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Robots, Automation and the demand for Industrial Space

by

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Abstract

We utilize the data set developed by Acemoglu & Restrepro (2017) depicting the likely adoption rate of robots by firms in each US MSA. Our focus is on the impact of this automation metric on the market for industrial real estate (factories and warehouses). We get similar results to their negative impacts of automation on local labor markets. Over the 1993-2007, MSA with an industry mix that that more rapidly automating are associated with significantly less construction of new industrial space, less growth in overall occupied space, and lower increases in industrial space rents. The use of industry mix based "estimated" robot adoption, and a wide range of applied control variables, suggests that this relationship is causal.

I. Introduction.

There has been extensive discussion in the last decade about the role of automation in both generating and eliminating jobs. Most recently the discussion has focused on the potential role of AI and supercomputing to revolutionize the service sector. Brynjolfson,[2015], Autor [2015] Martin Ford [2015] and Mckinsey [2015, 2017] all explore the question of whether electronic "Robots" can replace humans in accomplishing of a wide range of service tasks. Following Frey and Osborn [2013], Acemoglu and Restrepo [2016] go beyond speculation and provide a model that focuses on tasks and the role that automation plays in both taking over existing tasks and generating new tasks that still require human input.

In this discussion there has been little or no mention of real estate. What will automation do the demand for offices, stores, warehouses and factories? While automation has barely just begun in the service sector, in the industrial sector, automation has been on-going now for several decades. This should provide historical data and an empirical record with which to assess the impacts of automation on industrial space demand. With this in mind the question we ask is posed very broadly. When automation is considered as a "system", with not just a robotic factory floor, but also its own supply chain, parts and inventory storage system, repair facilities, – does it require more or less industrial space than the traditional more worker-based industrial factory system.

We attempt to answer this question in a remarkably straightforward manner. Using the same data from the IFR (International Federation of Robotics) as Acemoglu and Restrepo [A&R, 2017] we use their adoption rate of industrial robots between 1993 and 2007 across US metro areas, to further examine the economic impact of automation. They examine the impact on job growth and wage inflation, while we use the same data to study the impact on the construction rate of new space, total growth in occupied industrial space, and the increase in industrial rental rates. The data collected by A&R ends in 2007, just before the financial crisis, so as to best reflect longer term secular changes and not the enormous cyclic change that occurring during and after the Financial Crisis.

A central issue for this study, like that of A&R is whether the adoption rate of robotics is truly an exogenous variable on the right hand side? It is surely plausible, that increases in the cost and availability of labor actually cause the adoption of robots (rather than the reverse). In our case, real estate space is a far smaller input factor, and on the surface it would seem less likely that its cost and availability help to generate automation. Still we fully follow the prior study in its identification strategy. First, we do not use an actual adoption rate in each market, but rather the predicted adoption rate based on industrial mix (a so-called "Bartik Instrument"). As further controls, we also include a wide range of economic shock variables that hit these MSAs differentially over 1993-2007.

Our results are quite strong statistically, and suggest that an increase in the adoption rate of 1.37 robots per 1000 workers (a standard deviation in MSA-level robotic growth) reduces the cumulative growth of the stock from new construction by 13 percentage points, reduces the total consumption of industrial space by 10 percentage points and leads to 10 percentage points less growth in constant $ space rents between 1990 and 2007. Industrial automation is quite simply a more “space efficient” production technology that seems readily able to use existing industrial facilities.

II. IFR Robot adoption data

The main data used in this paper consist of counts of the stock of robots by industry, country and year from the IFR [2014] based on yearly sales surveys of robot suppliers. The IFR survey covers almost 50 countries from1993 to 2014, corresponding to about 90 percent of the industrial robots market. However, a complete yearly stock series of industrial robots by industry going back to the 90s is available only for a subset of 9 countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the UK. These countries account for 41 percent of the world industrial robot market[1]. Although the IFR reports data on the total stock of industrial robots in the United States from 1993 onward it does not provide industry breakdowns until 2004. This omission is quite constraining. Within the 9 EU countries, there is consistent data on the use of robots for a detailed set of 13 manufacturing industries (roughly at the three-digit level): food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; and other manufacturing industries (e.g. recycling).

Outside of manufacturing, the IFR further provides consistent EU data for the use of robots in six other broad industries (roughly at the two-digit level): agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and other non-manufacturing industries (e.g., services and entertainment). The IFR also provides the decile distribution of delivered robots for each of the 19 industries in each year.

As discussed more thoroughly in A&R [2017] IFR data are not without some shortcomings. First, not all robots are classified into one of the 19 industries. About 30 percent of robots are unclassified, and furthermore this fraction has declined throughout our sample. These unclassified robots are added to industries in the same proportions as in the classified data. Second, IFR data do not contain information on dedicated industrial robots[2]. Third, the data for Denmark is not classified by industry before 1996. For the missing years, estimates of the number of industrial robots were made by deflating the 1996 stocks by industry using the total growth in the stock of robots of the country. Finally, the IFR only reports the overall stock of robots for North America. Though this aggregation introduces noise in our measures of US exposure to robots, this is not a major concern, since the United States accounts for more than 90 percent of the North American market, and the use of an IV procedure (discussed below) should purge the US exposure to robots from this type of measurement error.

