# EMERGING ROBOTIC REGIONS: INSIGHTS FOR REGIONAL ECONOMIC DEVELOPMENT

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## INTRODUCTION

How technologies impact regional and national economies is an enduring debate that traverses the spectrum from optimism to pessimism. Factory automation and computerization were two major foci of this debate in the last half of the 20$^{th}$ century. Leaps in robotics and artificial intelligence (AI) technologies that have taken place in the first decade of the 21$^{st}$ century have shaped the most recent phase of the debate.

The literature on the topic tends to be 1) speculative and anecdotal in nature, and 2) focused on macro-level changes in productivity and employment. Three recent books, the *New Division of Labor* (Levy & Murnane, 2012), *The Second Machine Age* (Brynjolfsson & McAfee, 2014), and the *Rise of the Robots* (Ford, 2015), offer generalized interpretations of the impacts of technological change as well nationally-oriented policy recommendations such as education reform and the expansion of social safety nets. These discussions offer little to regional policy makers who must not only plan for potential job losses, but also strategize about how to remain competitive in a rapidly changing global economy.

Due in part to insufficient data about robots and AI, academic researchers have been slow to take up the issue. Standard industry and occupational data sources are not disaggregated sufficiently to distinguish robotics activities from other related categories. The few studies specifically examining the impact of robots have used data from the trade association of the robotics industry (Graetz & Michaels, 2015) or from a survey designed to distinguish robots from other types of production machinery (Jäger et al., 2015). These data and analyses, like the popular commentary on robots and jobs, are national in scope and fail to reflect substantial subnational variations that are apparent in the use of production technologies (Essletzbichler & Rigby, 2005; Rigby & Essletzbichler, 1997, 2005). Consequently, the dominant narrative about the rising robotic age tends toward technological determinism, treating mass roboticization as a universal and inevitable result of technological progress.

In light of current blind spots in the debate about emerging technologies and the economy, this paper has two purposes. First and foremost, it describes the geographical imprint of a growing and potentially disruptive industry that would otherwise not be discernible with current publically available data sources. This basic industry mapping allows for the characterization of differentiated and geographically embedded knowledge bases *within* an industry that are presently obscured by industrial taxonomies. Second, borrowing from evolutionary economic geography (EEG), the boundary-spanning properties of the field and industry are explored for insights leading to robot-aware local and regional economic development.

## ROBOTICS INDUSTRY DATA

It is not currently possible to identify robotics producers or those who work with robotics from traditional publicly available U.S. data because robots are only treated as subcategories of machinery in the North American Industrial Classification System (NAICS) and Standard Occupational Classification (SOC) codes. For example, SOC code 51-442 for *Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders*, includes those who 'set up, operate, or tend welding, soldering, or brazing machines or robots that weld, braze, solder, or heat treat metal products, components, or assemblies' (United States Bureau of Labour Statistics, 2010). A worker who uses a welding machine to hand-weld sheet metal may have very different skills, qualifications, and employment prospects than one who programs a robot to perform this task, but both would be identified by the same code under the current taxonomy (see Note 1, online appendix for further discussion of robotics and SOC codes).

Additionally, the U.S. Census Bureau's Annual Survey of Manufacturers (ASM) instructs establishments to include capital expenditures for robots in the 'New and Used Machinery and Equipment: All Other Expenditures for Machinery and Equipment' category (United States Census Bureau, 2014, 2015b). While not inaccurate, this categorization is broad: it includes all production equipment (e.g. 'motors, lathes, punch presses, etc.' [p. 13]), but excludes computers and software. Robots are pieces of production machinery, but they also require sophisticated software. Thus, it is unclear how an establishment that purchases both robots and the engineering and programming services necessary to integrate them into the production processes would report these expenditures on the form. This lack of clarity can cause systematic errors in collected data since the cost of installing and programming a robot (a process known as 'integration' described in the 'Robotics Industry' section below) has been estimated to add an additional 40% to 150% to the cost of the robot itself (Hunt, 2012).

The 2009 European Manufacturing Survey, analysed by Jäger, Moll, Somm, & Zanker (2015) marks the first attempt to isolate robot use in its questionnaire. Note 2, online appendix provides a brief description of how this is done.

The only data that specifically enumerate robots in the U.S. come from the International Federation of Robotics (IFR). These data, which compile robot sales from several national robotics associations and large suppliers (International Federation of

Robotics, 2012), are collected by country. Robotics trade associations, including the Robotics Industries Association (RIA) and the IFR use these data to report national sales trends in robotics. Graetz and Michaels (2015) also used these data to estimate the effects of robots on productivity and workers' hours and wages in 14 manufacturing industries within 17 member countries of the Organization for Economic Cooperation and Development (OECD). The authors report that robots are associated with productivity increases and a skill-biased trend in labour usage across country-industry pairs.

While Graetz and Michaels' (2015) focus is on macro-level rather than meso- or micro-level outcomes, some of their results suggest that there are significant regional variations in robot usage. The countries analysed differ significantly in robot density, which is measured by the number of robots per millions of hours worked (see Table 1 in Graetz and Michaels, 2015).

In addition to privileging a 'macro' perspective, analyses such as Graetz' and Michaels' also conceptualize robots as abstracted pieces of advanced machinery. Again, this abstraction may be a symptom of the way data are collected. But it is also problematic if the goal is to address the 'other side of the coin' when it comes to robots—the potential for innovation and economic development. While robotics is an innovative field, this innovation is not limited to the advancements in basic robotics science (e.g. robot vision or sensing, two of the most promising areas of robotics technology). The application of these new capabilities to commercial processes—integration—also requires innovation, albeit of a different type, often associated with 'low-tech' industries and 'synthetic' knowledge bases (see *Discussion* section). The entire realm of robotic innovation encompasses both the science involved in creating robots and the competencies involved in optimizing their use. The cost estimates for integration reported above suggest this latter component is a significant factor in the diffusion or robots. These evolving and complex sets of inputs to robotics highlight the difficulty of defining and studying high-technology industries and industrial clusters in a time of rapid technological change.[1]

In light of these difficulties, the immediate purpose of the robotics census (hereafter, the 'census') conducted and reported on in this paper is to serve as an initial step for enabling a more robust analysis of the robotics ecosystem. Ultimately, the goal is to understand the robotics industry in a way that accounts for the regional variations in industry presence and the deployment of robotic capabilities. This understanding is essential for addressing the potential positive and negative impacts of robotics that motivate local and regional policy responses.

## ROBOTICS CENSUS RESEARCH METHOD

Because robots are not treated as distinct categories for analysis in centrally collected NAICS or SOC data, the authors conducted a census of the U.S. robotics industry using two proprietary business databases (ReferenceUSA and ThomasNet), as well as the membership of the Robotic Industries Association (RIA)—the North American robotics trade association. Each firm that self-identified as a robotics-related firm was vetted individually via its website to determine the veracity of its claim. The census includes location, employment, sales, and country-of-ownership data for the U.S. robotics-related establishments. However, not all records from ReferenceUSA or

ThomasNet included employment and sales values. For these records, values were imputed (see Note 3, online appendix for imputation methodology).

In reporting the results of the census the term ‘robotics-related industry’ is used to describe the sector that has been captured. This cautious term is employed because, while the establishments in the database all specialize in some aspect of robotics, many of them are also engaged in related types of business. In particular, the database has captured general automation companies that manufacture controls, cables, and machine tools that have applications outside of robotics. The same is true for integrators: many integrators that specialize in robotics also perform factory automation services that do not involve robots. As a result, not all of the employees represented in the database work directly in robotics.

While the census is not a true census in the sense that it unambiguously accounts for every member of the U.S. robotics industry, it does capture all establishments that were available through widely-used business databases when the research was conducted—the period from May to September, 2015. Robots have been sold at record rates since about 2010, and the size of the industry is expected to grow rapidly in the near future (International Federation of Robotics, 2012, 2014; Robotics Industries Association, 2014, 2015), so a limitation of this type of point-in-time establishment count is that it will likely become out-dated quickly.

The definition of ‘robot’ that informs this research is the following: an actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks (International Organization for Standardization, 2012). This definition restricts robots to *physical* objects that have physical implications for their environments. In this way, it sets robots apart from artificial intelligence *in general*. While robots embody certain types of artificial intelligence technologies, the larger field includes purely informational activities like computer-based medical diagnoses, the generation of online content, or mining legal documents for important text.

