WORKING PAPER SERIES

Redeployment or Robocalypse? Workers and Automation in Ohio Manufacturing SMEs

Anna Waldman-Brown
Research Associate, MIT Work of the Future
PhD Student, MIT Department of Urban Studies & Planning
annawb@mit.edu

MIT Work of the Future Working Paper 03-2020

Date: April 9, 2020

MIT INDUSTRIAL PERFORMANCE CENTER

400 Main Street, E19-733, Cambridge, MA 02139

Redeployment or Robocalypse?

Workers and Automation in Ohio Manufacturing SMEs

Anna Waldman-Brown

This version written July 2019.
Revised paper published: March 7, 2020, *Cambridge Journal of Regions, Economy and Society*
Read published paper.

Abstract

Considering recent developments in artificial intelligence, how will today's automation technologies impact manufacturing workers? To understand the likelihood of an impending robocalypse, this paper explores how small factory owners in Ohio conceptualize automation. Due to the risk of replacing entire production processes and the still-relevant capabilities of old equipment, the firms interviewed for this study primarily automated in order to complement rather than replace existing technologies. This incremental, piecemeal strategy will hinder the introduction of more integrated automation systems that may presage fully-automated manufacturing, thus ensuring the existence of manufacturing jobs for the foreseeable future.

Keywords

Automation, employment, innovation, manufacturing, SMEs

I. Introduction[1]

With the rise of machine learning, internet-connected factories, and agile robots, the question of automation has dominated academic and mainstream media discussions. One cover of the New Yorker in 2017 featured a human panhandler on a street full of busy robots (Johnson 2017), and over 60% of surveyed American workers were worried about robot-driven unemployment (Paul 2018). Automation has likely aided in the USA's transition from manufacturing to service sector employment over the past few decades, leading to fewer mid-skilled jobs overall and a hollowing out of the middle class (Autor 2015). This transition has left American workers with lower wages and fewer benefits, particularly in midwestern states such as Ohio that remain reliant upon manufacturing jobs (Autor 2015; Mokyr, Vickers, & Ziebarth 2015; Glasmeier & Salant 2006).

Technologically-driven worker displacement is not a new phenomenon—and, in the past, the resulting increases in productivity have eventually created more jobs in other sectors (Paul 2018; Mokyr, Vickers, & Ziebarth 2015; Allen 2009). Experts even project underemployment in the American manufacturing sector: Giffi et al. (2018) estimate a shortage of 2.4 million manufacturing workers by 2028 as ageing workers retire, and they found that 89% of surveyed manufacturing executives from large and small firms believe there is already a talent shortage. However, past episodes have taught us that displaced workers themselves may not benefit from new job opportunities (Mokyr, Vickers, & Ziebarth 2015).

Instead of considering the big picture, it may be useful to focus on different kinds of workers and firms. For example, a stark trend in worker displacement emerges with respect to firm size: the overall US employment decline from 2006-2016 was 1.5 times higher for large manufacturers than for manufacturers under 500 employees (US Census 2017). In their study of Dutch automation and employment data, Bessen et al (2019) found that workers at smaller firms were less likely to lose their jobs during a spike in automation than workers in

[1] This research was fully funded by the MIT Work of the Future Task Force, and I would like to thank the Joyce Foundation for financial support. I am indebted to Elisabeth Reynolds, Suzanne Berger, Susan Helper, Michael Piore, Dan Traficonte, and Lindsay Sanneman from the MIT Work of the Future Task Force for conducting these interviews and workshopping theories, and to Anita Kafka, Laura Guild, and SJ Maxted for coordination. All these case studies draw from our collaborative notes. This paper would not exist without the invaluable critiques of Amy Glasmeier, Isadora Cruxen, Mariana Arcaya, and Paul Osterman, and my wonderfully critical colleagues Kevin Lee, Darien Williams, Silvia Danielak, Daniel Engelberg, and Maggie Yellen. Thanks to Paul Weaver, Edward Burnell, and Angela Acocella for fruitful conversations around manufacturing and ML. Finally, thank you to all the factory owners and workers in Ohio who introduced us to their world, and to MAGNET for sharing their survey data.

larger firms, and firms with fewer than 100 employees were 1.5 times less likely to spike in automation spending than firms with more than 500 employees. However, workers displaced from smaller firms suffered greater income losses due to difficulties in finding a new job. Differences in automation strategies could potentially generate these kinds of disparity.

Despite the importance of manufacturing employment for middle class jobs, we know little about *how* different kinds of firms are automating. Thus, this paper has two goals: to describe how individual factory owners within a particular sector and region conceptualize automation, and to question the likelihood of increasing technology-driven unemployment among these firms. This study is based on factory visits and interviews with small and medium factory owners in Ohio's metalworking sector.

II. Firms, New Technologies, and Automation

I use the term "automation" to refer to physical technologies that replace manual tasks with programmable tools, excluding software automation and purely mechanical technologies. Are today's automation technologies fundamentally different from historical advancements, and are we heading towards a robocalypse of runaway job loss? Instead of merely improving the efficiency, quality, and precision of various tasks, some hypothesize that current advances in artificial intelligence (AI) and robotics will enable machines to take over human capabilities such as discretion, complex maintenance, and self-improvement, driving humans out of particular jobs and potentially destroying work in the long-term (Brynjolfsson & McAfee 2014). In extreme cases, highly-automated factories could become "lights-out," employing so few workers for day-to-day production that the lights can stay off while robots manufacture and transport everything—although such a factory may need occasional human support to maintain equipment and retool machines when product lines change. The highest level of automation described by Kaber & Endsley (1997) goes a step further, depicting smart machines that can flawlessly adjust to new situations, perform inspections, and maintain themselves without any need for human intervention.

Depending on production complexity, the level of AI required for an entirely labor-less factory may need to approximate human intelligence to a degree that is unachievable with today's technologies (Brooks 2017). Nonetheless, the subset of AI known as machine learning remains a key component in nebulous manufacturing buzzwords such as "Industry 4.0," which relies upon interconnected machines that can automate *systems* of complex jobs rather than one-off tasks.

Machine learning (ML) algorithms, which can autonomously improve their own performance by generalizing from data, play a key role in this vision of streamlining machine-controllable factory operations (Silver et al 2017; Brynjolfsson & Mitchell 2017). Despite advancements in algorithms and data storage and processing, ML still requires substantial computational power, expertise, and instrumentation—all of which are expensive. Implementation will only be cost-effective when factories can provide large quantities of well-organized data for machines to learn, and when simple probabilistic models and human discretion prove insufficient. Several preconditions must be met before a production line can start "learning" how to become fully autonomous:

- There must be an integrated, controllable flow of products from one production stage to another
- Machinery must be equipped with sensors that can reliably monitor production and perform quality control
- Sensor data from across the factory must be integrated into a unified, machine-readable system that can perform analyses in real-time
- Machinery must be able to identify problems, fix itself, and/or notify technicians in case of errors
- Machinery must be able to self-adjust to new product lines

Training a factory to automate its own production will require the precise codification of performance metrics, training data, and production tasks, in addition to the extraordinary level of robotic dexterity and mobility needed for labor-less systems (Brooks 2017). SMEs that produce small batches of highly-customizable products face additional challenges: they will need large volumes of ML-readable training data before they can properly train the algorithms to anticipate every contingency (Brynjolfsson and Mitchell 2017). Since ML is relatively new and must be tailored to every individual factory setup, there are no off-the-shelf AI solutions that factories can purchase, so firms will need to hire or contract with expensive data scientists to analyze and optimize their systems.