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[1] Though the IFR also reports data by industry for Japan, these data underwent a major reclassification. A&R followed the recommendations of the IFR and excluded Japan from the analysis.

[2] Robots truly dedicated to one industry might better be thought of as “industry specific capital”. In this study, “Robots” are machines that can be significantly adapted and programmed to do a wide range of tasks – across multiple industries.

The IFR data is combined with employment counts by country and industry in 1990 from the EUKLEMS dataset [Jägger, 2016] to measure the number of industrial robots per thousand workers (across all industries) by country, industry and over time.

Figure 1 plots the evolution of the mean and the 30th percentile of robot usage across the nine European economies described above. It also includes the average robot density in the United States—recall that aggregate data for the United States are available since 1993, but broken down by industry only since 2004. In the sample of European countries, robot usage starts near 0.6 robots per thousand workers in the early 1990s and increases rapidly to 2.6 robots per thousand workers in the late 2000s. In the United States, robot usage is lower but follows a similar trend; it starts near 0.4 robots per thousand workers in the early 1990s and increases rapidly to 1.4 robots per thousand workers in the late 2000s. The US trends are closely mirrored by the 30th percentile of robot usage among the European countries in our data, showing that the US somewhat lags the EU in Robot adoption.

The IFR does not provide data about Robot sales to individual companies nor does the IFR have any information on where the companies eventually installed them. Robots are combined into production lines by separate firms called quite literally "Robot Integrators". Data on when and where the Robots were actually installed remains privileged information by the companies that purchased them. In many respects, not knowing the actual location of Robots helps to solve an obvious identification problem. The locations that firms select to "automate" might well depend on local labor market conditions, or in our case industrial space availability and its cost. Hence A&R create an instrumental variable called "Robot Exposure" which is based on local industry weights (employment) multiplied by the aggregate growth in Robots (per worker) for each industry – using the EU data.

III. Exposure to Robots

For local industrial mix data, A&R focus their attention on 722 US commuting zones – as defined by Tolbert and Sizer [1996]. These zones cover the entire US continental territory and are a mix of Metropolitan Areas (formerly Labor Market Areas) and then aggregations of counties for non-metropolitan areas. For each commuting zone, public use data was obtained from the 1970 and 1990 Censuses to get the share of employment by industry.

A&R complement these data with employment counts from the County Business Patterns CBP for 1990, 2000 and 2007, which again were aggregated to the commuting zone level. The Census measures employment from the household side, while the CBP approaches it from the employer side, making the two data sources complementary.

Using this data on the distribution of employment across industries in each commuting zone, we chose to use two of their constructed variables labelled "exposure to robots". The exact construction of these variables is as follows

$$\boldsymbol{Robot\ Exposure\ EU} = \sum_{i\in\tau} \boldsymbol{\ell_{ci}^{1970}}\left(\left(\frac{\boldsymbol{R_{i,2007}}}{\boldsymbol{L_{i,1990}}}\right) - \left(\frac{\boldsymbol{R_{i,1993}}}{\boldsymbol{L_{i,1990}}}\right)\right), \tag{1}$$

$$\boldsymbol{Robot\ Exposure\ EU30} = \sum_{i \in \tau} \boldsymbol{\ell_{ci}^{1970}} \left(\boldsymbol{p_{30}} \left(\frac{R_{i,2007}}{L_{i,1990}} \right) - \boldsymbol{p_{30}} \left(\frac{R_{i,1993}}{L_{i,1990}} \right) \right), \qquad (2)$$

In both versions, US commute zone industry weights are applied to either the average robot adoption in EU industries or to the adoption rate of the 30th percentile among all EU firms in that industry. Hence ℓ_{ci}^{1970} stands for the 1970 share of commuting zone c employment in industry i, which we compute from the 1970 Census. Then $(\frac{R_{i,t}}{L_{i,1990}})$ and $p_{30}(\frac{R_{i,t}}{L_{i,1990}})$ denotes the average and then 30th percentile of robot usage among European countries in industry i and year t. The main measure of (exogenous) exposure to robots is based on the 1970 values for the distribution of employment across industries, which enables us to focus on historical and persistent differences in the specialization of commuting zones in different industries, and to avoid any mechanical correlation or mean reversion with changes in overall or industry-level employment outcomes. The 30th percentile data is included as a robustness check since in the aggregate it matches the US data so closely.

One might argue that exposure to robots is a metric that is highly correlated across commute zones with a wide range of other variables reflecting both the economic shocks received by that zone over 1993-2007 as well as basic differences in each zone’s underlying economy. To control for potentially confounding changes in trade patterns, A&R utilize data on the exposure to Chinese imports from Autor, Dorn and Hanson (2013), and construct similar measures of the exposure to imports from Mexico. The trade exposure measures combine the distribution of employment across four-digit industries in the commuting zone and industry level imports and exports from the United Nations Comtrade database (which gives bilateral trade data at six-digit product level, which is aggregated to the four-digit level following Autor, Dorn and Hanson, 2013).

Following a similar procedure, A&R construct a measure of offshoring using data on the share of intermediate inputs that are imported by each four-digit industry. The offshoring data are from Wright (2014), who updates an earlier study to cover the entire period from 1993 to 2007. Finally, A&R constructed measures of the presence of growing industries and industries with a fast growing total and IT-based capital stock in each commuting zone. As with the above, these are constructed from the combination of zone-level industrial mix and national industry-level differences in the variable under consideration.