Robots are further distinguished by whether they are *industrial* robots or *service* robots. Industrial robots are those used in manufacturing processes, while service robots are used by service providers or individual consumers (International Federation of Robotics, 2012). Examples of service robots are Roombas (household robotic vacuums made by iRobot) or robots that make deliveries in hospitals. The current composition of the global robotics industry presently remains dominated by the older and more established industrial robotics sector. In 2013, the value of sales of industrial robots was US$9.5 billion while the value of service robot sales was US$1.7 billion (International Federation of Robotics, 2014). The census reflects this orientation: only 91 out of the 856 U.S. robot-related firms produce or work with service robots. Thus, the analysis of the census focuses mainly on industrial robotics. However, the emergence of the service robotics industry becomes a key question taken up in the *Discussion* section.

Finally, this research was verified by an industry expert, Mr. Alex Shikany, RIA Director of Market Analysis, with particular attention being paid to the section that follows—the characterization of the robotics industry.

## THE ROBOTICS INDUSTRY

The industrial robotics industry consists of two types of firms: *suppliers* and *integrators*.

<u>Suppliers</u>

Suppliers design, produce, and sell robots, robot components, and robot-specific technologies to robot-using manufacturers (RUMs) either directly or through integrators. In the census, original equipment manufacturers such as American Grippers, Inc., which makes tools for robotic arms, and Macron Dynamics, which makes motion control products for automation systems, are classified as suppliers. Robot manufacturers such as ABB and Fanuc are also suppliers.

Nearly all suppliers of industrial robots are headquartered outside of the U.S. According to the International Federation of Robotics (IFR), 28 of the Federation's robot-supplier members represent 12 countries (IFR, 2016), while four countries are home to three or more robot suppliers: Denmark and Switzerland each have three while Germany and Japan each have six. Adept, the lone U.S.-based member of the IFR supplier group, employs 95 people in two locations according to the census.[2] As of 2012, four major robot suppliers held 17.1% of the worldwide industrial robot market share (MarketLine, 2012), and each of these firms was headquartered outside the U.S.: Fanuc and Yaskawa Motoman (Japan); Kuka (Germany); and ABB (Switzerland).

This locational pattern implies that U.S.-based robot users import much of their robot stock. Indeed, the IFR reports that while the U.S. ranked fourth worldwide in the number of robot installations in 2011, most of these robots were imported from Japan or Europe (2012) (the IFR report does not provide exact import or export numbers for the

U.S.). As shown in Table A1 (see online appendix), the two countries that produce the most robots, Japan and Germany, each exported roughly three quarters of their domestically produced robots in 2011, as indicated by the export ratio. At the same time, Germany is also a significant importer of robots. Japan, in contrast, almost solely uses domestically produced robots in domestic manufacturing plants. Through 2011, China ranked in the top five of robot-using nations, and the rate of growth of its robot stock far exceeded that of any other nation (IFR, 2012).

These data reflect trade in actual industrial robots; they do not include trade in robot-specific components and software, which are significant inputs to robot installations. Examples of this kind of product are specialized grippers for the ends of robotic arms, positioners and drives for mounting and moving robots within factories, cables for robot wiring, and software and cameras for robot 'vision' systems. While some of these auxiliary suppliers may be original equipment manufacturers (OEMs), supplying components for the 'bodies' of actual industrial robots, most supply aftermarket peripheral equipment and software that optimize robot installations and performance.

Following the RIA's classification scheme, this census also categorizes these firms as suppliers. While the web-based research method precludes an exact determination of the products that the establishments make, a conservative estimate is that over 50% of the supplier establishments in the census are neither makers of actual robots nor subsidiaries of foreign robot makers. Thus, U.S.-based robot suppliers are generally engaged in the production of peripheral equipment rather than robots themselves.

Integrators

Because of the global, yet concentrated, pattern of robot production as well as the complex and highly customized nature of robotic systems, integrators have a pivotal role in designing and implementing robotic systems for RUMs.

Anecdotally, some RUMs have in-house robotics integration capabilities, most notably large automotive manufacturers. The extent of robotics expertise embedded in large end-product manufacturers and OEMs deserves further study. The only instance where it is revealed in the census is Boeing's entry: the aerospace manufacturer is an integrator certified under the RIA's integrator certification program. Some RUMs have even developed robots in-house, and successfully marketed them to other manufacturers, although the evidence of this phenomenon is limited largely to Japanese manufacturers in the 1970s and 1980s (Roy & Sarkar, 2015).

Integrators possess a unique set of knowledge and expertise. They also complete the robotics supply chain by providing the link between suppliers of robots (including robot components and auxiliary technology and devices) and their customers, the manufacturers.

Robotics integration is one example of the larger field of systems integration, which itself is a subcategory of firms that provide knowledge intensive business services (KIBS), ranging from accounting to management consulting to engineering. Integrators in particular work with and specialize in various types of complex technical systems, from information and communications technology to energy distribution (Hobday et al., 2005).They have an imperative to provide 'turnkey solutions,' or 'the entire set of activities involved in the design, construction, testing, and delivery of a fully functioning system.' (Davies, 2004, p. 748). This turnkey model is essentially the one by which robotics integrators operate.

While integrators often 'supply' customers with physical robot installations, the distinction made in the census is that integrators' installations are value-added systems, assembled from assortments of suppliers' products (see Note 4, online appendix for illustrative examples of integrator firms).

## RESULTS OF THE ROBOT-RELATED INDUSTRY CENSUS

### Evidence of Robotic Regions

While the robotics-related industry is small in the context of the entire U.S. economy (about 0.05% of the total nonfarm employment), it is significant in several regions. Fig. A1 (see online appendix), which maps robotics-related employment in core based statistical areas (CBSAs) (see Note 5, online appendix for CBSA definition) illustrates that the strongest concentration of robotics employment is in the traditional manufacturing hubs of the Midwest that border the Great Lakes—the area often referred to as the 'rust belt' or the 'frost belt.' Table 1 lists 30 CBSAs that the authors have initially classified as Robotic Regions. These Robotic Regions are designated based on the criterion of having at least seven robot-related establishments (the 85$^{th}$ percentile).

**Table 1 here**

Major manufacturing centers, as expected, factor prominently in this list: the Detroit and Chicago metropolitan statistical areas (MSAs) rank first and second in robotics-related establishments and fifth and seventh, respectively, in robotics-related employment. The Minneapolis, Cleveland, Cincinnati, Grand Rapids, and Los Angeles MSAs are also hubs for both manufacturing and robotics. The Seattle MSA, which is the headquarters of the aircraft manufacturer Boeing, ranks highly in employment but barely makes the list in terms of establishments, because Boeing employs 5,000 of the region's 5,367 robotics-related workers. However, all 5,000 of these employees likely do not work directly with robots, because, as mentioned at the outset of the paper, the census does not distinguish occupations within firms or establishments.

Several smaller regions such as the Iowa City, IA, Fort Collins, CO, Reno, NV, and Akron, OH MSAs, do not have enough robotics-related establishments to make the list of Robotic Regions, but they each demonstrate significant robotics employment, especially for their relatively small size. For example, each of these regions has more robotics-related employment than the much larger Washington, D.C. metropolitan region. These observations indicate that a simple count of robotics-related establishments and employees—though an important first step—can provide only a potential characterization of the U.S. robotics landscape. For this reason, the authors caution that the list of Robotic Regions in Table 1 is meant as a guide for further research rather than a definitive list of regions with robotics advantages.

Smaller regions display quite prominently in terms of location quotients (see Note 6, online appendix), an index of specialization. Values above '1' indicate regional specialization, and higher values indicate stronger specialization. The location quotients mapped in Fig. 1 generally correspond to the employment measures in Fig. A1 (online appendix) indicating that Robotics Regions demonstrate not only high overall levels of robotics-related employment, but also high levels *relative* to other regions. Indeed, Table A2 (see online appendix), which shows location quotients for MSAs with populations of at least 300,000 is similar to Table 1, although large metropolitan regions with high levels of overall employment fall lower on the list or drop off entirely (e.g. Los Angeles and New York) because their more diverse industrial compositions moderate the effect of any individual industry.

**Figure 1 here**

**Caption: Robotics-Related Location Quotients for CBSAs in the U.S.**

**Source: Authors' calculations based on robotics census and U.S. Census Bureau County Business Patterns 2013**

Robotics and Industrial Co-location

Robotics-related industry clusters demonstrate properties similar to other industries, albeit on a smaller scale (see Fig. A3 and Note 8, online appendix for further detail on comparative clustering). Robotics also co-locates with other related industries. The density of robotics-related firms in the Midwest (Figs. 1, A1, and A2) suggests that robotics is especially co-located with auto, metals, and machinery manufacturing, which are also concentrated in this part of the country.