Given these hurdles, the introduction of a highly-automated factory setup is likely to require "disruptive" (Christensen 2013) shifts to existing factories. Overhauling too many systems simultaneously can be expensive and counterproductive, as evidenced by numerous stories of overenthusiastic computerized mill introduction in the 1970s (Noble 1984). More recently, Elon Musk ignored the advice of his manufacturing engineers and attempted to turn Tesla's factory into an "unstoppable alien dreadnought" of a highly-automated assembly plant. When his robots failed to meet specifications, Musk had to build a manual assembly line in a makeshift tent (Duhigg 2018).

Indeed, previous literature on technology innovation (Glasmeier et al. 1998; Helper & Henderson 2014) suggests that SMEs like those in this study are likely to automate in an incremental rather than disruptive manner. Legacy firms in less competitive environments may even neglect to seek out productivity enhancements altogether (Simon 1955; Syverson 2011). Hayes (1985) describes how smaller firms tend to follow a "tortoise-like" strategy of "progress through incremental improvements," as compared to the "hare-like" firms that follow a riskier strategy of "progress through strategic leaps" (Hayes 1985, pg 8). While disruptive, hare-like firms may be likely to use new technology as a *substitute* for human tasks, more incremental firms may be more prone to introduce automation as a *complement* to existing work. Instead of replacing older tasks and equipment, complementary automation improves these tasks and/or adds new capabilities (Autor, Levy, & Murnane 2002 and Acemoglu & Restrepo 2018).

The recent literature on automation largely abstracts away from these firm-level differences and their effects on workers. Despite a history of in-depth, granular studies on labor and technology (Dore 1973; Noble 1984; Thomas 1994; Fernandez 2001; Autor, Levy, & Murnane 2002; Mutlu & Forlizzi 2008; Mazmanian, Orlikowski, & Yates 2013), most recent research has shifted to the macro-scale, assessing the possibilities of aggregate job loss through econometric models and large-scale surveys, as well as extrapolations based on current technologies and task-based cost-benefit analyses within firms (Brynjolfsson & McAfee 2014; Arntz, Gregory, & Zierahn 2016; Frey & Osborne 2017; Acemoglu and Restrepo 2017). These studies often do not allow for explorations at the level of individual firms, technologies, and workers. Indeed, Acemoglu and Restrepo (2017) make troubling assumptions about the uniform distribution of robots within similar industries, regardless of firm size, productivity, or even geographic location.

By considering individual firms, I hope to depart from these generalizations in order to better understand the firm-level impacts of automation upon current and future manufacturing workers.

III. Research Questions and Methodology

These perspectives on automation and labor bring us to three firm-level questions:

1. *How do the owners of small and medium Ohio metal factories conceptualize automation?*
2. *How has automation impacted their workers' tasks and workflow?*
3. *In the future, are these factory owners likely to substantially reduce their workforce due to automation?*

I explore these questions through semi-structured interviews with 21 small and medium factory owners and 14 manufacturing-related institutions in Ohio, as described below.

Research Focus and Methodology

The manufacturing sector provides around 8% of all American jobs (Bureau of Labor Statistics 2017). Roughly 70% of those jobs fall into the category of Small and Medium Enterprises (SMEs), defined as firms with fewer than 500 employees (SBA 2018), though most of our semi-randomly-selected firms employed fewer than 150 people. SMEs as a whole make up around 99% of total manufacturers in the country (United States Census Bureau 2012) and 98.6% of all manufacturers in Ohio, which is America's third-ranking state for manufacturing employment (Ohio Manufacturers' Association 2017). Ohio has a rich industrial history as one of America's key manufacturers; the state suffered from the decline of American manufacturing but has seen a "manufacturing renaissance" as American and foreign firms set up new high-tech production facilities across the state (Taylor 2016). Ohio also benefits from a wealth of national initiatives and experimental training programs for advanced manufacturing.

We selected the SMEs for this study through a semi-randomized process, focusing on metalworking firms with around 20-150 employees. We chose fabricated metal SMEs for the sector's automation potential and the fact that several members of our team had already interviewed similar firms. Metalworking also provides a tangible means of distinguishing manual from automated tasks in the context of a specific physical output. We later added three Cuyahoga County firms—including two with over a thousand employees—that we identified as being at the forefront of automation. To get a long-term view of firms' technological development and worker relations, 11 of our selected firms were re-interviews from 2011-2013. For more details on interview strategy and selections, see Exhibit A.

Additionally, we identified 14 key institutions that are part of the Ohio manufacturing ecosystem—including training centers, Advanced Manufacturing Institutes, unions, community colleges, trade associations, and policy advocacy groups. Following Weiss (1994), these interviews provided us with a "panel of knowledgeable informants" for understanding different perspectives on new technologies. Interviews were mostly held in Ohio's top three manufacturing counties: Cleveland (Cuyahoga County), Akron (Summit County), and Columbus (Franklin County). See Exhibit B for a map of manufacturing density across Ohio.

Our semi-structured interviews ranged from 90 minutes to six hours, and we visited factories whenever feasible. We cross-validated information gathered from firms with other interviewees such as worker advocates, personnel associated with exogenous training programs, and robot manufacturers. See Exhibit C for interview questions and methodology.

I employed grounded theory (Glaser and Strauss 1967) to inductively identify how automation has affected workers within firms; my theories emerged through interview coding, as well as eight months of roughly fortnightly research discussions with the interview team.

Limitations

Since we interviewed only surviving firms, we cannot address the extrinsic effects of more highly-automated firms outcompeting less productive incumbents, which may be a critical cause of technology-driven unemployment. Another key limitation is the fact that Ohio's manufacturing economy was booming at the time of the study; given the 4-5% unemployment rate in Ohio from 2018-2019, interviewed firms expressed difficulty in finding and retaining reliable and qualified workers (at least at owners' desired wages). Indeed, most firm owners were actively hiring and no one planned to lay off workers for any reason. In an economic downturn, factory owners may be much more willing to automate, provided they can procure the necessary capital costs for new equipment.

IV. <u>Findings</u>

The small firm owners in this study largely chose to automate in an incremental manner, minimizing disruptions to incumbent workers while generally increasing factory productivity. Most firm owners intended to complement incumbent workers' tasks rather than replace them. In cases where new technologies did replace human tasks, firm owners had no trouble redeploying their redundant workers. "When we bring in new technologies, our business grows and we add new jobs," said one small firm owner: "we've never laid anyone off because of productivity." In fact, firm owners had not displaced *any* incumbent workers due to automation (or for any other reason) since 2012, though several did expect to decrease their future overall employment due to automation. We found very few advanced technologies in operation. None of the firms had implemented ML, and only a handful were even collecting factory data. Our interviewees mostly seemed well-informed due to trade shows and connections to local manufacturing institutions. Many were actively trying to install new sensors and mentioned "Industry 4.0," yet they could not identify clear value propositions for current technologies.