Figure 2 shows data on the increase in robots use (in Europe) for the set of 19 industries covered in the IFR data. For each industry, we also show the rise in Chinese and Mexican US imports per thousand workers, the percent increase in the capital stock, and the percent increase in IT capital stock (both computed from data by the Bureau of Economic Analysis). To ease the comparison, these measures are normalized and present numbers relative to the industry with the largest increase for the variable in question. The figure reveals that the industries that are adopting more industrial robots are not the same industries affected by Chinese import competition, nor are they the same ones experiencing unusually rapid growth in total capital or IT capital. This strengthens the presumption that the use of industrial robots is a technological phenomenon that is largely unrelated to other trends affecting industries in developed countries.

Figure 3 depicts the geographic distribution across commuting zones of the A&R measure of exposure to robots—the source of variation to be exploited in this paper to identify the impact of industrial robots on industrial space demand and rents. The color scale indicates which commuting zones have experienced greater increases in the exogenous exposure to robots measure from 1993 to 2007. The figure reveals significant variation. Lightly colored zones have predicted increases in robots/worker of between .12 and .3. Darker areas have increases of between 1.1 and 4.87 robots/worker. While much of the "rust belt" is darker, higher adoption is also seen in parts of the West Coast and South East and North Central regions of the US.

In the original paper of A&R there is considerable discussion around the correlation between exposure to robots and the similarly constructed measures of exposure to other economic shocks. For example, the correlation between robot exposure and exposure to Chinese imports is only .049 across the 722 commute zones. Similarly that with respect to offshoring exposure is only .054. Other controls (exposure to Mexican imports, capital intensity and growth) have similarly low correlations with respect to exposure to robots. These weak correlations are reassuring against concerns that the effects of robots would be highly confounded by other major changes affecting local US labor markets. For this study, several additional controls were incorporated, but we need to further refine the geographic sample so as to match the availability of data on industrial space markets.

III. Industrial Space Market Data.

Since the 1970s, the nation's major commercial real estate brokerage firms have maintained what appears to be accurate inventory in selected markets of all industrial properties. The inventory covers all single floor metal buildings used for Manufacturing, distribution and warehousing that are in excess of 10 thousand square feet. The geographic coverage of these data has expanded so that by 1990 we were able to match them with 44 (generally the largest) commute zones that constituted mostly major MSA. The list of these markets is in Table 1. In each of these markets, this data (courtesy of CBRE) provided us with total industrial square feet (factories and warehouses) and vacancy rates in 1990 and then 2007. This allows a simple calculation of occupied square feet (space consumption) over a period that closely matches the A&R robot exposure measures. The data base also allowed us to track all new buildings constructed between 1990 and 2007. With these data we calculated the ratio of this cumulative construction to the 1990 stock.

CBRE also has a proprietary data base containing hundreds of thousands of industrial leases that they have negotiated since 1990. This data base contains the total consideration of each lease (undiscounted sum of rental payments due), lease term, and square feet. Forming the basis of realtor commissions this data is regarded as highly accurate. As described in Torto-Wheaton [1994] it is straight forward to estimate rental "Hedonic indices" over time – reflecting the average $ paid per square foot, for an identical parcel of space, leased for a given term. These indices should provide a much more accurate representation of the true cost of renting industrial space than more recent "posted asking rents" [CoStar.com]. This data provides us with a measure of what recently leased industrial rents were in 1990 and 2007. These are then deflated and used to calculate the % change in constant dollar rental rates.

In most parts of the US, new industrial facilities continue to expand with production processes that employ ever greater capital/worker. Such (robotically) automated plants, are sometimes felt to require greater floor space per unit good produced. Add this together with the continued growth of trade and the global supply chain, and with inventories moving from retail shelves back into new warehouses, and most of the studied 44 studied industrial markets generally saw significant expansion in their stock of occupied industrial space between 1990 and 2007.

In addition to the array of data from A&R, and the space data from CBRE, we also obtained the share of each zones workforce that had a college education in 1990 (US, 1990 Census), and the zone's level of total Industrial production both in 1993 and 2007 (Moody's: Economy.com). The college workforce share is an obvious summary measure of market's overall industrial structure, but the growth in production deserves some discussion.

In the first place, like past technological changes, robot automation should reduce production costs and spur output (relative to some status quo). In traditional production function theory, the overall change in space usage which results from robot adoption reflects two separate effects. The first is the pure rate of factor substitution between space and robots – controlling for any output effects – while the second is the increase in space demand that accompanies any induced increase in industrial production. This latter should always be positive, while the former can be of any sign. Hence if robot adoption reduces space demand it should do so even more when production is controlled for. If it increases space demand it should do so less with production controlled. Our incorporation of this control allows us to test for this proposition.

Table 2 provides a summary for all variables based on the sample of 44 msa with a full set of space market data. Across these markets, constant dollar industrial rents declined an average 4% cumulatively over the 14 years. The stock of space grew a cumulative average of 43% (based on new building construction), while total occupied space grew 34%. Industrial production increased on average by a larger 67%. The increase in exposure to robot adoption averaged .94 units/worker when the 30^{th} percentile of the EU data is used to calculate adoption and 1.92 units/worker when the EU mean is used. Figure 4 maps the geographic distribution of exposure to robot adoption across the US. There is a slight concentration in the Midwest, but also much adoption along the two coasts and in the South Central US.