To test this assumption, the authors calculated Pearson correlations between robotics-related employment in CBSAs and employment in the U.S. manufacturing sector overall, as well as the subsectors that correspond to those reported by the IFR (2012, 2014) as being the most intensive users of robots in the late 2000s and early 2010s. These tests confirm that the hypothesized associations are statistically robust (see Table A3, online appendix). The coefficients indicate moderate (information, chemical, computer, transportation, and food manufacturing) to strong (fabricated metal and machinery manufacturing) positive correlations. Machinery manufacturing has the largest coefficient which is likely due in part to robot manufacturing being a subset of this sector according to NAICS (United States Census Bureau, 2012, 2015b). In the census, 321 establishments identify themselves as being part of the machinery manufacturing subsector. However, a correlation stronger than .53 would be expected if robotics were simply a subset of machinery manufacturing. This magnitude of correlation suggests that the robotics industry has a unique geography that diverges from the machinery industry as a whole.

Part of this divergence may be due to the influence of the information sector (NAICS 51) on robotics. While its correlation, also shown in Table A3, is weak to moderate, the prominent status of the Boston, New York, and San Jose MSAs as Robotic Regions suggests the robotics-information connection may become more important as the robotics industry grows. These three MSA regions have NAICS 51 (Information) location quotients of 1.45, 1.49, and 3.08, respectively (United States Bureau of Labour Statistics, 2014). The implications of this connection for regions are taken up in the *Discussion* section of this paper.[3]

## Locations of Integrators and Suppliers

The U.S. robotics-related industry is primarily one of integrators. Integrators out-employ, outsell, and outnumber suppliers by a margin of approximately two-to-one, (see Table 2). The largest robotics-related firm in the U.S. is an integrator: Rockwell

Automation, headquartered in Milwaukee, WI, employs 18,256 people in 97 establishments. Emphasis on integration is a key characteristic of robotics in the U.S., and one that has received little attention in commentaries and research about robotics and automation in general. The two-to-one ratio of integrators to suppliers implies the U.S. specializes in the design and implementation of *robotics systems* rather than the design and production of robotic machinery.

**Table 2 here**

The locations of integrators and suppliers reveal different types of specialized innovation economies. Suppliers have a slight tendency to cluster in places associated with traditional high-technology and consumer-related innovation, while integrators have an intensified presence in traditional manufacturing economies (see Fig. A2, online appendix). This geographic dynamic is quantified via Integrator-Supplier ratios, which indicate the percentage of integrators relative to suppliers within a CBSA Table 3 lists these ratios for CBSAs with at least 600 total robotics-related employees. CBSAs with ratios less than .5 fall into a category labeled 'supplier-dense regions' in the table, and those with ratios above .5 are grouped into a category of 'integrator-dense regions.'

**Table 3 here**

Several observations emerge from this table. First, the canonical U.S. innovative regions—Boston and San Jose (Silicon Valley)—rank highly as supplier-dense regions.

The New York City region, known more for innovation in financial and creative services, also ranks highly in the measure of suppliers relative to integrators. These regions, in addition to Pittsburgh (the seventh-ranked supplier-dense region), are home to several top academic robotics programs: Stanford and UC Berkeley near San Jose, MIT in Boston, and Carnegie Mellon University in Pittsburgh. Based on prior research on university-industry spinoffs, such associations are expected (Mowery & Sampat, 2006), but without further research into the cultures and dynamics of the robotics-related industries, generalizing about these clusters is premature. However, these supplier-integrator differentials across space in the robotics industry suggest that corresponding *knowledge base* differentials may play a role in these geographies (see the *Discussion* section for elaboration on this concept).

Foreign Direct Investment and the Robotics Industry

Industrial robotics is a global, but concentrated, industry. In the U.S., some foreign robot makers have established North American headquarters while others have established small branch plants or sales offices (see Note 8, online appendix for branch plant or sales office criteria for inclusion in the census). As shown in Table A4 (online appendix), Michigan has received the bulk of robotic foreign direct investment. The four Michigan CBSAs on the list account for 18 establishments and 2,941 employees, amounting to 74% of all robotics-related foreign direct investment in the U.S. based on employment levels.

The impacts of foreign direct investment in the U.S. are varied and depend upon numerous factors. However, foreign robot manufacturers have not emulated their auto-manufacturing counterparts by establishing production facilities in the U.S.[4] The design and production of industrial robots largely remains overseas, while local expertise is involved in installing and enhancing them with peripheral technologies and equipment. The robot-related FDI that does exist in the U.S. demonstrates a clear pattern of geographical clustering, which suggests that these firms are fortifying their host regions' positions within 'global city-region networks' of robotics and related activity both domestically and abroad (Bathelt & Li, 2014).

## DISCUSSION

With the uneven geography of robotics as background, inferences are now drawn about this geography, suggesting hypotheses for further research, and situating discussion within the context of local economic development.

### Robotics as a Relational Industry

Robotics is highly *relational* in that it bridges boundaries across disciplines, industries, applications, and knowledge bases. The firms in the census possess a high degree of 'relatedness' (Essletzbichler, 2015; Neffke et al., 2011) and contribute to 'related variety' (Frenken et al., 2007) in a region's industrial portfolio. While the firms in the census are diverse, they maintain common commercial, technological, and cognitive threads.

Relatedness is often assessed through quantitative induction. For example, by using input-output tables to create a relational matrix of all manufacturing industries, Essletzbichler (2015) shows that inorganic chemicals and metallurgy are statistically related to most other manufacturing industries. For the 362 manufacturing subsectors that are identified by Standard Industrial Classification (SIC) codes, this matrix approach effectively quantifies relatedness.

However, for robotics, which does not have a SIC or NAICS code, this approach is not possible. Instead, we must start from a qualitative position to analyze the relatedness of the robotics industry. As an academic discipline, robotics brings together a heterogeneous set of intellectual communities. In 2009, authors from mechanical engineering and computer science departments each accounted for over 55% of publications in the top academic robotics journals (computer science accounted for the most of any discipline at just over 30%). At the same time, authors from electrical engineering departments published about 12% of these articles, while the contributions of biological and cognitive science researchers rose rapidly during a twenty year period from zero in 1989, to just over 10% in 2009 (Birk, 2011). Further, robotics is also an increasingly software-driven field (Birk, 2011), which suggests that the locational correlation with information-focused regions that we identified is a meaningful one rather than a statistical accident.

The diversity of the firms in the census reflects the intellectual diversity of the robotics field and is also emblematic of the relational quality of robotics. The database includes establishments specializing in a variety of technologies such as machine vision, motors and drives, industrial wiring and cabling, sensing, navigation, software, and industrial safety. Integrators act as relational agents by bridging the knowledge of these technologies across sectoral and spatial boundaries of robot suppliers and robot-using manufacturers.

Management scholars suggest industries specializing in products involving multiple technologies and components tend to assume a 'loosely coupled' structure driven by systems integration, to address the uneven rates of change of component technologies and the lack of predictability of how components will fit together as they evolve (Brusoni et al., 2001). Automotive and hard disk drive manufacturing—two primary users of robotics—are examples of industries with this loose, integrator-dependent structure (Brusoni et al., 2001). The robotics industry itself may fit into this category.

For theorizing the regional diffusion and impact of the robotics industry, the concept of relatedness appears particularly promising. Relatedness and related variety have become prominent in regional development studies, particularly by scholars who approach the topic from an evolutionary economic geography (EEG) perspective. EEG emphasizes the idea that economic units—individuals, firms, and institutions—evolve together, and that this co-evolution is spatially and socially contingent (Martin & Sunley, 2015; Pike et al., 2009; Schamp, 2010).

The conceptual underpinnings of grouping industries based on relatedness in EEG are similar to those of a Porterian industrial cluster—broadly, a set of co-located and related industries (Porter, 1998, 2003). However, rather than assuming that existing cluster strength *determines* the growth trajectory of the industries within it and the region that contains it (e.g. Delgado et al., 2014), the EEG approach allows for assessments of how clusters themselves evolve based on the degree of the relatedness of their industries and other more traditionally studied factors such as transportation costs and institutional characteristics (Boschma, 2015; Martin & Sunley, 2015).

Industrial related variety is hypothesized to facilitate productive regional evolution (i.e. economic growth) by acting as a balance between regional industrial diversity and specialization (Asheim et al., 2011). The interplay between regional diversity (formally called 'urbanization') and specialization ('localization') has long been of interest to scholars who study agglomeration. While excessive urbanization exposes a region to a higher variety of sectoral shocks (by virtue of having more sectors within a regional industrial portfolio), as well as industrial disconnectedness and a lack of focus, excessive specialization may promote industrial 'lock-in' preventing a region's firms from shedding unproductive routines and abandoning the production or use of outdated technology. Additionally, regional diversity may promote combinatorial innovations, while specialization may lower costs by allowing firms to share resources (Boschma, 2015; Coenen et al., 2015).