I begin with a brief exploration of disruptive automation, to identify the few cases in which firms are replacing older technologies wholesale and to explore why these cases are unusual. I then detail several forms of complementary automation, including the addition of newer machines and the augmentation of old equipment.

LABOR-DISPLACING AUTOMATION

Our interviews revealed relatively few cases of technologies that entirely replaced human labor on specific tasks, as detailed in Table 1.

TABLE 1: Labor-displacing automation

New Technology	*Technology Replaced*	*Automation Rationale*	*Worker impact*
Welding robot (as explained by a robot integrator describing his customer firms)	Usually 1 or 2 manual welding cells	Lack of skilled welders, potential increase in speed and precision (depending on job)	Expert welders retained and trained to operate robots, fewer new hires
Cobot to load or rearrange metal parts for another machine	Person manually rearranging or loading parts	Increased speed and precision, worker retention	Redeployed workers, fewer new hires

Micro-pulse welding (testing out tech before purchasing)	Manual welders who have to wait for material to cool down	Replaces 10 hours of labor with 10 minutes	Redeployed workers to improve rest of production process
Inspection cameras for quality control	Inspectors and machine operators	Worker retention, potential quality improvements	Redeployed workers, fewer new hires
3D printer (borrowed through partnership, not purchased) ("3D Firm")	Milling molds and casting (~75% of business still uses old mills)	Replaces 10 days of production with 2 days, improved quality and capability for more complex jobs	Some workers retrained, most still working with older technology

Only three SME owners in this study explicitly mentioned a desire to move towards fully-automated factories. The first owner expected 3D printing capabilities to dramatically improve, and the other two ran *low*-mix and *high*-volume firms that were already highly-automated. The second owner produced automotive components in a highly-automated factory, and hoped to decrease his number of workers from 180 to 30 over the next ten years before becoming fully autonomous. The third firm was even larger, and the director of business development believed he needed to get labor out of his plants over the next 2-3 years to remain competitive. "I'm focusing on making labor-less factories," he told us. Nonetheless, all three firms had increased their workforce in recent years, during Ohio's economic recovery after the 2008 recession.

Most low-mix, high-volume firms are large producers, which likely follow a different automation strategy from SMEs. High-volume runs of the same products allow for streamlined, flow production in which the setup costs of automation can be amortized over larger batch sizes. Instead, the other SMEs in this study were mostly high-mix, low-volume firms: they produced a wide variety of different, often customized products (high-mix), but a small number of each individual product (low-volume).[2] A number of interviewees told us that most low-mix, high-volume firms had either gone abroad in search of cheaper, lower-skilled labor, or they had lost out to foreign competitors.

The 3D printer was arguably the most "disruptive" technology in our study. One piece of equipment can replace multiple production steps across multiple machines, while cutting production time by a factor of five. Yet this 3D printer only accounted for a quarter of the acquiring firm's revenue after several years of operation, and the firm's owner had no immediate plans to sell his older equipment. The problem was that the printer's feedstock was vastly more expensive than traditional molding and casting materials, and the firm lacked the in-house design expertise to model 3D printable parts. Still, the firm's owner believed that he could "go foundryless" in about 10 years by substituting all his firm's molding and casting with 3D printed parts. He predicted this could result in many fewer jobs within his factory if his production volume remained constant, but he also believed his business would become so productive compared to traditional competitors that his own workforce would grow. After introducing the 3D printer, he had to retrain his incumbent workers in the delicate art of extracting and processing 3D printed parts.

In contrast, the lead engineer of a welding robot integrator that primarily builds robots for SMEs emphasized that their robots "won't replace welders." Even though the firm was attempting to make welding robots as "human as possible," all their robots still required a human welding "champion" to set up and program the robot, and to troubleshoot when things invariably went wrong. We asked several of the firm's research and development engineers when they thought that ML will allow welding robots to diagnose problems and self-correct without human intervention. The engineers laughed and told us about an AI conference where a state-of-the-art image recognition algorithms misidentified a cat as a bowl of guacamole after it turned its head. To demonstrate the complexity of error diagnostics for welding, the firm's roboticist brought over a poorly-welded block of metal and listed a dozen variables that might have caused the problem—from the diameter of the welding wire to the properties of the metal block to the room's temperature and humidity. Even the firm's welding experts and metallurgists could not always identify problems, so how could they program a robot to figure this out? Any minor variance in welding wire, for example, wreaks

[2] For example, a tailor who makes customized clothes is a high-mix, low-volume manufacturer. A large fashion brand like Gap or Levi's that mass-produces clothes would be a low-mix, high-volume manufacturer.

havoc on a welding robot if not properly anticipated and codified. Yet an experienced human welder can easily adjust to such unpredictability.

Across all the firms and institutions we visited, we only encountered one machine—a metal-forming servomechanism press—that actually employed machine learning. The machine was in a prototyping stage, and would reduce both the rework required to fix damaged parts and the supervision necessary for safe operation. It was therefore likely to replace occasional *tasks* rather than full-time *jobs*, similar to the non-ML servo metal-bender and sensor-augmented metal press mentioned below.

Building New Factories

As a firm owner outside of Ohio told our team, bringing advanced technology into a legacy factory is "like giving a caveman a rocket ship and asking him to fly to the moon." Even the high-tech firm Amazon told our researchers that they only introduce their latest automating technologies into *new* fulfillment centers rather than retrofitting older, less-automated warehouses. Older facilities would have to be torn apart and re-organized to accommodate automated transport robots, since these robots require predefined tracks. Although older warehouses were only half as productive as automated facilities, Amazon was expanding so quickly that the firm could not afford any downtime.

Indeed, two of the "hare-like" firms (Hayes 1985) in this study were building highly-automated factories abroad. This allowed them to expand capacity without having to retrofit their older Ohio factories, which would continue operating as long as they remained profitable. The first owner was retooling a mostly-defunct Mexican plant that the firm had built in 2009, as a response to his 120% turnover rate in Mexico. He attributed his difficulty in retaining workers to the large multinational manufacturers in the same city that offered better worker salaries and benefits.

The second firm's owner was building a new factory in Romania, due to his strong belief in a highly-automated future and his fear of rising labor costs. This firm owner was a software engineer who described himself as "obsessed with new technologies." After his Romanian factory was complete, he planned to sell his SME to set up manufacturing automation startups with his friends. He believed most smaller firms were "stuck in place," and he could only do research and development and experiment with automation by founding a new company.