The simple correlation between exposure to robots and all three space market variables (rent, occupied and total stock growth) is seen in Table 3 to always be negative with R2 values of between .09 and .25. With 44 observations these are significant. The only significant correlation between the various control variables and robot exposure occurs with the exposure to Mexican imports variable. The control variables also are generally not highly correlated with our dependent (space market) variables. Finally, the two calculations of exposure to robots are so highly correlated between each other (.989) that we can anticipate no more than a scaling of the results using one or the other.

IV. Results and Robustness checks.

Tables 4-6 examine a range of models explaining (respectively) the growth in real rents, total occupied stock and new construction rate for our sample of 44 MSA. In each Table, the first frame presents results using the robot exposure variable based on the 30th percentile of EU robot adoption across industries, while the 2nd frame uses the variable based on industry average EU adoption rates. The results are quite similar with the coefficient for the robot exposure variable being about 50% larger when the 30th percentile measure is used relative to the mean. This is totally consistent with the high correlation between these measures and their difference in means – as discussed around Tables 1 and 2. The first column in Tables 4-6 gives the simple bivariate results, while various controls are added across the columns. All of the controls are applied in the regression reported in the 6th column.

An initial observation is that for basically all specifications and for all three outcomes, the impact of exposure to robots is negative – and significant. Greater exposure to robots reduces industrial rent growth, reduces the construction rate of new industrial space and reduces the growth in total occupied industrial space. A second general observation is that the inclusion of industrial production (column 2 versus 1) always yields a larger (negative) coefficient – as was discussed in section III and as would be predicted by a derived factor demand equation. Interestingly in most regressions industrial production has a significant effect on space demand only when paired with exposure to Chinese imports. With other controls included its coefficient is generally much diminished.

Next, the 6th column where all controls are applied obviously has the highest R2 values, but also has the largest coefficient, with the most significance, for the robot exposure variable. Controls just do not seem to reduce these results. The one possible exception is exposure to Mexican imports, which tends to reduce (but not eliminate) the significance of the robot variable. Interestingly it has this effect only when included by itself. The robot variable is unaffected by the use of Mexican imports in the full formulation (column 6).

V. Economic Impacts.

With the data in Table 2 and our parameter estimates from Tables 4-6, it is straighforward to examine the economic impacts that greater exposure to robots had on MSA level industrial space markets. Using the results for Robot Exposure that were calculated with EU industry mean values, the average increase across the 44 MSA in this measure was 1.92 robots/worker with a standard deviation of 1.37. A (linear) increase in robots/worker of 1 std deviation has the following point estimate impacts, using the equation in the final column of Tables 4-6 - that employs all of the control variables.

First, cumulative (constant dollar) Rent growth averaged -4.0% when adjusted for inflation with a wide std deviation across MSA of 21%. A 1 std deviation increase in Robot exposure per worker further reduces this growth in rents to -14.0%. Rents declined siginificantly more in markets with greater exposure to robots.

Next, the cumulative growth in occupied stock averaged 34% across our 44 markets with a std deviation of 19% . A 1 std deviation increase in Robots per worker reduces this growth in overall space consumption to 24%. The channels through which the reduction in space use occurred were both a reduction in new space construction, but also an increase in occupancy rates within the existing stock.

Cumulative new construction of space averaged 43% when conpared to the 1990 stock. It had a std deviation across markets of 32%. A 1 std deviation increase in Robots per worker reduces the contruction rate to 30%.

There is a straightforward identity between the growth in occupied space within a market, the rate of new space construction and changes in vacancy or occupancy rates. This is shown below in equation (3), where *OS* is occupied stock, *S* total stock, *V* vacancy rate and *C* new space completions.

