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Manufacturing on Autopilot: Ohio Automation on Manufacturing Wages and Employment

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Abstract

In 2017, automation was forecasted to see a 47% increase in the next two decades (Bughin et al. 2017). With the usage of algorithms, automation can now be used for more than routine tasks and has the ability to replace labor in cognitive tasks, greatly expanding the range of roles in the labor market it could take on (Frey et al. 2017). With this, there will be the subsequent impacts on Ohio's economy and productivity levels in manufacturing and productivity. Ohio is a main state in manufacturing, and 7.6% of Ohio jobs have a high level of exposure to automation (Exposure to Automation in Ohio 2021). We use data from the Bureau of Labor Statistics to create initial data visualizations on Ohio's manufacturing employment. Through this initial research, we hypothesize a negative correlation between robotic expenditures and manufacturing employment and wages. However, in the future, we hope to run regressions with variables such as robotic expenditures and robot count using data from national manufacturing surveys.

Literature Review

A Dive into Automation

McKinsey Global Institute produced a report in January 2017 that analyzes how these technologies' could automate current labor tasks and impact workforce productivity. Specifically, labor costs that can be associated with work that's more prone to automation will be decreased within the labor markets. If human-preformed labor tasks are automated, supply will increase and could be redeployed to other roles if demand allows. One of the key types of automation replacing human labor are robots. The paper "Robots and Jobs: Evidence from U.S. Labor Markets" from NBER says there is little evidence of the equilibrium impact of robots on employment and wages. The study estimates the equilibrium impact of one type of industrial robots on U.S. labor markets, utilizing data from the International Federation of Robotics. The authors discuss the outcomes of the displacement and productivity effect. They utilize the measure of exposure to robots using data from the IFR on the increase in robot usage in 19 industries and Census data for employment shares.

Economists Carl Benedikt Frey and Michael A. Osborne released a paper in 2017 and found the pace of technological innovation is increasing, and more sophisticated technologies are making laborers redundant. Frey and Osborne highlight that automation and computerization, historically, were used for routine tasks, but, now with algorithms, it can replace labor in cognitive tasks that are not limited to routine, expanding the range of roles in the labor market it could take on. In turn, Frey and Osborne provide evidence that wages and educational attainment exhibit a strong negative correlation with the probability of automation and computerization. McKinsey displays models showing that some of the key hinderings of implementation are the lag in developed technology and the ability to implement it into workable products. They reference the past implementation rates of 25 previous technologies in hardware, software and business and consumer technologies, finding that the timeframe between commercial

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availability and widespread (90%) implementation ranges from 8-28 years; for a rate of 50% implementation, this timeframe ranges from 5-16 years. The researchers then incorporated these historical examples into S-shaped curves, concluding that implementation of automation technologies will depend on several factors, such as overcoming public policy barriers. They note that the modeled timeframe for physical activities (those that are labor-intensive) is longer in emerging economies because of lower wages compared to the cost of hardware-based automation solutions, and the pace of robotic implementation will differ in the development level of economies and the type of activity of it.

Exposure to Automation in Ohio

According to the Ohio Department of Job and Family Services, for 2018 employment, 7.6% of Ohio jobs have a high level of exposure to automation. This is slightly lower than the 8.1% average in the U.S. However, 35.4% of Ohio jobs have a moderately high level of exposure to automation compared to the 32.3% average in the U.S. Those with education at a high school or less than high school level has the highest exposure to automation on occupation. It is projected that there will be employment growth of 6.2% for low exposure occupations and decrease in employment growth of 2.7% for high exposure occupations. There are projected to be 263,389 annual openings in Ohio for jobs. In the 2018 paper, “Manufacturing a High-Wage Ohio,” by Michael Shields, manufacturing employed about 12.9% of the state’s workers at the time of publication. Not only was Ohio a state with a large manufacturing employment rate, average sector wages in 2016 were $59,000 per year, exceeding other sectors by $11,000. However, Shields doesn’t account for the gender wage gap in this statistic, and this is also pre-pandemic.