Would his startup be likely to out-compete Ohio's legacy, under-automated factories? There is some possibility, yet the majority of SMEs we interviewed claimed to have found robust competitive niches regardless of their level of technological advancement. Very few of these legacy firms seemed to be laggards. Firm owners were constantly on the lookout for new technologies that could meet their demands for affordability and versatility, and most were not concerned about being out-competed by automation at home or cheaper labor abroad.

COMPLEMENTARY AUTOMATION: ADDING NEW (OR LESS OLD) MACHINES

At least eight out of the 21 interviewed firms purchased a machine over the last seven years that provided novel, automating capabilities for the firm—yet most firms had retained their incumbent equipment. None of them had reduced their headcount. Many of the technologies they described were purchased new, and most had come onto the market within the past decade. See Table 2 for these examples of complementary technology acquisitions.

TABLE 2: Complementary technology acquisitions

New Technology	*Technology Replaced*	*Automation Rationale*	*Worker Impact*
New automated laser welding robotic cells ("Laser Firm")	None	Capability to take on new jobs that require welding	Incumbent workers learned new technology
New welding robots	Manual welding with mechanical jigs (still in use)	Lack of skilled welders (at firm's proposed salary), improved speed	Incumbent welders learned new technology; firm able to take on new welding jobs
New and lightly-used CNC mills ("Mill Firm," "Pipe Firm," and others)	Manual welding and casting (still in use)	Much faster (from 8 weeks to 1-2 days); replaced 6 machines with one CNC, better precision;	All but 4 workers out of 12-15 retrained by one company: 3 workers still work on old mills and 1 retired. Another firm hired new workers

		capability for new small-batch jobs	but only cross-trained one incumbent worker.
Used CNC lathes	None	In-sourcing a machining process; capability for new jobs	Incumbent workers already familiar with similar technology
New metal-bending machines with servomechanisms to provide feedback ("Pipe Firm" and others)	Metal-bending with hydraulic feedback system (old machines sold, but factory didn't change)	Higher quality presses (decreased product rework rate from 50% to 10%)	Operators can supervise 6 servos at a time instead of 3-4 hydraulic machines; maintenance had to reskill

All these technologies resulted in workforce reorganization and some form of labor-replacement. The laser welding cells and used computer numerical control (CNC) lathes replaced previously outsourced tasks and represented entirely new capabilities for the purchasing firm, leading to new jobs within the firm. The laser welding cell allowed "Laser Firm" to successfully bid for large jobs that would overwise have gone overseas (thus potentially replacing workers abroad). The other technologies replaced both incumbent machines and incumbent workers' tasks, but none provided a wholesale replacement for the older equipment.

The most striking example of complementary acquisitions came from a century-old factory making precision metal parts, "Mill Firm." The owner had recently inherited the firm from his father and moved into a new facility, where he could add several large machines without getting rid of any older equipment. The factory floor showcased four generations of milling machines:

- 25 semi-computerized machines (purchased pre-1950s)
- 6 new semi-computerized machines with additional spindles (purchased in 2015)
- 9 new CNC machines (purchased in 2007)
- 2 new, highly-advanced CNC machines (purchased in 2017)

Half of Mill Firm's workers work on the older machines, and half work on the CNC equipment. The firm continues to purchase older equipment from machine shops that go out of business, since manual machines can quickly perform large-volume jobs that would take too long to run on CNCs. Several firms mentioned that CNC equipment lacked the capabilities of older, more robust manual or semi-computerized models. Sometimes it simply takes more time to program a CNC toolpath than to have an experienced machinist manually mill a one-off part.

Just as these firms add new equipment without displacing older machines, they tend to incrementally branch into new products without detracting from existing relationships with longstanding customers. Although larger firms may face pressure from their customers and end users to constantly innovate their product lines and install state-of-the-art technologies, many of these SMEs have made the same, reliable parts for the same customers on the same machines for decades. Several firms only purchased new machines to add new parts or new processes to their product portfolio; these firms' entire goal for automation was to branch into new territory without disrupting existing production lines.

Due to competition from international mass manufacturers, interviewees explained that most of Ohio's SMEs compete on the basis of quality and customization rather than price and quantity. These firms promise frequent customer interactions, a willingness to design and prototype new solutions, and a strict attention to quality and detail—following the model of flexible specialization described by Piore and Sabel (1984). In the words of one lead engineer: "you want us to do it, we'll build it." This entropic production model leads to an additive, incremental strategy for growth; since SMEs lack the economies of scale to begin with, they have every incentive to keep making something if customers will keep paying for it. Additionally, firms may be unaware which of their product lines are most profitable (Syverson 2011), which leads them to continue making everything.

Complementary Automation: Reluctance to replace old machines

Many firms were unwilling to get rid of any equipment that still worked, even after buying newer replacements. The owner of an oil and gas supplier, "Pipe Firm," recently bought a new, greatly-improved metal press and decided to sell her firm's old press to make room. When her father who had formerly run the firm found out about this sale, he became emotional and recalled how his grandfather, Pipe Firm's founder, had mortgaged his home for that machine. Pipe Firm's reluctance to replace older machines mirrored its reluctance to replace older workers, although this may have been a result of a close-knit, family-run firm rather than nostalgia for Ohio's industrial past. In 2016, Pipe Firm's owner started introducing new CNCs to digitally mill out parts instead of welding and casting them. Her customers wanted everything faster, and upgrading to CNCs was the only way to meet their demands. She offered CNC classes to all her manual machine operators; most agreed to learn computerized machining, one decided to retire, and three stubborn mill-operators remained at the firm because there was still enough work to be done on the old machines.

Several SME owners also mentioned a fear of replacing multiple machines with a single piece of equipment: if that single, critical piece of equipment breaks, then the entire production line must shut down until it can be fixed. Automation can bring a new level of complexity to formerly-manual tasks, making it critical for shop-floor technicians to know how to deal with the inevitable failures in order to avoid downtime. Digital equipment can be harder to diagnose and repair than manual machines, which might only require readjusting knobs rather than reprogramming or debugging a computer. When we asked one SME worker performing a simple repetitive task whether he thought his job could be replaced by a robot, the worker replied, "that's just another thing that'll break." Even after automating, the owners of firms like Pipe Firm opted to hold onto outdated, manual equipment for occasional jobs and emergency situations rather than putting all their trust in new technology.

In fact, some firm owners were just as concerned about finding skilled technical experts for their old manual equipment as they were about attracting young talent for their computerized equipment. Four factory owners, including the owner of Mill Firm, bemoaned the loss of hands-on shop classes in high schools and community colleges; they could not find technicians who knew how to make things with their hands. To quote Laser Firm's owner, Ohio community colleges are "too busy with flashy stuff, like 3D printing" rather than training students on the older production equipment which still comprises the bulk of his firm's production. Another firm owner complained that young workers "have learned on the latest and greatest machinery" but his factory only had older equipment.

SME owners were also unwilling to go into debt if they could avoid it, leading to a risk-averse strategy for machine acquisition. SMEs lack the risk capital of larger firms to invest in unproven technologies; the metal-casting firm had to borrow its state-of-the-art 3D printer from a separate research institution since it could not afford its own machine. Mill Firm's owner told us that he generally followed the advice of his father who used to run the factory: "we only take business to make parts that we already have the experience and machines to make."