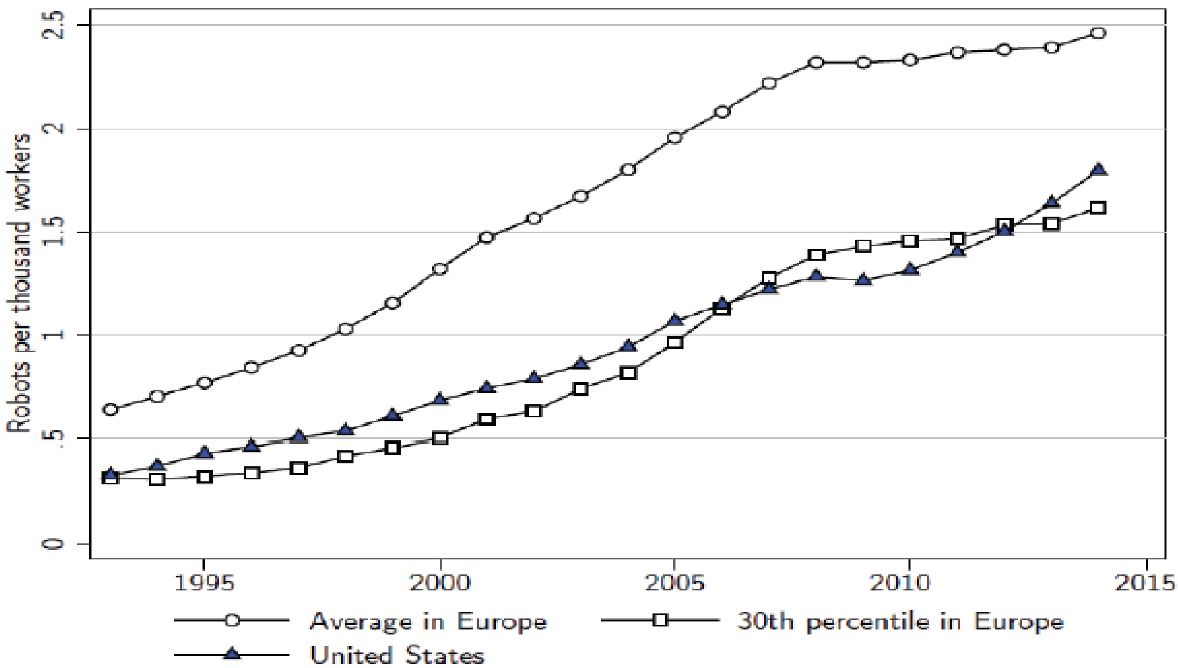
$$\frac{\boldsymbol{OS_t}}{\boldsymbol{OS_{t-1}}} = \frac{\boldsymbol{(1-V_t)S_t}}{\boldsymbol{(1-V_{t-1})S_{t-1}}} = \frac{\boldsymbol{(1-V_t)}}{\boldsymbol{(1-V_{t-1})}}\left(1+\frac{\boldsymbol{C_t}}{\boldsymbol{S_{t-1}}}\right) \quad if\ S_t = S_{t-1} + C_t \tag{3}$$

In equation (3), let t represent 2007 and t-1 1993. From Table 2 the average LHS value across the 44 MSA is 1.34 which drops to 1.25 with a 1 standard deviation increase in exposure to robots. The second term on the RHS averages 1.43 and it drops to 1.30 with a 1 standard deviation increase in exposure to robots. Hence using (3) the ratio of occupancy rates in 2007/1993 (the first term on the RHS) averages .937. Occupancy rates in the existing stock generally fell over this period. With robot exposure the occupancy ratio rises to .958 (or occupancy in the existing stock fell less). Greater exposure to robots reduced the construction rate of new space by approximately 13 percentage points and increased the occupancy rate in the existing stock by 2-3 percentage points. This leads to the observed overall decline in space usage of approximately 10 percentage points.

Industrial automation with robotics appears to be, quite simply, a more "space efficient" production technology that seems not always to require the construction of new facilities, and that is able to adapt and use existing industrial space.

Appendix

Figure 1: Industrial robots in the United States and Europe.



Note: Industrial robots per thousand workers in the United States and Europe. Data from the International Federation of Robotics (IFR).

Figure 2: Growth in Robot use and other Economic variables by Industry.