While the optimum balance between diversity and specialization is more of a theoretical construct than an achievable policy goal, working towards it may be especially beneficial for declining regions because related variety not only offers cushioning against economic shocks, but also more 'recombinatory options' (Boschma, 2015, p. 737) through which a region may adjust its path. Examples of this type of 'path renewal' (Coenen et al., 2015) have been documented in Pittsburgh's shift from a center of steel production to steel technology development (Treado, 2010) and in the transition of a region in Northern Sweden from an economy based in forest product extraction and production to one based in high value added biorefinery technology (Coenen et al., 2015).

This paper identifies robotics as a boundary-spanning industry and points to the relevance of Boschma's question (2015), 'are boundary-spanning industries affecting the capacity of a region to develop new growth paths?' (p. 744). Determining the answer is particularly relevant for Robotic Regions such as Detroit and Cleveland that are still managing decline and coping with a history of overspecializations in outdated industries. Their strong robotics communities may offer related variety upon which to build new technologically relevant paths.

## Differentiated Knowledge Bases in the Robotics Industry: The Persistent Importance of 'Low-Technology'

Working toward path renewals for declining regions requires an understanding of the 'differentiated knowledge bases' (Asheim et al., 2011) and their geographical patterns within the robotics industry. These knowledge bases can be distinguished by the prevalence of *analytical* versus *synthetic* knowledge. According to Asheim and Gertler (2006), 'an analytical knowledge base dominates economic activities where scientific knowledge is highly important, and where knowledge creation is often based on formal models, codified science, and rational models. Prime examples are biotechnology and information technology' (p. 296). In contrast, synthetic knowledge 'prevails in industrial settings where innovation takes place mainly through the application or novel combination of existing knowledge' (p. 295). An example of an analytically dominant environment in robotics is an academic or industrial laboratory where researchers are developing a novel artificial intelligence algorithm or neural network architecture. A paradigmatic example of a synthetic knowledge-dominant process is integrating robots into a production system on the shop floor. In the latter case, established technology is configured, often inductively, to provide a custom solution to a specific problem.

The robotics census results suggest that there is a spatial aspect to this knowledge base differentiation within the robotics industry. The regions with high supplier-integrator ratios can be expected to embody an analytical knowledge base, with product-oriented research and development privileged over industrial process applications. Places with lower supplier-integrator ratios (i.e. proportionally more integrators) can be expected to have an emphasis on synthetic knowledge.

Of the top ten supplier-dense regions (Table 3), four (New York, San Jose, Philadelphia, and Boston) are prominent global centers in the analytically-dominant fields of either life science/biotechnology and information technology (or both in the case of San Jose and Boston), and three (San Jose, Boston, and Pittsburgh) are homes to major academic robotics research centers. MIT near Boston and Carnegie Mellon University in Pittsburgh rank among the top 20 institutions in the world in terms of robot research publications (Ghiasi & Larivière, 2015), although the list is otherwise dominated by Asian institutions.

A closer look at these regions' types of robot firms supports the importance that knowledge base has for the nature of the local robotics industry. While traditional industrial robots are largely designed and produced outside of the U.S., the U.S. is home to robot producers who have focused on alternative and emergent styles of robots. Indeed, U.S. robotics research demonstrates a comparative advantage in mobile robots, telerobotics, and humanoid robots, while lagging in industrial robots and industrial robot applications (Ghiasi & Larivière, 2015). Collaborative robot[5] maker Rethink is based in the Boston area, and Teradyne, a Boston-area automation and test equipment company, recently acquired Denmark-based Universal Robots (Teradyne, 2015), which is one of the leading collaborative robot suppliers. iRobot, the maker of Roomba robotic vacuums, is also headquartered in the Boston area. Adept, a producer of automated vehicles for use in factories and warehouses, maintains its U.S. headquarters in Silicon Valley.

These coastal regions also tend to lag in industries that are intensive robot users. With the exceptions of Boston's and San Jose's significant advantage in computer and electronic product manufacturing, these regions' location quotients in industries such as transportation, machinery, and electrical equipment manufacturing are quite low.

In contrast to supplier-dense regions, integrator-dense regions are found mostly in the U.S. interior where synthetic manufacturing related knowledge bases are more prevalent.[6] In these places, learning-by-doing and learning-by-using occur through the process of robotics systems integration. This is one way that robotics is relational, bridging not only the scientific innovations in robotics to their practical applications, but also the 'high-tech' industries of electrical and computing machinery to the 'low-tech' industries of basic and fabricated metals, food products, and non-pharmaceutical chemicals[7] (the terms high- and low-tech here are in quotes to suggest that the dichotomy is false; 'low-tech' industries in fact display many 'high-tech' characteristics [Hansen and Winther, 2014]) . These relationships have important regional innovation implications, but the association of analytical knowledge with low technology means that it often flies under the statistical and policy radar.

## Robot-Aware Regional Economic Development Policy

Following Asheim et al. (2011), regional development policies should take into account local related variety and knowledge bases because they each have different and complementary implications for development. While synthetic knowledge is more difficult to codify and travels better through local networks (Asheim et al., 2011; Cohendet & Amin, 1999), analytical, science-based knowledge may be served better by supporting its transmission between, rather than within regions (Asheim et al., 2011; Cohendet & Amin, 1999). Britton (2003), for example, shows how both intra- and interregional networks support different aspects of the Toronto electronics cluster. Likewise, the distance between the production and use of advanced manufacturing technologies (including robots) factored heavily in the ultimate adoption and effectiveness of these technologies (Gertler, 1995). This distance can be defined literally in terms of physical distance, as well as conceptually as 'cultural' distance: users and producers who thought about technology differently had difficulty working together to implement it.

In light of these properties, we borrow from Hansen and Winther (2014) four concrete policy recommendations aimed at further reducing distances and enhancing the relational capacity of the entire robotics industry. Because of their emphasis on 'low-tech' industries, these policies are oriented toward integrator-dense regions with strong synthetic knowledge bases. These regions can 1) develop innovation strategies that recognize the importance of incremental, synthetic, or 'low-tech' innovations as opposed to dominant science-based models, 2) support robotics-related capital and R&D investment for low- or medium-tech SMEs, 3) foster academic-industry collaborations aimed at robotics process improvements (these would include research universities as well as community and technical colleges), and 4) understand and facilitate supplier-customer relationships, encompassing robot suppliers, robot integrators, and robot-using manufacturers. In Hansen and Winther (2014), these recommendations are generalized and based on the Danish experience. Here, they are tailored to the robotics industry and supply chain and meant, using a specific case, to illustrate the point made by Hansen and Winther and others (e.g. Patel & Pavitt, 1994; Tunzelman & Acha, 2006): that 'high-tech' and 'low-tech' are not oppositional, but rather complementary forces in economic evolution. This concept is especially important as low-tech industries like food, metals, and some chemical products are consistently intensifying their robotics use (International Federation of Robotics, 2014).

Of course, crafting strategy around low-tech, synthetic knowledge cannot single-handedly 'save' a declining region. However, the examples of path renewal cited above (forestry and steel) have a common focus on the 'high-tech end of…low-growth sectors' (Tunzelman & Acha, 2006, p. 410). Rather than job-creating, they may be 'job-preserving' or 'job-changing' (Hansen & Winther, 2014) which can be important to regions looking for stability in a time of upheaval. As a relational industry, robotics is illustrative of these possibilities.

For supplier-dense regions with more of an analytical knowledge base and basic research presence, policy makers can encourage university-industry and commercial collaborations according to existing strengths. The U.S. emphasis on non-industrial and mobile robots opens the door for a wide set of boundary-spanning collaborations involving healthcare, transportation, and security to name a few. For example, 'Mcity,' a collaboration between the University, the State of Michigan, and several local automotive companies, is an entire mock city meant for researching and testing autonomous vehicles located on the campus of the University of Michigan (Mobility Transformation Center, 2015; Paukert, 2015).

## CONCLUSION

Rapid cross-sectoral developments in robotics and artificial intelligence have the potential to be disruptive. As such, they have generated much popular media prediction, speculation, and hand-wringing. Scholarly and popular literatures of this century have focused on macro-level changes in productivity and employment stemming from these technologies. But these 'big-picture' interpretations fail to consider the spatially contingent implications of technology development and diffusion. Consequently, as robotics and AI infiltrate local production and services economies, policy makers, economic developers, and leaders lack insight into the impacts and responses they should consider for their regional economic resilience.