Laser Firm's owner referred to a very large contract with an automotive supplier as the "anchor job" that justified his investment in laser-welding robotic cells. The need for such an "anchor job" to justify a new acquisition was a common thread, appearing in five of our firm interviews. One firm's owner lamented the fact that one of his new, large customers had not put in its entire order up-front. He would then have bought a cobot to replace his temp workers on the assembly line, saving him considerable expense. However, it was now too late and he would have to wait for another job that would justify investing in a cobot.

Complementary Automation: Augmenting old machines

While most firm owners were reluctant to get rid of their legacy technologies, some were willing to augment them. See Table 3 for examples of technology augmentations. I eliminated the "Worker Impact" column since firm owners described minimal impacts, and no new skills were required on a daily basis.

TABLE 3: Technology Augmentations

New Technology	*Technology Augmented*	*Automation Rationale*
Sensors to collect data	Multiple machines	Ideally provides information to optimize production, although firm not sure how to analyze data
Adding on CNC controls	Manual, decades-old mills, presses, etc.	Allows operator to control machine by pushing buttons and/or coding rather than manual controls
Sensor-controlled system for feeding material Sensors to detect defects	Metal presses; stamping machines (Used by 3 different factories; one custom-built solution, others off-the-shelf)	Automatically stops press when misfeed detected Catches problems faster than manual operators in order to minimize wasted material and defective production runs
Variable speed controls	Manual thread rollers	Allows for variable rather than binary (high/low) speeds for increased precision

Air clutch for emergency stop	Metal presses	Replaces mechanical clutch, which was banned by new OSHA standards to protect the hands of machine operators

These augmentations generally reduced errors and allowed firm owners to assign fewer workers to perform the tedious task of supervising and manually halting machines, so workers could spend more time on other tasks. Several interviewees mentioned that adding sensors to machines might create new jobs for data analysts and/or sensor experts within their firms in the future.

Still, these firms were merely gathering and storing sensor data from their machines without performing in-depth data analyses to improve production processes. Among the few SMEs that were collecting sensor data, not one had aggregated all this information into a single machine-readable format—and most admitted that they were merely storing data without any concrete plans for analysis. A high-tech, large firm that makes automation equipment had installed sensors on many of their factory machines years ago, yet the engineers in this firm were only beginning to explore the potential of their collected sensor data. This large, advanced firm was among the only factories we visited that could even start thinking about applying ML to improve its production.

Instead of analyzing data, most augmenting firms focused on sensor-controlled feedback systems and machine controllers. Some of these technologies were new, but many (such as the CNC controls) came on the market decades ago. Firms had only recently adopted them for the same reasons mentioned above—a low tolerance for risky new technology, the lack of an explicit "anchor job" justifying the investment, and perhaps a general lack of incentives for firms in less competitive environments to continually improve productivity.

The owner of Laser Firm, for example, was used to working in a very niche market. He explained how he decided to add a sensor-controlled feedback system for the first time in 2000, after his first wave of Asian competition: "we can't compete with $1/day jobs, so we need to compete with our heads." His metal press used to occasionally feed itself two sheets of material, damaging the machine and halting production. After installing sensors, he was able to double the press's speed while allowing operators to supervise two or three machines instead of one at a time. This spared workers the monotony of having to constantly watch one press, and allowed them to take on other much-needed jobs within the factory—while reducing downtime and allowing the firm to compete globally.

V. **<u>Discussion</u>**

Analysis

By delving into firm owners' automation strategies and motivations, I hope to demonstrate why lights-out factories are both an unachievable and impractical goal for Ohio's metalworking SMEs. Given owners' penchant for legacy equipment, the lack of risk capital for unproven technologies, and the variability of production tasks within high-mix, low-volume firms, most SMEs in our study were unlikely to displace large numbers of workers due to automation. The firms in our study were loath to replace single pieces of ancient equipment, never-mind overhauling their entire factories to introduce the sensors and interconnected systems necessary for high levels of automation. Such systems tend to be customized, all-or-nothing solutions (Brooks 2017), which are particularly difficult to integrate into the hodgepodge factories of most SMEs. Instead, firm owners automated in a piecemeal fashion—and only when forced by their customers and/or competitors.

I identify three key cases in which these SMEs did invest in new technologies:

1. When a well-proven technology is nearly guaranteed to pay for itself within a short period of time, ideally over the course of a single "anchor job"
2. When the technology involves minimal disruption to a firm's existing workflow and capabilities—indicating a complementary rather than substitutive technology
3. When the technology provides a specific competitive edge with respect to *immediate* exogenous pressures, including cost competition from foreign firms, customer demands for quality improvements or novel products, and the ability to branch into new markets

These findings complicate the prevailing task-based model of worker displacement, which assume some quantifiable point at which a particular task instantly becomes more cost-effective to automate (Frey & Osborne 2017; Arntz, Gregory, & Zierahn 2016; Acemoglu & Restrepo 2016). It is important to note that such models provide a framework for consideration rather than a crystal ball to foretell the future. Their lack of granularity cannot allow for heterogeneity across jobs and firms. Our interviews indicate that overall worker impacts may depend less upon which specific tasks a given technology can displace, and more upon the business strategies adopted by firm owners—although more evidence is needed.

Another challenge for estimating labor displacement is that SME workers' jobs are themselves non-routine, which may differ from the more Taylorized and predictable jobs held by workers in larger firms. This variability across jobs allows SME owners to readily redeploy their workers, as demonstrated by the several firms that did not reduce their headcount after halving the need for machine supervision.

Finally, the automation of some task does not necessarily mean that the task has been fully mechanized. Most interviewed firms continued using their legacy equipment for occasional jobs after installing new technologies. New capital equipment is expensive, and retooling an entire process can be very costly—from the downtime required to replace an older machine, to worker retraining costs and the loss of workers' process knowledge that is often tied up with the old equipment (Oi 1962). To more accurately predict worker displacement, perhaps task-based models could better account for these capital costs. Such calculations could also add in variables to account for the age and size of establishments across different sectors, since new factories and well-endowed multinationals are likely able to automate more readily.

Redeployment or Robocalypse?

Just as firm owners had little incentive to get rid of their obsolete technologies, they had no reason to get rid of reliable yet less up-to-date workers in the tight labor market of 2018-2019. Their calculations may change in the future if highly-customizable, low-batch automation were to become less risky and more compatible with legacy equipment. SMEs might then increase their rate of automation, although the lights-out factory will likely remain out of reach for older firms.

Overall, very few of the SMEs in this study seemed to be laying the groundwork for an impending robocalypse. None of the low-volume, high-mix firms in this study met the preconditions required for factories to start autonomously improving themselves. Even the large automation technology firm replete with sensor-enabled machines was struggling to meaningfully consolidate and analyze its datasets across all its different types of equipment. The SMEs that hacked together their own sensors were likely to run into even more trouble.