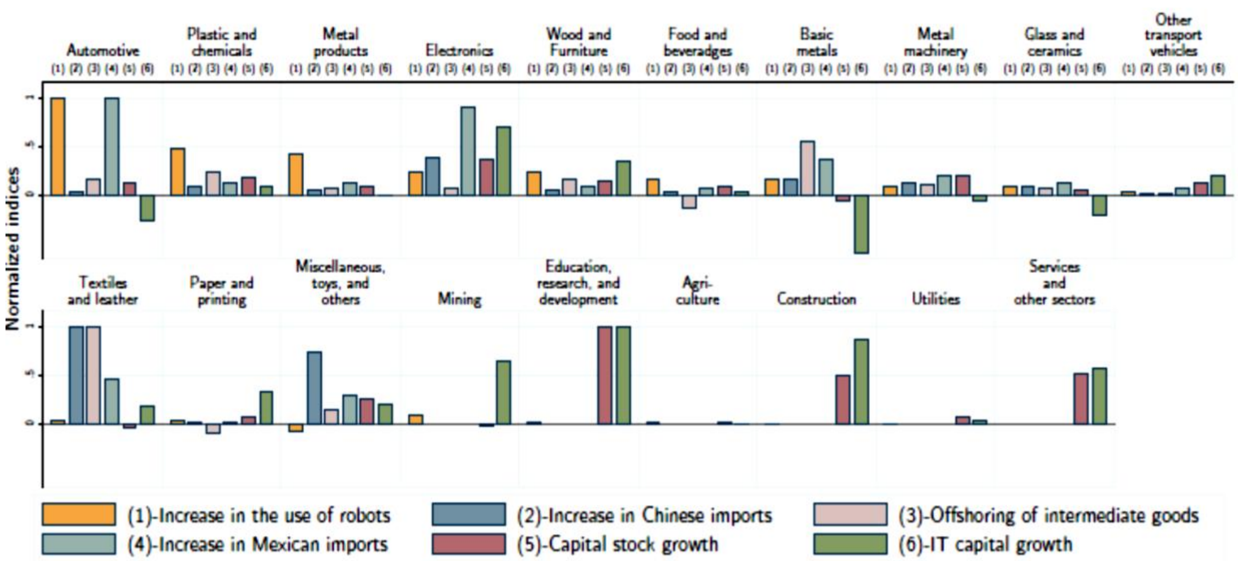


Figure 3: 722 Commute Zone Exposure to Robots, 1993-2007

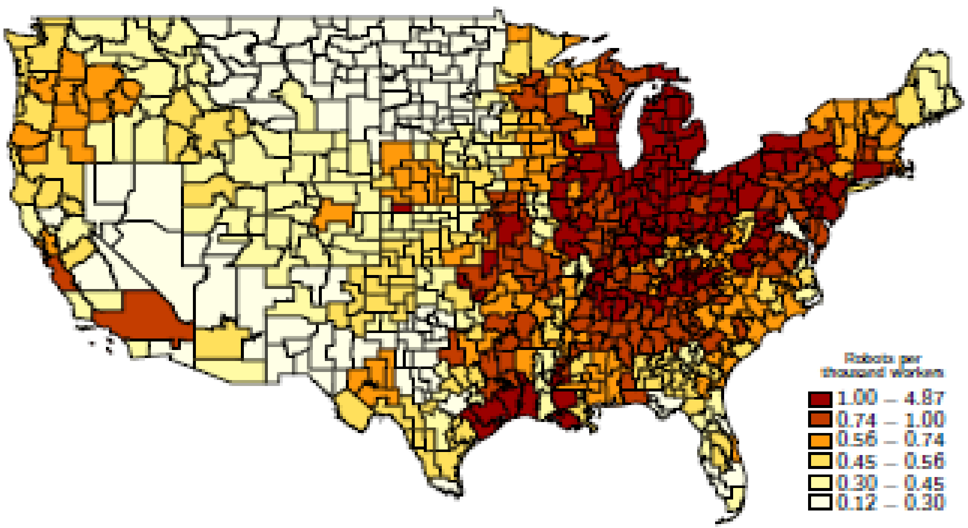


Figure 4: 44 MSA, Exposure to Robots 1993-2007

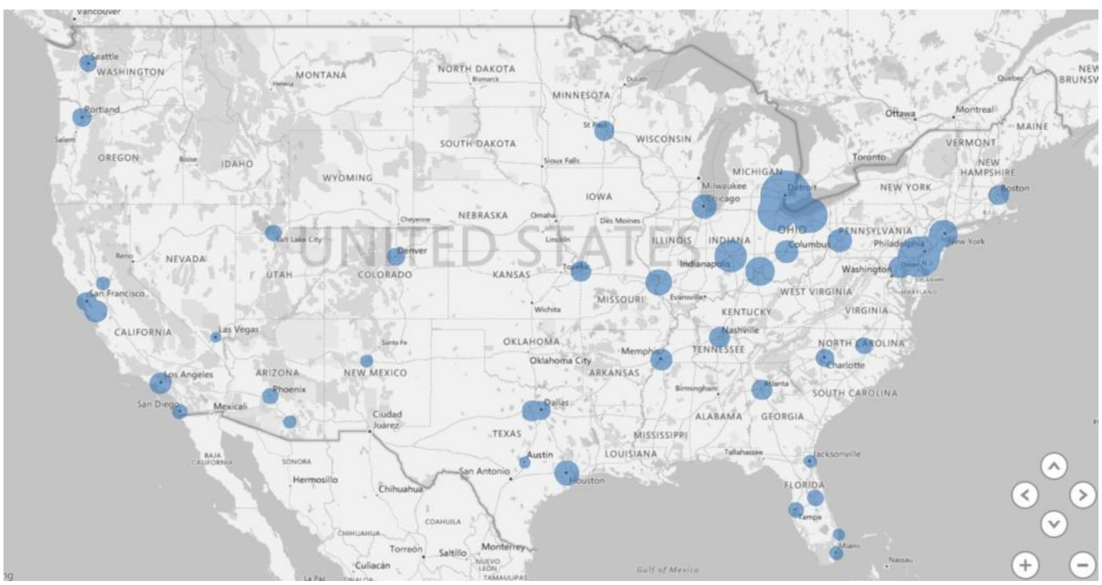


Table 1: list of 44 MSA markets

Albuquerque	Denver	Nashville	San Jose
Atlanta	Detroit	New York	Seattle
Austin	Fort Worth	Newark	St. Louis
Baltimore	Houston	Orlando	Tampa
Boston	Indianapolis	Philadelphia	Trenton
Charlotte	Jacksonville	Phoenix	Tucson
Chicago	Kansas City	Portland	West Palm Beach
Cincinnati	Las Vegas	Sacramento	Wilmington, DE
Cleveland	Los Angeles	Salt Lake City	Memphis
Columbus	Miami	San Diego	Pittsburgh
Dallas	Minneapolis	San Francisco	Raleigh