2023 research from Policy Matters Ohio discusses that while Ohio has restored the number of jobs lost to the pandemic, that recovery was confined to only Columbus, Cincinnati, Springfield, and Dayton — metro areas with significant job growth. This research also found rising tensions between laborers and those overseeing the labor in the forms of wage negotiation, childcare and work-from-home flexibility. They saw pay growth was limited to low-wage jobs. However, this pay increase wasn’t enough to reverse inequity between more and less privileged workers, saying that low wages especially harm workers of color, women, and migrants — all of whom are more likely to be underpaid. While outlining the current effects of the pandemic on Ohio’s labor market, they cannot yet conclude if these issues will become structural changes to the workforce.

Initial Data Visualizations and Analysis

Overall, there’s an observable downward trend in employment in manufacturing in Ohio from 2000-2024, suggesting a long-term decline in manufacturing due to automation or a shift in economic structure. In 2007-2008, there’s a sharp decline in employment that aligns with The Great Recession, and the market slowly recovered. Another sharp decline is noticeable in 2020 due to the COVID-19 lockdowns and supply chain disruptions. However, employment levels in manufacturing recovered significantly faster than they did post-recession. Since 2020, there’s been some fluctuation due to the volatility of the market and the changes in interest rates. As highlighted with the general trend line, employment in manufacturing has been declining for the past two decades.

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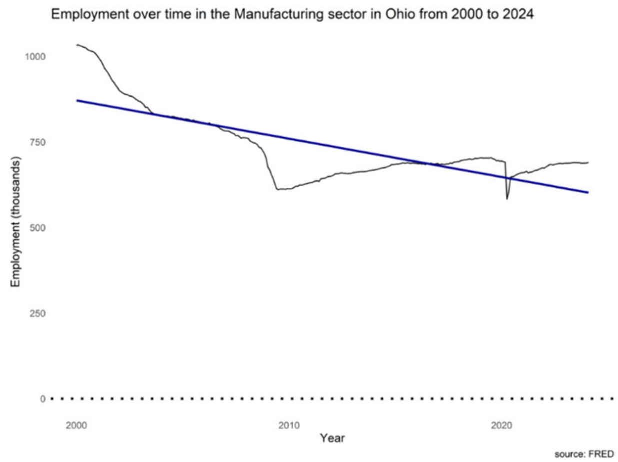
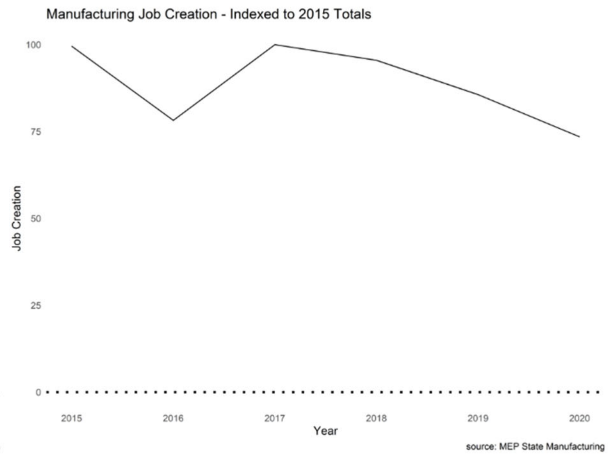
Figure 1. (left) Employment count of Ohio's manufacturing sector from 2000 to 2024; **Figure 2.** (right) Job creation within Ohio's manufacturing sector from 2015 to 2020





Analyzing the trend of manufacturing job creation in Ohio from 2015-2020, as indexed to the 2015 baseline, we observe an initial uptick in job numbers from 2015-2016, suggesting a period of growth or resurgence in the manufacturing sector. However, the trend reverses after peaking in 2017, with job creation entering a consistent decline through to 2020. This steady decrease, particularly after a year of growth, indicates a shift in the sector's employment landscape. The reasons behind such a shift could range from economic policy changes to industry-wide restructuring, but the data distinctly shows that from 2017 onward, the number of manufacturing jobs being created each year was falling.