Furthermore, highly-automated firms must be able to exercise a high degree of control over upstream and downstream factory inputs, like the wire fed into welding robots. They must also install control systems that can seamlessly integrate with every generation of machine within the factory, without having to retool expensive key components such as dies. Most SMEs make a highly-variable set of products, which makes it difficult to set up an autonomous flow of parts between production stages.

Firm owners' assessments of their own competitiveness and continued productivity growth indicated that they were not laggards, either. Since most SMEs in this study operated in non-competitive niches or had complex proprietary processes, they seemed unlikely to be out-competed in the near-term.

Nonetheless, this study does not indicate whether or not increased automation will lead to a continuing decline in manufacturing jobs. In cases where firms' productivity increases as a result of automation, competing firms may suffer job losses as they lose market share. Alternatively, the number of jobs could remain constant while consumption increases instead. In some cases, however, firm owners only automated to improve quality—which is a difficult variable to measure.

If Ohio's manufacturing boom begins to decline, even these thriving SMEs may be forced to streamline production by abandoning less lucrative product lines, automating production when feasible, and laying off non-essential workers. Some of these firms already went through a similar crunch during the Great Recession. Still, the eventual impact upon workers and jobs is unlikely to be wholly determined by technological factors, as managerial attitudes will continue to play a substantial role.

Future Research and Implications

Future research could delve deeper into the connection between managerial strategies and technology-driven displacement (Thomas 1994), perhaps by studying how firms of different sizes implement the same type of technology. These findings indicate that high-mix, low-volume firms may be less likely to displace workers than low-mix, high-volume firms. Surveys across different types of manufacturers (Feller, Glasmeier, & Mark 1996; Bessen et al 2019; Leigh et al 2018) could explore this potential discrepancy. Future work could explore the extrinsic impacts of manufacturing automation at various regional scales, as well as the extent to which today's firms are automating to improve quality rather than productivity.

Considering both the technical challenges to full automation and firm owners' rational aversions to disruptive change, the SMEs in this study will probably remain a reliable source of jobs for the foreseeable future. Given these long-term job prospects, perhaps Ohio's industrial policies ought to focus more specifically on maintaining SME competitiveness, and supporting the regional industrial ecosystems in which these small firms and their largely irreplaceable workers tend to thrive (Berger 2013).

Acknowledgements

In addition to my dedicated professors and colleagues from the MIT Work of the Future Taskforce (mentioned in Footnote 1), I am indebted to Amy Glasmeier, Isadora Cruxen, Mariana Arcaya, Paul Osterman, and David Autor for their invaluable suggestions and ideas, in addition to my wonderfully critical colleagues Kevin Lee, Darien Williams, Silvia Danielak, Daniel Engelberg, and Maggie Yellen. Thanks to Paul Weaver, Edward Burnell, and Angela Acocella for fruitful conversations around manufacturing and ML. Finally, thank you to all the factory owners and workers in Ohio who introduced us to their world.

References

Acemoglu, D., & Restrepo, P. (2017) Robots and jobs: Evidence from US labor markets, *NBER working paper*, (w23285).

Acemoglu, D., & Restrepo, P. (2018) Artificial Intelligence, Automation and Work, No. 24196, National Bureau of Economic Research.

Allen, R. C. (2009) Engels' pause: Technical change, capital accumulation, and inequality in the British industrial revolution, *Explorations in Economic History*, *46*(4), 418-435.

Arntz, M., Gregory, T. and Zierahn, U. (2016) The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis, *OECD Social, Employment and Migration Working Papers*, No. 189, OECD Publishing, Paris.

Autor, D. 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, D. H., Levy, F., & Murnane, R. J. (2002) Upstairs, downstairs: Computers and skills on two floors of a large bank, *Industrial and Labor Relations Review*, *55*(3), 432–447.

Berger, S. (2013) *Making in America: From Innovation to Market*, Cambridge, MIT Press.

Bessen, J. E., Goos, M., Salomons, A., & Van den Berge, W. (2019) Automatic Reaction - What Happens to Workers at Firms that Automate? *SSRN Electronic Journal*, 1–61.

Brooks, R. (2017, October 6) The Seven Deadly Sins of AI Predictions, *MIT Technology Review.*

Brynjolfsson, E., & McAfee, A. (2014) *The second machine age: Work, progress, and prosperity in a time of brilliant technologies,* WW Norton & Company.

Bureau of Labor Statistics (BLS). (2017) *Employment by major industry sector,* United States Department of Labor, Washington DC, available from https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm.

Christensen, C. M. (2013) *The innovator's dilemma: when new technologies cause great firms to fail*, Cambridge, Harvard Business Review Press.

DiMaggio, P.J. and Powell, W.W. (1983) The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality, American Sociological Review, 48(2), 147-160.

Dore, R. (1973). *British Factory, Japanese Factory: The Origins of Diversity in Industrial Relations*, Berkeley, University of California Press.

Duhigg, C. (2018, December 13) Dr. Elon & Mr. Musk: Life Inside Tesla's Production Hell, *Wired*.

Ewick, P. and Silbey, S.S., (1998) *The common place of law: Stories from everyday life*, Chicago, University of Chicago Press.

Feller, I., Glasmeier, A., & Mark, M. (1996) Issues and perspectives on evaluating manufacturing modernization programs, *Research Policy*, *25*(2 SPEC. ISS.), 309–319.

Fernandez, R. M. (2001) Skill-Biased Technological Change and Wage Inequality: Evidence from a Plant Retooling, *American Journal of Sociology*, *107*(2), 273–320.

Frey, C. B., & Osborne, M. A. (2017) The future of employment: how susceptible are jobs to computerisation?, *Technological forecasting and social change*, *114*, 254-280.

Gibbons, R. and R. Henderson (2012) Relational Contracts and Organizational Capabilities, *Organization Science,* 23(5): 1350-1364.

Giffi, C. A., Wellener, P., Dollar, B., Manolian, H. A., Monck, L., and Moutray, C. (2018) Skills gap and future of work study, *Deloitte* and *The Manufacturing Institute.*

Glaser and Strauss (1967) quoted in Allen, N., & Davey, M. (2018) The Value of Constructivist Grounded Theory for Built Environment Researchers, *Journal of Planning Education and Research*, *38*(2), 222–232.

Glasmeier, A. K., Fuelihart, K., Feller, I., & Mark, M. M. (1998) The Relevance of Firm-Learning Theories to the Design and Evaluation of Manufacturing Modernization Programs, *Economic Development Quarterly*, 12(2), 107–124.

Glasmeier, A., & Salant, P. (2006) Low-Skill Workers in Rural America Face Permanent Job Loss, *American Psychology Society*, *14*(2), 243–246.

Hayes, R. H. (1985) Strategic planning-forward in reverse, *Harvard Business Review*, *63*(6).

Helper, S., & Henderson, R. (2014) Management practices, relational contracts, and the decline of General Motors, *Journal of Economic Perspectives*, *28*(1), 49-72.

Johnson, R. K. (illustrator) (2017, October 23) "Tech Support" magazine cover, *New Yorker*.