Table 2 Summary Statistics, 44 MSA

Panel A

Variable	Mean	S. Dev.	Min	25^{th} pct.	Median	75^{th} pct.	Max
Real rent 1990	6.91	1.9	3.27	5.52	6.29	7.96	11.82
Real rent 2007	6.63	1.76	2.71	5.38	6.45	7.98	10.26
Real Rent % growth	-0.04	0.21	-0.43	-0.22	-0.02	0.10	0.32
Occupied stk. 1990	1.8E+5	1.6E+5	18317.	79210.	1.3E+5	2.0E+5	7.4E+5
Occupied stk. 2007	2.3E+5	2.0E+5	26363.	1.2E+5	1.9E+5	2.7E+5	9.8E+5
Occ. stk. % growth	0.34	0.19	0.08	0.21	0.32	0.43	1.14
Exposure to robots 1993 to 2007 (EU30)	0.94	0.84	0.2	0.48	0.75	1.03	4.87
Exposure to robots 1993 to 2007 (EU)	1.92	1.37	0.43	1.13	1.62	2.25	8.42
Industrial prod. 1993	275.03	129.68	82.5	192.96	227.44	318.03	693.42
Industrial prod. 2007	531.44	256.73	335.47	409.15	415.56	446.68	1244.59
Ind. Prod. % growth	0.67	0.21	0.16	0.57	0.66	0.78	1.40
Completions ratio	0.43	0.32	0.06	0.27	0.37	0.52	2.09

Panel B

Variable	n	Mean	S. Dev.	Min	Max
Share of population with college in 1990	44	0.21	0.04	0.10	0.30
Exposure to Chinese imports 1993 to 2007	44	3.01	1.84	0.86	11.74
Exposure to offshoring from 1993 to 2007	44	0.04	0.03	0.00	0.17
Exposure to Mexican imports 1993 to 2007	44	1.58	0.84	0.21	4.48

Table 3: correlation Matrix of Variables, 44 MSA

	Rent Growth	Occupied	Construction	Robots 30	Robots avg	production	College %	Chinese	Offshore	Mexican
Rent growth	1									
Ooccupied St	0.4701	1								
Construction	0.3666	0.9512	1							
Robots 30	-0.4859	-0.4075	-0.2863	1						
Robots avg	-0.5053	-0.4373	-0.3209	0.9896	1					
Production	-0.017	0.0618	0.0205	0.1499	0.2022	1				
College %	-0.2001	-0.2976	-0.3639	-0.0625	-0.0317	0.2324	1			
Chinese	-0.1606	-0.1219	-0.1742	-0.0772	0.0244	0.5181	0.5116	1		
Offshore	-0.0968	-0.2747	-0.2263	0.1824	0.1925	-0.2707	0.0218	0.2318	1	
Mexican	-0.4449	-0.2599	-0.2056	0.6464	0.6854	0.3914	0.1241	0.3964	0.1741	1

Table 4: The impact of the exposure to robots on real rent growth (log differences)

Panel A: exposure to robots (EU30 measure)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-0.119***	-0.128***	-0.134***	-0.122***	-0.0772**	-0.123**
	(0.0255)	(0.0235)	(0.0251)	(0.0265)	(0.0365)	(0.0515)
Industrial production growth		0.121	0.231*	0.0600	0.147	0.354**
		(0.125)	(0.128)	(0.153)	(0.124)	(0.146)
Share of population with college		-1.316				-0.774
		(0.925)				(0.928)
Exposure to Chinese imports			-0.0362**			-0.0318
			(0.0146)			(0.0244)
Exposure to offshoring				0.0724		1.344*
				(0.791)		(0.733)
Exposure to Mexican imports					-0.0737*	-0.0401
					(0.0416)	(0.0583)
Constant	0.0700*	0.277	0.0373	0.0291	0.0488	0.103
	(0.0398)	(0.201)	(0.0698)	(0.125)	(0.0897)	(0.217)
Observations	44	44	44	44	44	44
R-squared	0.236	0.303	0.313	0.239	0.283	0.367

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: exposure to robots (EU measure)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-0.0764***	-0.0822***	-0.0825***	-0.0804***	-0.0542**	-0.0751**
	(0.0174)	(0.0157)	(0.0163)	(0.0182)	(0.0243)	(0.0303)
Industrial production growth		0.151	0.231*	0.0990	0.157	0.346**
		(0.117)	(0.127)	(0.142)	(0.121)	(0.145)
Share of population with college		-1.274				-0.856
		(0.902)				(0.926)
Exposure to Chinese imports			-0.0300**			-0.0243
			(0.0139)			(0.0221)
Exposure to offshoring				0.232		1.255*
				(0.727)		(0.716)
Exposure to Mexican imports					-0.0643	-0.0406
					(0.0422)	(0.0559)
Constant	0.105**	0.287	0.0516	0.0363	0.0586	0.137
	(0.0454)	(0.193)	(0.0719)	(0.118)	(0.0884)	(0.216)
Observations	44	44	44	44	44	44
R-squared	0.255	0.323	0.315	0.264	0.295	0.370

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The impact of the exposure to robots on occupied stock growth (log differences)

Panel A: exposure to robots (EU30 measure)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-0.0899***	-0.102***	-0.105***	-0.0847***	-0.0850***	-0.111***
	(0.0293)	(0.0273)	(0.0299)	(0.0264)	(0.0306)	(0.0355)
Industrial production growth		0.196	0.264**	0.0618	0.131	0.184
		(0.120)	(0.105)	(0.156)	(0.123)	(0.152)
Share of population with college		-1.711				-1.496
		(1.017)				(1.159)
Exposure to Chinese imports			-0.0314*			-0.0108
			(0.0177)			(0.0238)
Exposure to offshoring				-1.195		-0.709
				(1.290)		(1.263)
Exposure to Mexican imports					-0.0150	0.0189
					(0.0497)	(0.0464)
Constant	0.426***	0.671***	0.357***	0.430***	0.357***	0.673**
	(0.0450)	(0.240)	(0.0832)	(0.154)	(0.110)	(0.318)
Observations	44	44	44	44	44	44
R-squared	0.166	0.315	0.250	0.212	0.184	0.337

