (see Brynjolfsson et al. 2022 for details). Approximately 35,000 establishments responded with sufficient information to identify the presence of robots.[3]

II. Establishment and Geographic Patterns

The data reveal some notable patterns.[4] First, robotics adoption appears to vary by establishment size; it has a much weaker relationship with establishment age. Moreover, robot intensity (the number of robots per employee) also appears to vary by size, suggesting there may be a minimum efficient scale associated with robotics adoption. Second, establishments with robotics have higher capital expenditures, including higher information technology (IT) capital expenditures, than establishments without robotics. This finding suggests that establishments with robotics are making complementary investments, including in IT capital, a pattern seen with other types of technologies (Bresnahan, Brynjolfsson & Hitt 2002; Brynjolfsson, Jin & McElheran 2021). Third, establishments are more likely to report having robotics if other establishments in the same Core-Based Statistical Area (CBSA) also report having robotics, even after controlling for industry. Fourth, robotics adoption varies

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

[2] We use the word "robotics" to refer to any robot-related capital expenditure, whether it refers to purchase of an actual robot or not.

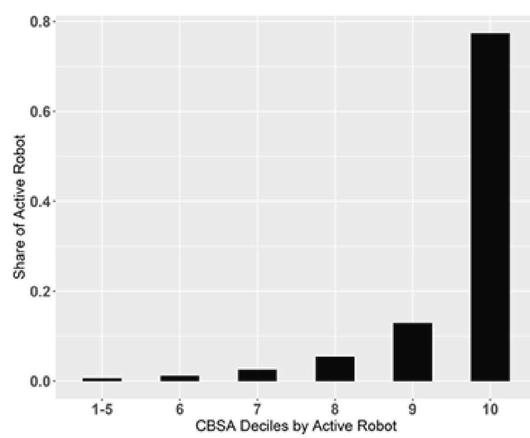
[3] In contrast to the Census Bureau's publicly released robotics tabulations, in this paper we use only reported values for the presence of robots. This is because, despite being relatively accurate at the tabular level, imputations of robot presence are noisy at the establishment level. See Goldschlag et al. (2022) for details.

[4] For more in- depth discussion of these patterns, see Brynjolfsson et al (2022).

significantly by geographic location. For example, the top ten percent of CBSAs, by share of active robots, have over 77 percent of all robots. The patterns of geographic variation we observe cannot solely be explained by differences in industry composition across geographies. For example, if we focus just on the Auto Manufacturing industry (NAICS 336), the bottom quarter of states, by robot use rate (having robotics present), have an average use rate of less than 1 percent. In contrast, the 25 percent of states with the highest use rates have an average use rate of 39 percent. These patterns suggest that robot adoption is far from uniform. Rather it varies with geographic factors.

III. Robot Hubs

We want to understand what local characteristics are associated with robot activity. To better focus our analysis of geographies that exhibit higher-than-expected use rates, we create a binary indicator that flags CBSAs with higher usage than one would expect given their industry mix. We identify these geographies in several steps. First, we de-mean CBSA-industry-level (3-digit NAICS) use rates by subtracting from each the associated national industry-level use rates. This provides a measure of how intensely 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. Weighting is important to address the fact that some industry-geography cells are quite small. Finally, we identify the geographies in the top 25 percent of the average, de-meaned use rate distribution that also have at least 20 reported establishments. We call these locations “Robot Hubs.” Geographies that are flagged as Robot Hubs have, across their manufacturing industries, relatively high robotics use even in comparison with the typical use rates in those industries.



To explore the characteristics of Robot Hubs, we run a series of OLS regressions, at the CBSA level, on a binary indicator for whether the CBSA is a Robot Hub (*Robot Hub)*. We also include several CBSA-level variables. 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*). Robot integrators are firms that facilitate the organization and installation of robotic equipment. We combine data on the percentage of employees with union membership (*Union Membership*). We create an indicator for whether the CBSA has a long history of manufacturing activity, defined as being a CBSA in the top 40 of manufacturing employment 30 years earlier, based on data from the Business Dynamics Statistics (*Top Manuf 30 Yr Prior*). Using data from the American Community Survey we construct the share of population with a high school degree or less (*Share of High Sch Deg*) and the share of population with a bachelor's degree (*Share of Bachelor's Deg*). Using data from the Bureau of Labor Statistics' Occupational Employment and Wage Statistics program, we construct the share of employees working in a STEM-related occupation (*Share of STEM Workers*) and the share of production workers (*Share of Prod Workers*).[5]

TABLE 1—ROBOT HUB AND CBSA CHARACTERISTICS

	Dependent Variable: Robot Hub Indicator		
	(1)	(2)	(3)
Has Integrator	0.2419	0.2465	0.1955
	[0.07756]	[0.08597]	[0.08624]
Union Membership (%)		0.01552	0.01637
		[0.005349]	[0.005126]
Top Manuf 30 Yr Prior		-0.05441	-0.08223
		[0.08841]	[0.09049]
Share of High Sch Deg			0.007648
			[0.006134]
Share of Bachelor's Deg			0.01324
			[0.00881]
Share of STEM Workers			0.008282
			[0.01199]
Share of Prod Workers			0.02049
			[0.009091]
Observations	250	250	250
R-squared	0.05146	0.08207	0.133

Source: Annual Survey of Manufactures; authors' calculations.

In Table 1 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 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 percent more likely to be considered a Robot Hub. In columns 2 and 3 we sequentially add variables to the regression.

[5] STEM occupations are identified using the Bureau of Labor Statistics' 2010 Standard Occupation List (SOC) for STEM classification. Production employment is identified using the 2-digit SOC code 51 "Production Occupations."

The coefficient on *Has Integrator* remains positive and statistically significant, ranging in value from approximately 0.2 to 0.25. In column 3, which includes all the CBSA-level variables, *Has Integrator*, *Union Membership*, and *Share of Prod Worker* are all positive and statistically significant. None of the other variables are significant. More results are available in Brynjolfsson et al. (2022).

IV. Conclusion

We describe new data collected by the U.S. Census Bureau's Annual Survey of Manufactures for reference year 2018. This is the first establishment-level data on the use of robots in U.S. manufacturing, with data on approximately 35,000 establishments.

Using these data, we show that the distribution of robots is skewed geographically, even when one accounts for the different mix of industry and manufacturing employment. Some locations, which we call "Robot Hubs", have many more robots than one would expect if the distribution of robotics was uniform, after accounting for industry and manufacturing employment. These Robot Hubs are not areas that have a particularly strong manufacturing history, but they do have at least one robot integrator, and they have a higher share of production workers.

The Robot Hub patterns may be useful to researchers who are relying on more aggregated data on the presence of robots, such as the data from the International Federation of Robots used in earlier studies, including Acemoglu & 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.

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