Kaber, D. B., & Endsley, M. R. (1997) Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety, *Process Safety Progress*, *16*(3), 126-131.

Leigh, N. G., & Kraft, B. R. (2018) Emerging robotic regions in the United States: insights for regional economic evolution, *Regional Studies*, *52*(6), 804-815.

Levinthal, D. A. (1997) Adaptation on rugged landscapes, *Management Science* 43(7): 934-950.

Mazmanian, M., Orlikowski, W. J., & Yates, J. (2013) The Autonomy Paradox: The Implications of Mobile Email Devices for Knowledge Professionals, *Organization Science*, *24*(5), 1337–1357.

Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015) The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?, *Journal of Economic Perspectives*, *29*(3), 31–50.

Mutlu, B., & Forlizzi, J. (2008) Robots in organizations: the role of workflow, social, and environmental factors in human-robot interaction, *Proceedings of the 3rd ACM/IEEE international conference on Human robot interaction*, pp. 287-294.

Noble, D. (1984) *Forces of production*, New Jersey, Transaction Publishers.

Ohio Manufacturers' Association. (2019) Ohio Manufacturing Counts, The Ohio Manufacturers' Association, retrieved from ohiomfg.com.

Oi, W. Y. (1962) Labor as a quasi-fixed factor, *Journal of political economy*, *70*(6), 538-555.

Paul, M. (2018) Don't fear the robots, Samuel DuBois Cook Center on Social Equity at Duke University and Roosevelt Institute joint paper, 4–7.

Piore, M., & Sabel, C. (1984) *The Second Industrial Divide,* New York, Basic Books.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A. and Chen, Y. (2017) Mastering the game of go without human knowledge, *Nature*, *550*(7676), p.354.

Simon, Herbert A. (1955) A behavioral model of rational choice, *The Quarterly Journal of Economics*, 69(1), 99-118.

Syverson, C. (2011) What Determines Productivity?, *Journal of Economic Literature*, *49*(2), 326–365.

Taylor, P.L. (2016, November 7) Why the Midwest Is About To Become America's Next Silicon Valley, *Forbes*.

Thomas, R. J. (1994). *What machines can’t do: politics and technology in the industrial enterprise*. Berkeley, CA: University of California Press.

US Census. (2017) Statistics of US Businesses, retrieved from https://www.census.gov/programs-surveys/susb.html.

Weiss, R.S. (1995) *Learning from strangers: The art and method of qualitative interview studies,* New York, Simon and Schuster.

Supplementary Materials

- *Exhibit A: Detailed Firm Selection Methodology and Results*
- *Exhibit B: Manufacturing Density in Ohio*
- *Exhibit C: Relevant Interview Questions and Methodology*
- *Exhibit D: List of Interview Codes*

Exhibit A: Firm Selection Methodology and Results

1. Initial firms were randomly selected from a database compiled by the US Small Business Association of several hundred "high impact" Ohio manufacturing firms with 20-500 employees—defined as "enterprises whose sales have at least doubled over [the period of 2004-2008] and which have an employment growth quantifier of two or more over the same period" (Tracy 2011, pg. 19). In addition to including our subset of firms for re-interview, this selection limited our scope to firms that were competitive prior to major economic impacts such as the 2007-2009 financial crisis—with the expectation that these firms may have more successful practices for adopting novel technologies and retraining workers appropriately.
2. We narrowed down these firms to select "Primary Metal Manufacturing," corresponding to NAICS category 331.
3. We eliminated all firms with fewer than 20 employees or more than 500 employees, to focus specifically on small and medium enterprises which are larger than mom-and-pop artisanal firms.
4. We selected the firms my colleagues had previously interviewed, and then added 43 randomized additional firms by choosing every tenth firm from an alphabetized list of 300 eligible firms across Cuyahoga County. These firms came from a 2017 database compiled by YourEconomy of all Ohio metalworking firms in the state, though we narrowed our geographic selection of new firms to maximize interview time and avoid excessive travel.
5. We contacted the firm owners of all these firms via email, phone, and/or mail. For our first set of interviews, about a quarter of owners responded. Several firms declined our request and stated that they had not introduced new technological equipment, so we suspect some of the accepting firms may have self-selected. (Firms that operate

within less competitive sectors may not be up-to-date on modern technologies, as Karshenas & Stoneman (1993) found in their UK study.) We scheduled interviews with 13 of the 43 new firms.

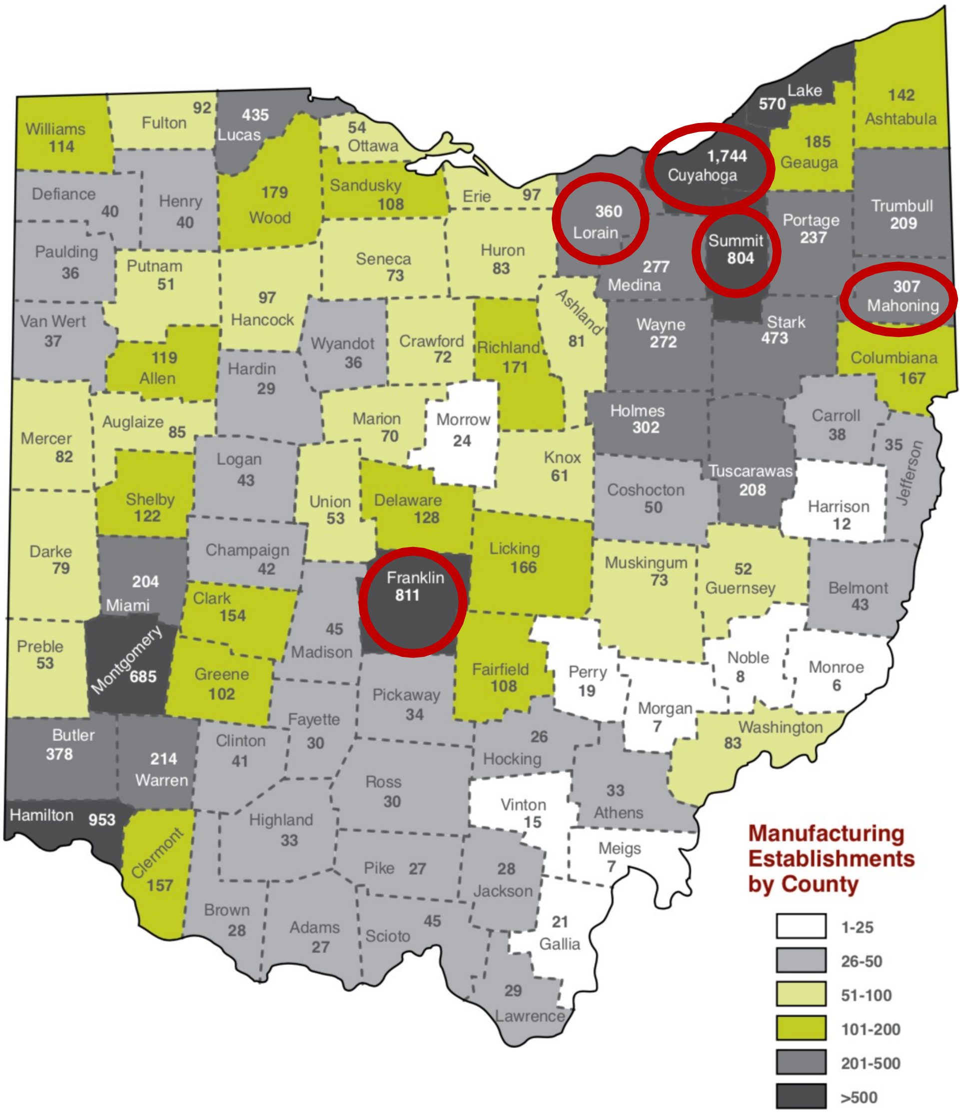
6. We set up interviews with all responding firm owners who were also available to meet over the period of our January and March trips to Ohio. We requested factory tours as well as group interviews with workers in charge of new technology integration.