In response to this critical knowledge deficiency, this paper has reported the results of a census of the robotics industry, focusing on manufacturing, the largest and oldest sector associated with robotics. It contributes the first description of the geographical imprint of this emerging industry.

Several Robotic Regions stand out as especially well-positioned to be leaders in robot-related innovation. However, these regions form a heterogeneous group, and their differences are related to their relative robotic advantages. Midwestern Robotic Regions tend to rely on the synthetic knowledge of integrators to incorporate robots into production processes, while coastal regions specialize in the analytical pursuits of generating new robotics technology. Rather than viewing the research and development focus of the analytical regions as superior to the applied integration knowledge that predominates in the rust belt, both types of knowledge are highly relational and provide opportunities for regional path renewal. Policy makers should recognize that innovation and robotic diffusion are not independent of each other. They are in fact linked geographically and commercially by integrators, a group that has been overlooked by commentary and analysis on the topic. Increasing understanding about this group and their relational capabilities will be key to successfully responding to 21st century technological change on the local and regional levels.

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[1] See Waxell (2009), Kile & Phillips (2009), and Kelton et al (2008).

[2] The Japan-based multinational automation firm Omron acquired Adept in October of 2015 (Omron, 2015).

[3] Unfortunately, data relating to the year of establishment for robotic firms is unreliable (the distribution is highly bimodal, indicating a systematic reporting error), so it is not possible to assess changes in the geography of the robotics industry over time.

[4] Swiss robot supplier ABB is a recent exception, announcing plans to open a production facility at its North American headquarters in Auburn Hills, MI (Detroit-Warren-Dearborn, MI MSA) (Phillips, 2015).

[5] Collaborative robots generally perform light-duty tasks such as assembly or packaging, in the same workspace as human laborers. This is in contrast to traditional industrial robots, which are usually physically separated from their human counterparts because of safety concerns (SHIKANY, 2014).

[6] The relatively even ratios of the Detroit and Chicago regions should be interpreted carefully: because of significant foreign direct investment in these areas, some of the supplier presence may be in the form of regional sales offices. Despite efforts to limit the presence of these establishments, the database likely captures some sales activity. This potential 'hidden' focus on sales as opposed to research and development may inflate the supplier-integrator ratio in some regions, suggesting that it should not be taken as a direct proxy for a knowledge base.

[7] These classifications follow the OECD (2011) manufacturing technology intensity definition based on R & D intensity.

## TABLES AND FIGURES FOR MAIN TEXT

**Table 1: Establishment and Employment Counts for "Robotic Regions"**

| MSA | Establishments | Employment |
|---|---|---|
| Detroit-Warren-Dearborn, MI | 66 | 3,012 |
| Chicago-Naperville-Elgin, IL-IN-WI | 42 | 2,367 |
| Boston-Cambridge-Newton, MA-NH | 36 | 2,068 |
| Los Angeles-Long Beach-Anaheim, CA | 29 | 1,513 |
| New York-Newark-Jersey City, NY-NJ-PA | 24 | 1,192 |
| Cincinnati, OH-KY-IN | 21 | 1,391 |
| San Francisco-Oakland-Hayward, CA | 21 | 531 |
| Minneapolis-St. Paul-Bloomington, MN-WI | 20 | 2,265 |
| Pittsburgh, PA | 19 | 715 |
| San Jose-Sunnyvale-Santa Clara, CA | 19 | 656 |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 19 | 610 |
| Cleveland-Elyria, OH | 18 | 8,411 |
| Dallas-Fort Worth-Arlington, TX | 18 | 380 |
| Milwaukee-Waukesha-West Allis, WI | 17 | 8,971 |
| Atlanta-Sandy Springs-Roswell, GA | 17 | 460 |
| Grand Rapids-Wyoming, MI | 15 | 2,512 |
| Charlotte-Concord-Gastonia, NC-SC | 15 | 556 |
| Indianapolis-Carmel-Anderson, IN | 13 | 294 |
| Houston-The Woodlands-Sugarland, TX | 13 | 552 |
| Raleigh, NC | 13 | 285 |
| Columbus, OH | 9 | 5,351 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | 9 | 238 |
| St. Louis, MO-IL | 9 | 218 |
| Louisville/Jefferson County, KY-IN | 8 | 398 |
| Dayton, OH | 8 | 219 |
| Nashville-Davidson-Murfreesboro-Franklin, TN | 8 | 174 |
| Boulder, CO | 8 | 86 |
| Seattle-Tacoma-Bellevue, WA | 7 | 5,367 |
| Davenport-Moline-Rock Island, IA-IL | 7 | 236 |
| Rochester, NY | 7 | 197 |

*Source: Authors' Database*

**Table 2: Robotics-Related Establishments, Employment Size, and Sales by Type of Firm**

| | **Total** | **Integrators** | **Suppliers** |
|---|---|---|---|
| Establishments | 856 | 518 | 338 |
| Employment | 65,198 | 42,168 | 23,030 |
| Sales Volume | $14,294,641,435 | $9,339,847,435 | $4,954,794,000 |