The impact of automation on manufacturing in Ohio seems to align with the broader narrative of technological advancement leading to the reduction in traditional manufacturing roles. The decline in job creation post-2017 points towards the integration of automation systems that can perform tasks previously done by human labor. This can lead to a decreased demand for traditional manufacturing roles and could potentially push the sector toward a more technology-oriented workforce. The consistent downturn in job creation in the years following the peak suggests that manufacturing facilities may have increasingly adopted automated solutions, possibly reflecting a state-wide pivot towards embracing these efficiencies, despite the potential impact on job numbers.

Future Steps

Hypothesis and Literature Review

After analyzing general trends of employment in the manufacturing industry for Ohio, we have a strong structure to use an econometric model to determine the correlation between automation on manufacturing employment. We hypothesize robotic expenditures are negatively correlated with Ohio manufacturing and employment jobs based on our initial literature review and data exploration. Robots in the manufacturing industry are sometimes employed as substitutes and complements. We hope to dive deeper into whether the substitution and income effect for employees and robots can deduce a determinant outcome for employment and wages.

We will conduct a detailed literature review of "The Work of the Future Building Better Jobs in an Age of Intelligent Machines" by Autor, Mindell and Reynolds which is about the cumulation of economic literature on automation. We will also conduct additional literature reviews on papers including Helper, Martins & Seamens (2019), Autor (2022), Acemoglu, Lelarge & Restrepo (2020), and Feigenbaum & Gross (2020)

Methodology

The Annual Survey of Manufactures and Annual Capital Expenditures included survey questions on robotic equipment in 2018 which has data on "industrial robotic expenditures, the number of new robots purchased, and the total stock of robots in operation." This data is restricted by time especially due to the COVID-19 pandemic in 2020. We would use this data to correlate the change in robots with employment while controlling for industry. We would run regressions on three variables.

$$firm\_employment_{i,t} = \beta_0 + \beta_1 percent\_robotic\_exp_{it} + z_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$
$$wages = \beta_0 + \beta_1 percent\_robotic\_exp_{i,t} + w_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$

Where:
Θ_i , Θ_t: industry and time fixed effects ; $z_{i,t}$: other controls for employment; $w_{i,t}$: other controls for wages

We use total employment and average wages of a firm from years 2018-2019. The main regresser is the percentage of total firm expenditures that are robotic expenditures. We control for the firm's industry and time fixed effects. We would brainstorm potential controls that impact the firm employment and average wages for $z_{i,t}$ and $w_{i,t}$ respectively. This regression will allow us to analyze the average change in firm employment and wages associated with a one percentage point increase in robotic expenditures as a share of total expenditures holding constant time, firm industry and $z_{i,t}$, $w_{i,t}$.

$$firm\_employment = \beta_0 + \beta_1 new\_robots_{i,t} + \beta_2 total\_robots_{i,t-1} + z_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$
$$firm\_employment = \beta_0 + \beta_1 new\_robots_{i,t-1} + \beta_2 total\_robots_{i,t-1} + z_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$
$$wages = \beta_0 + \beta_1 new\_robots_{i,t} + \beta_2 total\_robots_{i,t-1} + w_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$
$$wages = \beta_0 + \beta_1 new\_robots_{i,t-1} + \beta_2 total\_robots_{i,t-1} + w_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$

The main regresser in these regressions is new robots purchased this year. We control for the firm's industry and time fixed effects, total robots from the previous year and additional controls that impact employment and wages. We also add a lag for new robots purchased to account for robotic implementation time, as it might take longer to set up larger robots and train employees for full functionality. This regression would allow us to analyze the average change in firm employment and wages associated with one new robot purchased holding constant total robots from the past year, time, firm industry and $z_{i,t}/w_{i,t}$.

$$firm\_employment = \beta_0 + \beta_1 total\_operating\_robots_{i,t} + z_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$
$$wages = \beta_0 + \beta_1 total\_operating\_robots_{i,t} + w_{i,t} + \Theta_i + \Theta_t + \varepsilon_{i,t}$$

The main regresser in these regressions is total operating robots for the firm. We control for the firm's industry and time fixed effects and additional controls that impact employment and wages. This regression will allow us to analyze the average change in firm employment and wages associated with one additional robot in operation holding constant time, firm industry and $z_{i,t}/w_{i,t}$.

By running these regressions, we hope to find robotic expenditures and the number of robots in operation have a negative correlation with firm employment and average wages.

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