Our research team interviewed a total of 21 manufacturers and 14 related institutions:

1. On-site interviews with 11 regional manufacturing-related institutions, and phone interviews with 3 institutions, selected through snowball sampling
    a. Including 1 regional labor union, 1 policy think tank, 2 community colleges, 2 universities, 3 government-funded manufacturing consultancies, and 2 regional associations
2. On-site interviews with 21 metal fabricators in Ohio, selected through a semi-randomized process
    a. Including 2 large firms and 19 SMEs
    b. Including 11 re-interviews and 10 new firms
    c. We toured 13 factories

Exhibit B. Manufacturing Density in Ohio

Our interviews all took place within the counties of Franklin, Lorain, Cuyahoga, Summit, and Mahoning (image via Ohio Manufacturers' Association 2019).



Source: 2016 County Business Patterns

Exhibit C. Interview questions and methodology

Each interview was conducted by two to four researchers, including if possible (in the case of re-interviews) the original researcher who visited the firm in 2012. To approach the question of worker replacement from an indirect angle (given its politically-charged nature), we asked instead about productivity increases, economic benefits, and how improvements were measured. Discussions were not recorded, but all researchers present took detailed notes and wrote frequent direct quotes to best capture the interviewees' phrasing and intentions. Within two days of conducting an interview, a lead interviewer summarized the interview into a three to five-page synoptic memo, and other attending researchers added their own notes to create a comprehensive document for each organization visited. Occasional differences of interpretation were reconciled through discussion among attending interviewers and emailed questions to interviewees. Copies of the interviews were filed on a secure wiki database at MIT.

Relevant interview questions for firm owners

Introduction: Interviewer describes the WotF Project in general, and says a bit about what we are hoping to get out of the interview.

"We are conducting a study of the impact of new technologies in manufacturing . We are interested in the experience of companies that have introduced new technology over the past 5 years. We are interested in how a company decides to bring in a new technology; we would like to know what new skills were required to bring the new technology on line and how and where those skills were acquired; and, in general, in the kinds of changes in a company's organization and workforce that are set in motion with the introduction of these technologies…"

Company History

For re-interviews, skip the general questions about company information five years ago. Instead, ask targeted questions about specific technologies identified by previous researchers.

“First we’d like to just understand a bit about your company...” Rapport-building; background questions on the firm and interviewee’s role within the firm. Ask some basic questions about changes to the firm in the past five years (e.g., “How many employees are there right now? How many were there five years ago?”). Get the interviewee used to thinking about changes within this five-year period.

“What are the principal products made by the company? 5 years ago? Today. Who were/are the principal customers of the company—5 years ago? Today. Roughly what proportion of the business are done with your top customers? Principal competitors? Your competitive advantage?”

“What’s your average batch size, and your overall volume for product per day/week? How often do you rotate between products? How large is your product catalogue? Do you do a lot of customized production?”

“How many full-time, or ‘core’ employees, does the firm employ?”
“What were those numbers like five years ago; has anything changed?”
“Are there any temp workers—if so, how many are there?”
“How does that number vary over the year? Over time?”

“Do you hire temp workers directly or through an intermediary agency; on your own payroll or by contract with the agency? Do you employ contract workers?”
“If so, in what kind of jobs and with what kinds of contracts?”

“What is the age range of your core workers? Of temps?”
“What is the turnover among our regular employers?”

“Can you tell us about the backgrounds of your employees—what kind of training they had prior to joining the firm, where they went to school, etc.?”
“What proportion of your employees have this type of training before joining the firm?”

“When you need to hire new employees, how do you find them?”

“If you had (or when you have) a job vacancy which is unfilled, how do you manage that—is the work covered by other workers? Does it simply not get done? Are you late in delivery orders? Do you turn down orders? Etc.”

Uptake of new technologies within the firm.

“Can you take us through a few of the most important new technologies that you have introduced over the past five years—so from roughly 2013-2018? [Go through all of these questions for each of the technologies]

(1) “How did the firm actually incorporate the technology into its production line—did you receive any external assistance in doing so, like using an integrator? Any outside funding for this?”
    a. “Where in the business is this technology used: production, testing, prototyping, etc.? Do you expect it to be used in other business activities in the future?”
    b. What specific tasks does this technology perform? How were each of those tasks performed before you got this new equipment?

(2) “With respect to the workforce: before the intro of the new technology, who used to do this work? What kind of skills did they have? Who does this job now? Skills required? How do they acquire them? What are the original workers doing now?”

“How has the use of this technology changed employees’ tasks or roles at the firm?”
“What has the response been to this new technology on the part of employees—have they reacted positively? Negatively?”
“How many people are needed to operate this new technology?”

“What kinds of training do you provide your employees?”

“What kinds of specific skills does it take to make effective use of [technology previously mentioned]?”
If struggling to think of specific skills:

"For example, does operating this piece of equipment require software skills?

"Reading/communicative skills?"

"Quantitative skills—do people need some basic abilities in math?"

Other technologies: Questions focusing on technologies that have not previously been discussed. These questions will need to be tailored somewhat specifically to each firm. For example, if the firm is generally known to be doing a lot of prototyping, we will want to ask about 3D printing.

"Has your firm used or considered using______in your production processes?"
(robots, collaborative robots ['cobots'], 3D printing, sensors, automated vehicles, or other forms of automation)

"Is the firm considering taking up any of these new technologies in the near term—say, within the next three to five years?"

"What are some of your considerations in deciding whether or not to incorporate these technologies?"

Ecosystem:

"Finally to wrap up: we'd like to know whether any outside organizations have assisted in this process. First—in learning about the new technology—did you work with any organization? organizations like community colleges, or unions, or the manufacturing extension program (MEPs or MAGNET) or training centers, the U.S. Employment Service, etc. If yes: What has your experience been building out skills with this partnership?"

"Can you tell me about one particular instance in which you worked with this institution?"

"Did you turn to external institutions in looking for capital to pay for the new equipment we've discussed?"

"Does your firm collaborate with other firms or institutions, or use any shared space or facilities?"