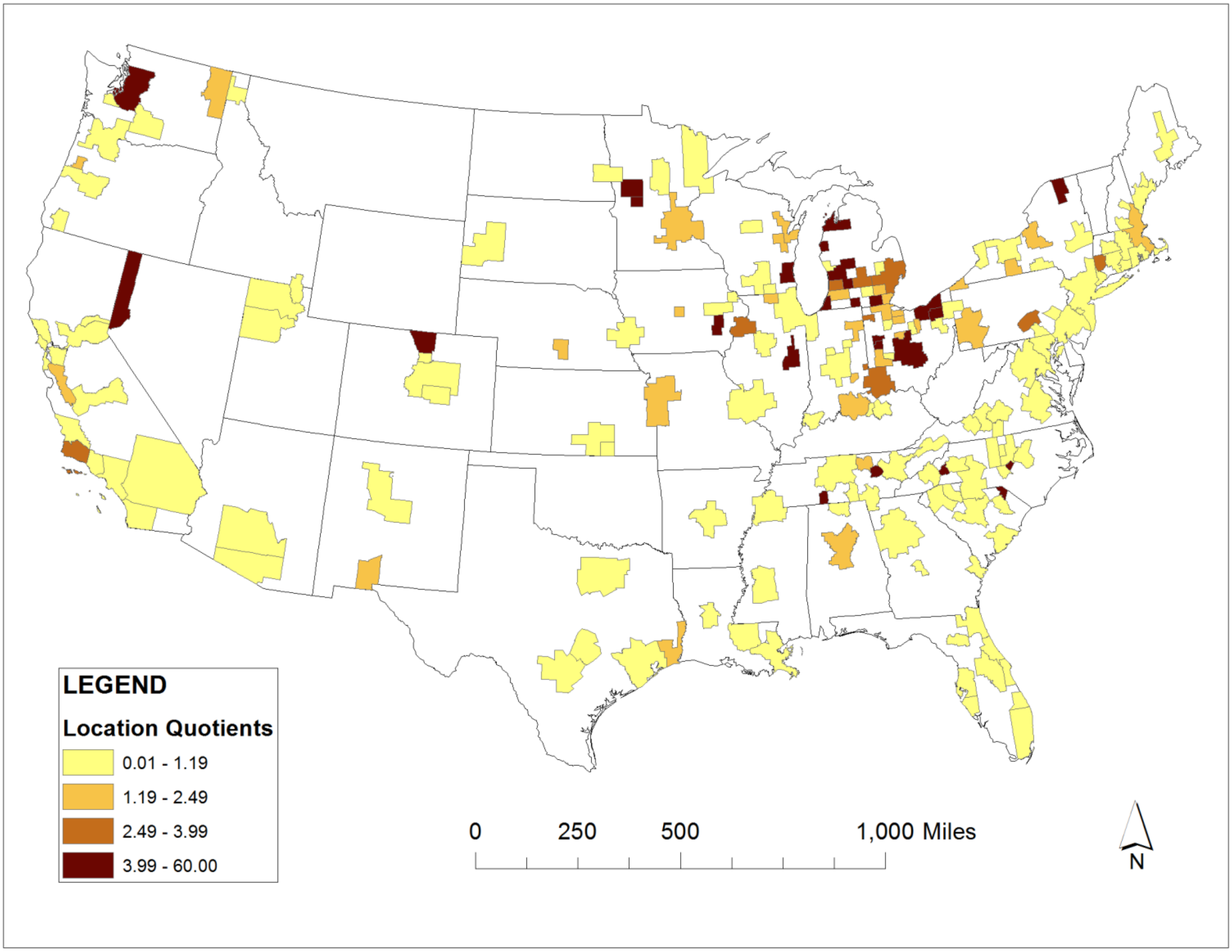
*Source: Authors' database*

**Table 3: Supplier-Integrator Ratios for CBSAs with at Least 600 Robotics-Related Employees**

| Type of Region | CBSA | Integrator Employment | Supplier Employment | Total Employment | Integrator-Supplier Ratio |
|---|---|---|---|---|---|
| **Supplier-Dense Regions** | Columbus, OH | 358 | 4,993 | 5,351 | 0.07 |
| | New York-Newark-Jersey City, NY-NJ-PA | 121 | 1,071 | 1,192 | 0.10 |
| | San Jose-Sunnyvale-Santa Clara, CA | 76 | 580 | 656 | 0.12 |
| | Boston-Cambridge-Newton, MA-NH | 287 | 1,781 | 2,068 | 0.14 |
| | Grand Rapids-Wyoming, MI | 389 | 2,123 | 2,512 | 0.15 |
| | Birmingham-Hoover, AL | 81 | 250 | 331 | 0.24 |
| | Pittsburgh, PA | 190 | 525 | 715 | 0.27 |
| | Los Angeles-Long Beach-Anaheim, CA | 564 | 949 | 1,513 | 0.37 |
| | Minneapolis-St. Paul-Bloomington, MN-WI | 849 | 1,416 | 2,265 | 0.37 |
| | Dallas-Fort Worth-Arlington, TX | 152 | 228 | 380 | 0.40 |
| | Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 254 | 356 | 610 | 0.42 |
| **Integrator-Dense Regions** | Kansas City, MO-KS | 835 | 0 | 835 | 1.00 |
| | Iowa City, IA | 750 | 0 | 750 | 1.00 |
| | Wapakoneta, OH | 600 | 0 | 600 | 1.00 |
| | Milwaukee-Waukesha-West Allis, WI | 8,874 | 97 | 8,971 | 0.99 |
| | Seattle-Tacoma-Bellevue, WA | 5,302 | 65 | 5,367 | 0.99 |
| | Cleveland-Elyria, OH | 8,198 | 213 | 8,411 | 0.97 |
| | Louisville/Jefferson County, KY-IN | 383 | 15 | 398 | 0.96 |
| | Akron, OH | 600 | 34 | 634 | 0.95 |
| | Houston-The Woodlands-Sugar Land, TX | 407 | 145 | 552 | 0.74 |
| | San Francisco-Oakland-Hayward, CA | 351 | 180 | 531 | 0.66 |
| | Detroit-Warren-Dearborn, MI | 1,762 | $1,250 | 3,012 | 0.58 |
| | Chicago-Naperville-Elgin, IL-IN-WI | 1,333 | $1,034 | 2,367 | 0.56 |
| | Atlanta-Sandy Springs-Roswell, GA | 240 | $220 | 460 | 0.52 |
| | Charlotte-Concord-Gastonia, NC-SC | 287 | $269 | 556 | 0.52 |
| | Cincinnati, OH-KY-IN | 704 | $687 | 1,391 | 0.51 |

*Source: Authors' Database*

**Figure 1: Robotics-Related Location Quotients for CBSAs in the U.S.**



**Online Appendix**

1. Eight-digit SOC codes for robotics technicians (17-3024.01) and robotics engineers (17-2199.08) have been established but they are for descriptive purposes only (O*NET, 2015). Occupational data are not collected to this degree of specificity by the U.S. Census Bureau or the Bureau of Labour Statistics (United States Bureau of Labour Statistics, 2015; United States Census Bureau, 2015b)
2. The 2009 European Manufacturing Survey has assessed robots as separate pieces of technology by asking establishments ~~including~~ two ~~questions, asking establishments a~~questions: a) whether they use robots and b) how intense this use is. Responses to the "intensity" question take the form of a three-level "high, medium, and low" scale, based on the judgment of the respondent. The specific instructions for answering this question are as follows: "Extent of actual utilization compared to the most reasonable potential utilization in your factory: Extent of utilized potential 'low' for an initial attempt to utilize, 'medium' for partly utilized and 'high' for extensive utilization" (Jäger et al., 2015, p. 76). While still subjective, this strategy achieves a more accurate representation of robot usage at the firm level than any ~~so far~~ used thus far in the United States.~~.S.~~ However, it has not been analysed yet on a subnational level, nor does it account for the inputs of integrators in robotic systems.
3. In the case of employment, 683 out of the total 856 records had exact employment values. Another 44 had only employment ranges. For records with ranges, the

midpoint of the range was used as the value. For the remaining 129 records (15% of the entire database), the median employment size based on type of establishment (integrator or supplier) was assigned to the record. The median integrator employment size is 20 and the median supplier size is 15. The same process was performed for sales data. A total of 39 records had sales ranges, and 212 records (25% of the entire database) were imputed based on median values. The median annual sales value for integrators is $6,419,000 and the median value for suppliers is $6,423,500 (see Table A4).

4. A typical example of an integrator firm is Creative Automation, a 40-employee firm in Southeastern Michigan that 'provides turnkey automation solutions for industry' (Creative Automation, 2016). However, large automation firms with many branch plants factor prominently in the industry. Lincoln Electric and Rockwell Automation branches together account for 26% of U.S. integrator establishments (136 of 518) and 53% of integrator employment (22,486 of 42,168).

5. According to the U.S. census, 'the term *Core Based Statistical Area* (CBSA) is a collective term for both metro and micro areas. A metro area contains a core urban area population of 50,000 or more ~~population~~, and a micro area contains an urban core population of at least 10,000 (but less than 50,000) ~~population~~. Each metro or micro area consists of one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core'[A1] (United States Census Bureau, 2015a). Our analysis of

robotics-related establishments covers all CBSAs. The CBSAs with robotics-related establishments are designated by yellow polygons in Fig.~~ure~~ A2. We identified 13 robotics-related establishments that are located in places that are not part of a CBSA.

6. Location quotients are commonly used indicators of comparative industrial advantage. Following (Leigh & Blakely, 2013), they are calculated according to the formula:

$$LQ = \frac{\left(\frac{e_i}{e}\right)}{\left(\frac{E_i}{E}\right)}$$

Where:

$e_i$ = local employment in industry $i$

$e$ = total local employment

$E_i$ = national employment in industry $i$

$E$ = total national employment

7. The robotics-related industry demonstrates a familiar intra-industry clustering pattern. Figs. 1 (main text), A1, and A2 show this phenomenon cartographically, with obvious concentrations in Midwestern CBSAs. Fig. A3 compares histograms of CBSAs' location quotients in robotics to those of other similar and related industries. All of the distributions, including robotics, have a strong positive skew and a long tail, characteristic of phenomena that follow a power-law. The robotics-related industry's notably high skewness value is attributable to most CBSAs having no identifiable robotics-related employment in the census.

~~7.~~8. Branch plants of suppliers based outside of the U.S. are only included in the census if they have 10 or more employees. Small (less than 10 employee) branch plants are assumed to be regional sales offices and thus not reflective of the scientific or technical knowledge bases that the census is designed to capture. This rule has one exception—suppliers headquartered outside of the U.S. with *only* one U.S. location. In these cases, small establishments are included in the census because they represent a large supplier's sole U.S. presence. For integrators, all branches, regardless of size, are included in the census.