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: exposure to robots (EU measure)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-.0594***	-.0678***	-.0667***	-.0579***	-.0638***	-.0748***
	(0.0213)	(0.0191)	(0.0204)	(0.0194)	(0.0197)	(0.0206)
Industrial production growth		0.223*	0.267**	0.0928	0.140	0.186
		(0.111)	(0.103)	(0.146)	(0.119)	(0.141)
Share of population with college		-1.683*				-1.556
		(0.992)				(1.127)
Exposure to Chinese imports			-0.0267			-0.00633
			(0.0166)			(0.0208)
Exposure to offshoring				-1.057		-0.718
				(1.221)		(1.182)
Exposure to Mexican imports					0.000127	0.0269
					(0.0453)	(0.0417)
Constant	0.456***	0.681***	0.370***	0.435***	0.370***	0.699**
	(0.0561)	(0.234)	(0.0856)	(0.150)	(0.108)	(0.305)
Observations	44	44	44	44	44	44
R-squared	0.191	0.344	0.265	0.238	0.215	0.363

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: The impact of exposure to robots on 1990 to 2007 completions/1990 stock

Panel A: exposure to robots (EU30 measure)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-0.107*	-0.127**	-0.130**	-0.0957**	-0.0927*	-0.139**
	(0.0545)	(0.0508)	(0.0583)	(0.0463)	(0.0482)	(0.0596)
Industrial production growth		0.258	0.368**	0.0167	0.135	0.244
		(0.167)	(0.170)	(0.249)	(0.181)	(0.253)
Share of population with college		-3.266				-2.933
		(1.999)				(2.292)
Exposure to Chinese imports			-0.0558*			-0.0166
			(0.0327)			(0.0407)
Exposure to offshoring				-1.927		-1.058
				(2.433)		(2.396)
Exposure to Mexican imports					-0.0302	0.0272
					(0.0967)	(0.0912)
Constant	0.529***	1.071**	0.472***	0.589**	0.472**	1.073
	(0.0853)	(0.476)	(0.153)	(0.288)	(0.190)	(0.665)
Observations	44	44	44	44	44	44
R-squared	0.082	0.255	0.161	0.113	0.089	0.272

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: exposure to robots (EU measure)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-0.0740*	-0.0861**	-0.0838**	-0.0687*	-0.0756**	-0.0976***
	(0.0409)	(0.0367)	(0.0397)	(0.0352)	(0.0321)	(0.0335)
Industrial production growth		0.295*	0.374**	0.0575	0.142	0.251
		(0.159)	(0.168)	(0.234)	(0.176)	(0.235)
Share of population with college		-3.237				-3.001
		(1.960)				(2.235)
Exposure to Chinese imports			-0.0501			-0.0124
			(0.0306)			(0.0346)
Exposure to offshoring				-1.731		-1.029
				(2.314)		(2.229)
Exposure to Mexican imports					-0.00663	0.0420
					(0.0879)	(0.0800)
Constant	0.571***	1.087**	0.489***	0.596**	0.489**	1.102*
	(0.109)	(0.472)	(0.159)	(0.285)	(0.190)	(0.641)
Observations	44	44	44	44	44	44
R-squared	0.103	0.277	0.173	0.132	0.111	0.292

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

References

Acemoglu, Daron and Pascual Restrepo (2016), "The Race b etween Machine and Man : Implications of Technology for Growth, Factor Shares and Employment" NBER Paper 22252.

Acemoglu, Daron and Pascual Restrepo (2017) "Robots and Jobs: Evidence from US Labor Markets" NBER Paper 23285.

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

Autor, David H., David Dorn, and Gordon H. Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103(6): 2121–68

https://www.costar.com/products/costar-leasecomps

https://www.economy.com/products/data/historical-us

Ford, Martin, *Rise of the Robots,* Basic Books, (2015)

Frey, Carl B. and Michael A. Osborne (2013) "The Future of Employment: How Susceptible are Jobs to Computerization?" Mimeo. Oxford Martin School.

International Federation of Robotics (2014) Wold Robotics: Industrial Robots.

Jägger, Kirsten (2016), "EU KLEMS Growth and Productivity Accounts 2016 release - Description of Methodology and General Notes."

Mckinsey Institute, *The Four Fundamentals of Workplace Automation*, November, 2015:

McKinsey (2017) "Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation." Report from https://www.mckinsey.com.

Tolbert, Charles M., and Molly Sizer (1996) "US Commuting Zones and Labor Market Areas: A 1990 Update." Economic Research Service Staff Paper 9614.

Torto, R. and Wheaton, W, (1994) "Office Rent Indices and their Behavior over Time", *Journal of Urban Economics*, 35,2.

Wright, Greg C. (2014) "Revisiting the Employment Impact of Offshoring," *European Economic Review* 66:63–83.