## Supplemental Figures and Tables

**Figure A1: Robotics-Related Employment in the U.S.**

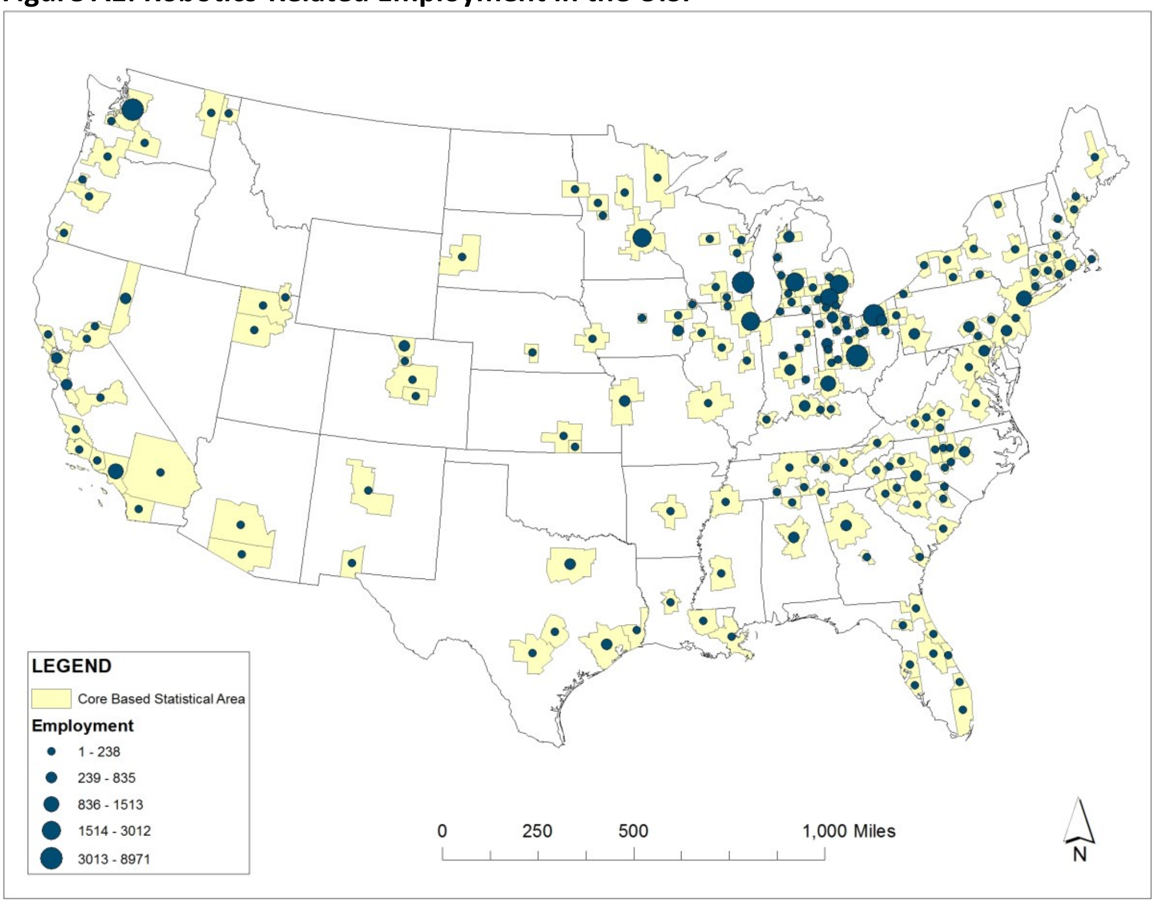


**Figure A2: Robotics-Related Establishments in the U.S. by Type (Integrator/Supplier)**

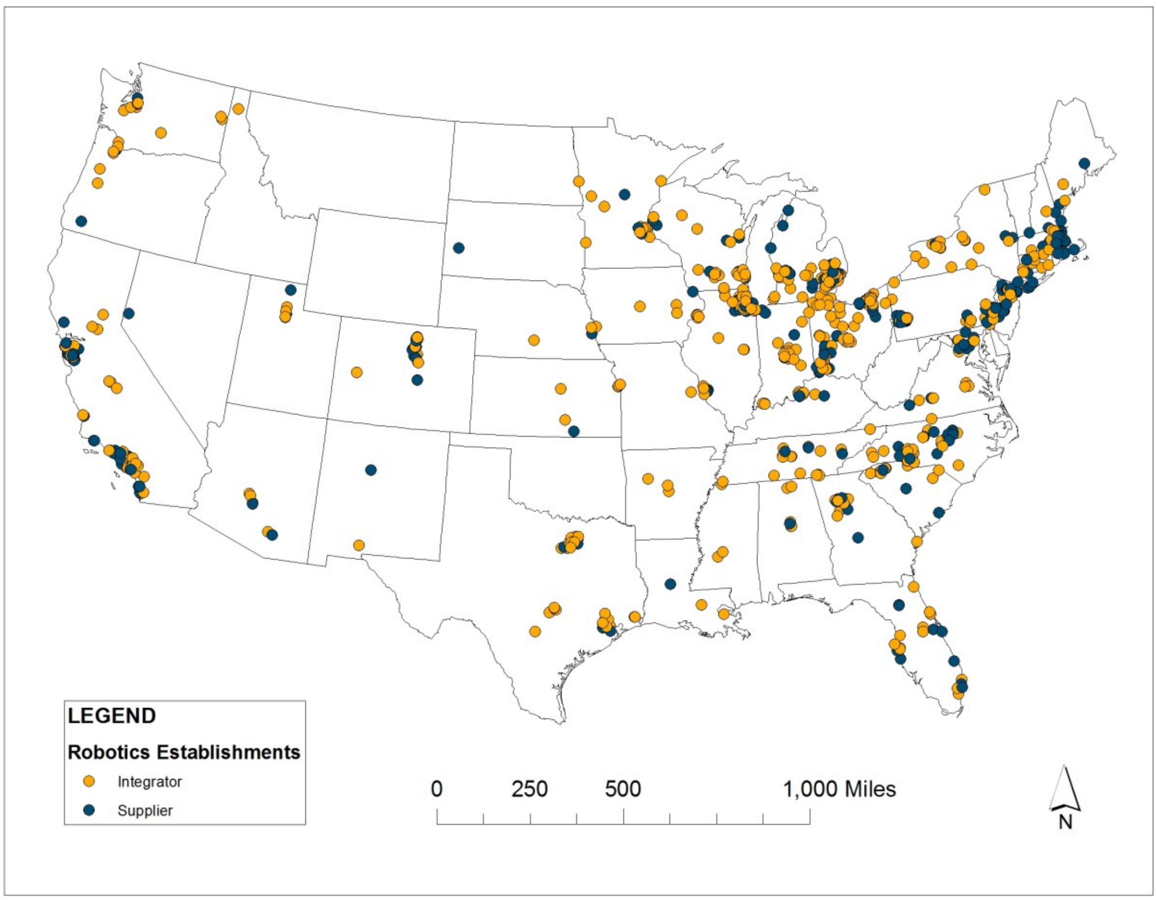
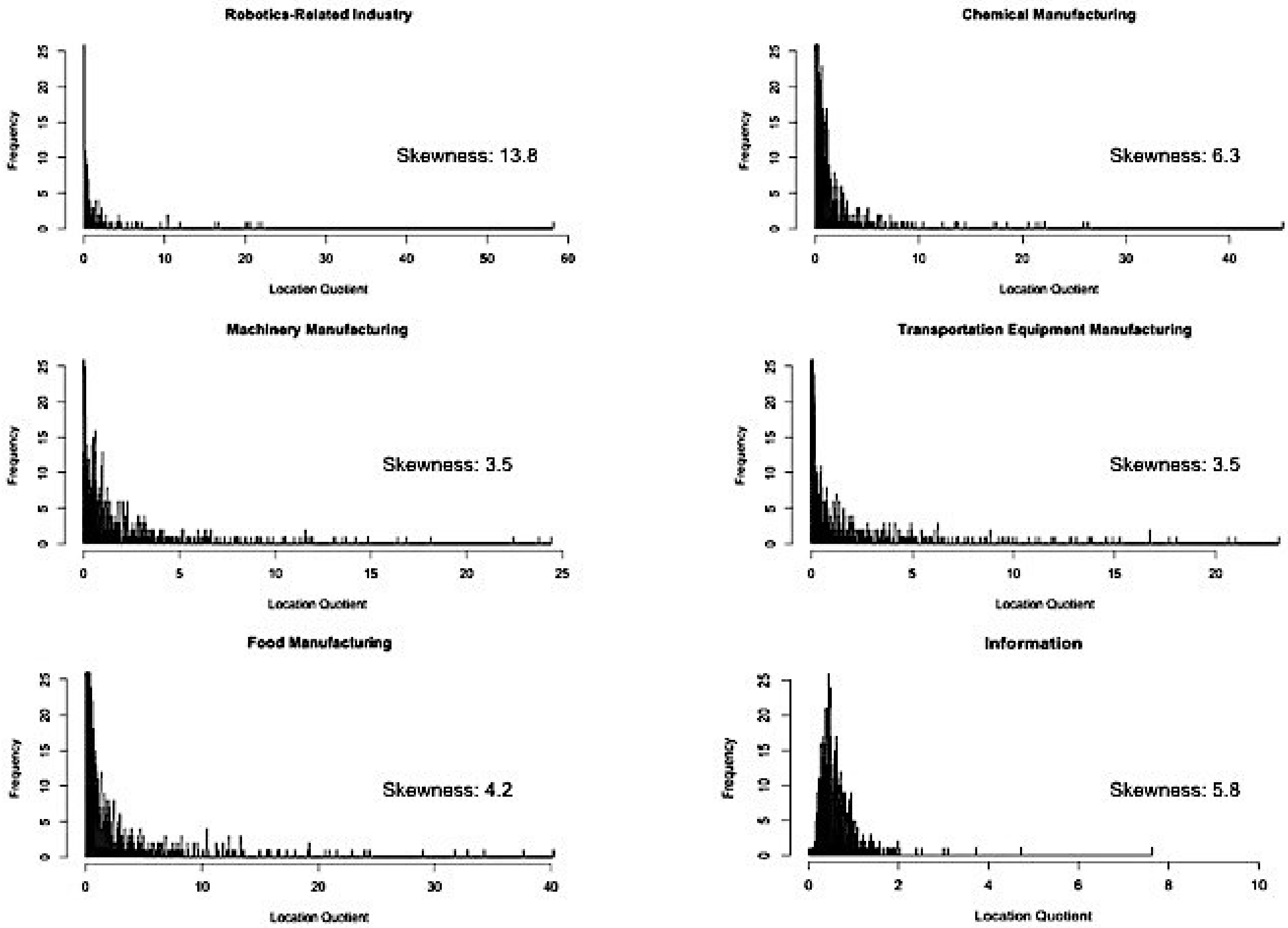


**Figure A3: Histograms and Skewness of Robotics and Other Industries' Location Quotients**




*Source:*
*Robotics location quotients: Authors' calculations based on robotics census and US Census Bureau County Business Patterns 2013*
*Other industry location quotients: US Census Bureau County Business Patterns 2013*
*Frequencies greater than 25 not displayed*

**Table A1: Robot Imports and Exports for Germany and Japan, 2011**

| | Japan | Germany |
|---|---|---|
| Domestic Production | 98,182 | 18,947 |
| Imports | 214 | 15,255 |
| Exports | 70,502 | 14,669 |
| Import Ratio (Imports/Domestic Production x 100) | .8 | 80.5 |
| Export Ratio (Exports/Domestic Production x 100) | 71.8 | 77.4 |

*Source: Adapted from IFR, 2012(International Federation of Robotics, 2012)*

**Table A2: Location Quotients for Robotic Regions with Populations > 300,000**

| MSA | Location Quotient |
|---|---|
| Milwaukee-Waukesha-West Allis, WI | 21.62 |
| Cleveland-Elyria, OH | 16.67 |
| Columbus, OH | 11.81 |
| Grand Rapids-Wyoming, MI | 10.34 |
| Seattle-Tacoma-Bellevue, WA | 6.46 |
| Fort Collins, CO | 4.61 |
| Reno, NV | 4.33 |
| Akron, OH | 4.04 |
| Harrisburg-Carlisle, PA | 3.46 |
| Detroit-Warren-Dearborn, MI | 3.37 |
| Cincinnati, OH-KY-IN | 2.87 |
| Davenport-Moline-Rock Island, IA-IL | 2.66 |
| Santa Maria-Santa Barbara, CA | 2.57 |
| Lansing-East Lansing, MI | 2.55 |
| Minneapolis-St. Paul-Bloomington, MN-WI | 2.39 |
| Fort Wayne, IN | 2.20 |
| Spokane-Spokane Valley, WA | 2.17 |
| Beaumont-Port Arthur, TX | 2.09 |
| Toledo, OH | 2.05 |
| Ann Arbor, MI | 1.93 |
| Rockford, IL | 1.78 |
| Kansas City, MO-KS | 1.72 |
| Boston-Cambridge-Newton, MA-NH | 1.60 |
| Green Bay, WI | 1.53 |
| Syracuse, NY | 1.39 |
| Louisville/Jefferson County, KY-IN | 1.35[A2] |
| Birmingham-Hoover, AL | 1.35 |
| Kalamazoo-Portage, MI | 1.32 |
| Dayton, OH | 1.28 |
| San Jose-Sunnyvale-Santa Clara, CA | 1.27 |
| Pittsburgh, PA | 1.20 |
| Raleigh, NC | 1.13 |

| | |
|---|---|
| Boulder, CO | 1.12 |
| Charlotte-Concord-Gastonia, NC-SC | 1.07[A3] |
| Chicago-Naperville-Elgin, IL-IN-WI | 1.07 |

*Calculated by Authors*
*Robotics data: Authors' database*
*Industry employment data: U.S. Census Bureau County Business Patterns 2013*

**Table A3: Correlations between Robotics and Related Industries based on CBSA Employment**

| Sector | NAICS | Coefficient (Pearson's R) | Standard Error | t-Statistic | p-value |
|---|---|---|---|---|---|
| Manufacturing - Total | 31-33 | 0.48 | 0.00 | 16.4 | 0.000 |
| Fabricated Metal Mfg | 332 | 0.51 | 0.00 | 18.1 | 0.000 |
| Machinery Mfg | 333 | 0.53 | 0.00 | 18.9 | 0.000 |
| Food Mfg | 311 | 0.37 | 0.00 | 12.1 | 0.000 |
| Transportation Mfg | 336 | 0.44 | 0.00 | 14.6 | 0.000 |
| Computer & Electronic Product Mfg | 334 | 0.37 | 0.00 | 12.1 | 0.000 |
| Chemical Product Mfg | 325 | 0.34 | 0.00 | 10.9 | 0.000 |
| Information | 51 | 0.33 | 0.00 | 10.61 | 0.000 |

*Calculated by Authors*
*Robotics data: Authors' database*
*Industry employment data: U.S. Census Bureau County Business Patterns 2013*

**Table A4: Extent of Robotics-Related Foreign Direct Investment (FDI) in Metropolitan and Micropolitan Areas**

| Metropolitan/Micropolitan Area | Employ -ment | Sales Volume | Establish -ments |
|---|---|---|---|
| Grand Rapids-Wyoming, MI | 2,093 | $32,750,500 | 3 |
| Minneapolis-St. Paul-Bloomington, MN-WI | 1,016 | $269,425,00 | 3 |
| Detroit-Warren-Dearborn, MI | 723 | $243,423,00 | 12 |
| New York-Newark-Jersey City, NY-NJ-PA | 565 | $77,112,500 | 3 |
| Harrisburg-Carlisle, PA | 501 | $6,423,500 | 1 |
| Chicago-Naperville-Elgin, IL-IN-WI | 431 | $132,136,50 | 8 |
| Providence-Warwick, RI-MA | 200 | $169,872,00 | 2 |
| Atlanta-Sandy Springs-Roswell, GA | 163 | $51,597,000 | 3 |
| Los Angeles-Long Beach-Anaheim, CA | 122 | $20,385,000 | 4 |
| Houston-The Woodlands-Sugar Land, TX | 120 | $6,423,500 | 1 |
| Ann Arbor, MI | 110 | $197,291,00 | 2 |
| San Jose-Sunnyvale-Santa Clara, CA | 106 | $43,316,000 | 2 |
| Beaumont-Port Arthur, TX | 100 | $11,000,000 | 1 |
| Torrington, CT | 90 | $38,158,000 | 1 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | 75 | $25,687,500 | 2 |
| San Francisco-Oakland-Hayward, CA | 52 | $16,315,000 | 3 |
| Cincinnati, OH-KY-IN | 45 | $34,061,500 | 3 |
| San Diego-Carlsbad, CA | 45 | $12,847,000 | 2 |
| Dallas-Fort Worth-Arlington, TX | 35 | $31,195,000 | 2 |
| Indianapolis-Carmel-Anderson, IN | 30 | $6,423,500 | 1 |
| Huntsville, AL | 20 | $6,419,000 | 1 |
| Jackson, MS | 20 | $6,419,000 | 1 |
| Burlington, NC | 15 | $6,423,500 | 1 |
| Charlotte-Concord-Gastonia, NC-SC | 15 | $3,050,000 | 1 |
| Jackson, MI | 15 | $6,423,500 | 1 |
| Pittsburgh, PA | 15 | $6,423,500 | 1 |
| Reading, PA | 15 | $6,423,500 | 1 |
| Spartanburg, SC | 15 | $6,423,500 | 1 |
| Sidney, OH | 11 | $12,949,000 | 1 |
| Boston-Cambridge-Newton, MA-NH | 10 | $21,266,000 | 1 |
| Milwaukee-Waukesha-West Allis, WI | 10 | $2,648,000 | 1 |

*Source: Authors' database, only establishments with 10 employees or more displayed.*

## Appendix References

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